Opening the Black-Box of Managerial Talent*

Audinga Baltrunaite Giulia Bovini Sauro Mocetti
Bank of Italy†

January 24, 2020

Abstract

This paper studies the role of managerial talent in determining corporate performance. For this purpose, we build a matched firm-director panel dataset for the universe of limited liability companies in Italy, tracking directors across different firms over time. We measure managerial talent by their ability to boost firms' total factor productivity, estimated with a two-way fixed effects model. First, we find that managerial talent influences a number of corporate features conducive to positive firm performance. Namely, we show that talented managers are better able to forecast the firm performance; they diminish their middle-management layers and move towards highly-skilled workers at all organization levels; they are also associated with the adoption of good managerial practices and advanced technology. Second, and more importantly, we find complementarities between managerial ability and the other key internal drivers of productivity. While the workforce human capital, the use of good managerial practices and the adoption of new technologies do boost firm productivity on their own, there are synergies between each of them and the presence of talented management. Overall, our results indicate that able leaders are valuable to the firm not only because of good decisions they make, but also because of how such decisions are put in practice.

Keywords: Board of directors, corporate governance, productivity, managers, managerial practices, human capital, technology.

JEL classification: G34, L20, M10, D24.

*The paper was previously circulated under the title "Directors' Talent and Firm Productivity".

†We thank Matteo Bugamelli, Federico Cingano, Jan Eeckhout, Mike Elsby, Silvia Giacomelli, Patrick Kline, Enrico Moretti, Paolo Sestito, Eliana Viviano and participants at the Bank of Italy seminar (Rome, April 2019), Petralia Applied Economics Workshop (Petralia, Juy 2019), 34th Annual Congress of the European Economic Association (Manchester, August 2019), 34th Italian Conference of Labour Economics (Novara, September 2019), research seminar at UC Berkeley (Berkeley, October 2019) and "Recent trends in firm organization and firm dynamics" conference (Rome, December 2019). 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 productivity differences among firms are strikingly large (Melitz, 2003; Syverson, 2011).[1] Recent literature argues that such heterogeneity may be determined by management quality, both in terms of people who manage the firm and practices adopted within the firm (Bloom and Van Reenen, 2010; Syverson, 2011; Gibbons and Henderson, 2013). Yet, very little is known about managers' role within internal firm organization and the ways they influence firm performance.

In this paper we combine unique administrative and survey data on firms and their managers to open the black-box of the role of management quality in explaining the firm-level variation in total factor productivity (TFP henceforth). First, we analyze what talented managers do to boost firm productivity by examining a broad range of corporate decisions conducive to positive firm performance, such as recruiting skilled workers, using structured managerial practices or adopting advanced technology. Second, and more importantly, we shed light on the existence of complementarities between good managers and these efficiency-boosting firm organization features.

In order to measure managerial talent, we build a matched firm-director dataset covering the universe of the non-micro limited liability companies in Italy and identities (and personal characteristics) of their directors.[2] Our dataset covers the period 2005-2017, tracking directors across different firms over time. Directors are similar to plant managers for firms in our sample, whose average size is 66 employees (nearly 80% of firms have less than 50 employees) and, hence, we interchangeably use the terms *directors* and *managers* throughout the paper. Our proxy for managerial talent is based on the director fixed effect in a two-way fixed effects model - inspired by the work of Abowd et al. (1999) - and represents the individual contribution to the variation of the firms' TFP, conditional on firm fixed effects and sectoral and geographical non-parametric time trends. The average of the estimated manager fixed

[1] In a typical four-digit manufacturing industry in the U.S., establishments at the 90th percentile of total factor productivity distribution make almost twice as much output with the same inputs as plants at the 10th percentile (Syverson, 2004).

[2] We exclude firms constantly below the 10 employees threshold over our temporal window.

effects at the firm level is, therefore, our measure of its management talent.

We find that management talent matters for firm productivity, which rises when a better manager takes charge. The estimated impact is sizable: a one standard deviation change in management talent leads to about three fourths of a standard deviation variation in the firm performance. Including management talent in a regression of firms' TFP on firm-fixed effects increases the predictive power of the model by 19% (adjusted R-squared rises from 0.53 to 0.63). This impact is in the ballpark of the estimates obtained by previous studies (Bertrand and Schoar, 2003; Graham et al., 2012).[3] We also find that the role of the management varies across firm types and across different contexts in which they operate. Namely, the impact grows with firm size and age (and, arguably, the complexity of organizational processes to be managed within the firm) and it is larger in firms exposed to higher competition (e.g., in more agglomerated areas or in sectors more exposed to international trade).[4]

We then use our measure of managerial talent to study what good managers do to boost firm performance, as well as to shed light on complementarities between managerial talent and other key drivers of firm productivity. First, we find that managerial talent comes along with a number of corporate features conducive to positive firm performance. Talented managers appear to possess a more accurate set of information regarding current and future performance. More precisely, we show that our measure of managerial ability is associated with lower forecasting error. Better-informed decisions by talented managers, in turn, might imply a better use of the productive inputs.[5] Indeed, we find that firms with talented leadership downsize their middle-management and move towards high-skilled workers at all

[3]The estimation of managerial talent via a high-dimensional two-way fixed effect model relies on the assumption that sorting of directors into companies is as good as random, conditional on firm time-invariant characteristics and other observed covariates. The empirical tests of this assumption lead to a conclusion 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. Yet, there is some evidence of sorting based on the trend component of productivity, thus suggesting that our estimates of the contribution of managerial talent to a firm TFP could be slightly overstated in levels.

[4]These results mirror those found in Bloom and Van Reenen (2010) with reference to the managerial practices.

[5]Malmendier and Tate (2005) and Ben-David et al. (2013) show that managerial overconfidence and miscalibration can account for significant corporate investment distortions.

organization levels. Moreover, we find that talented managers are more likely to adopt good managerial practices and introduce advanced technologies within the firm. The above-mentioned results are in line with what a good manager is expected to do. Therefore, on top of being interesting themselves, these findings are largely reassuring about the presence of informational content in our managerial talent measure.

Second, we examine complementarities between managerial talent and the other key internal drivers of firm productivity. While high-skill workforce, use of managerial practices, adoption of innovation and technology do boost firm productivity on their own, there is evidence of the positive interaction between each of them and managerial talent. Namely, the positive impact of the share of workforce with a college degree doubles when moving from a firm at the 25th to one at the 75th percentile of board talent, suggesting that good managers are more capable of exploiting the workforce skills and allocating them efficiently within the firm. An effect of similar size is estimated on the interaction between managerial talent and the managerial practices score. It suggests that while there are some practices that are in principle always better (e.g. to promote and reward competent employees, or to collect some information before making decisions), these practices are even more efficiency-enhancing 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). Finally, while the adoption of advanced technologies coincides, on average, with an increase in the firm TFP, the impact is significantly higher when the firm is run by talented management.

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.[6] Other studies

[6] 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. (2012) 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

exploit a similar strategy to identify manager fixed effects within a single firm or organization: Lazear et al. (2015) use data from a large services company; Fenizia (2019) relies on data from the Italian Social Security Agency. Instead of focusing on manager fixed effects, other related studies investigate the role of managers' 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; and Bandiera et al. (2020) 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.[7]

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 Bloom and Van Reenen (2010) contain a comprehensive analysis of 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.

Beyond managerial practices, Syverson (2011) identify other crucial "levers" of productivity under the control of the management. They include the quality of productive inputs, in particular in terms of human capital of the workforce, and the adoption of innovation, in particular in terms of new technologies.[8] Interestingly, several papers have documented the existence of complementarities between these internal drivers of productivity and, in particular, between the adoption of information technology, human capital of the workforce and

correlated with manager fixed effects estimated in the regression of firm outcomes.

[7]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.

[8]See Bugamelli et al. (2018) for a deeper discussion of internal and external drivers of firm productivity in Italy.

managerial and workplace practices (Brynjolfsson and Hitt, 2000; Black and Lynch, 2001; Bartel et al., 2007; Aral et al., 2012; Bloom et al., 2012).[9]

Our paper contributes to the existing literature along three main directions. First, concerning the measure of managerial talent our paper is close to Bertrand and Schoar (2003) and to the subsequent papers based on a similar two-way fixed effect model. We extend their analysis by exploiting additional sources of variation due to board interlocking and, more importantly, by using a larger and more representative sample of firms. Indeed, the empirical evidence on the importance of managers for firm performance is typically based on small and not representative sample of firms: Bertrand and Schoar (2003) base their analysis on the sample of 500 CEOs of large publicly traded companies; Lazear et al. (2015) and Fenizia (2019) focus instead on a single large firm operating in service or public sector, respectively, with the sample size limited to several hundred individuals.[10] The larger sample size allows us to explore the role of managers' quality also for smaller firms and to examine heterogeneous effects across different categories of firms.

Second, 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 talented managers are more likely to take more informed decisions. Unsurprisingly, businesses led by more capable management improve the quality of productive inputs and upgrade the workplace organization and practices. Our results complement and extend those obtained by Bender et al. (2018) and Cornwell et al. (2019) who show that firms adopting better management practices hire and retain better workers, and fire more selectively.

Finally, we examine the complementarities between managerial talent and other internal levers of firm productivity, such as human capital of the workforce, use of managerial practices and technology adoption, bridging the gap between different strands of literature

[9]See also Brynjolfsson and Milgrom (2013) for a more detailed discussion of the theoretical and empirical evidence on complementarities within organizations.

[10]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 U.S., the U.K., France, and Germany, while Bloom and Van Reenen (2010) - of around 6000 large firms in 17 countries worldwide.

that have examined these factors separately.[11] Previous literature shows that the same "best practice" or innovation may produce heterogeneous results across firms, possibly due to the presence of complementarities among production inputs. Indeed, the success of a practice or innovation crucially depends on the other organizational features in which it is embedded (Brynjolfsson and Milgrom, 2013). Our results show that talented managers - the actors responsible of these organizational choices - are able to extract more value added from the similarly skilled workforce, the same managerial practice and the same technological innovation. Therefore, they are valuable to the firm not only because of good decisions they make, but also because of how they are put in practice.

The structure of the paper is as follows. Section 2 describes the data and institutional context. Section 3 discusses the construction of our measure of managerial talent. Section 4 sheds light on managerial choices taken by talented leaders. Section 5 examines complementarities between managerial talent and other drivers of productivity within the firm. Section 6 concludes.

2 Data and institutional context

The analysis relies on three main datasets. First, we use the *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 and directors, i.e., name, surname and personal identification code. We use this information to identify the governance structure and the age, gender and place of birth of the directors.

Corporate governance structure of Italian privately-held limited liability companies is freely decided by their stockholders. Key corporate decisions may be concentrated in the

[11] One notable exception is Bender et al. (2018) who examine complementarities between managerial practices and managers, although the latter are not directly observed and proxied with the employees at the top quartile of the skill distribution.

hands of a single director (*amministratore unico*) or granted to a collegial governance body, i.e., the board of directors (*consiglio di amministrazione*).[12] An average (non-micro) Italian company is lead by a board of directors, usually composed of two or three members (Baltrunaite et al., 2019). A typical director is an Italian 50-year-old male, born in the province where the firm is located. Females and young individuals are the two demographically underrepresented groups, accounting for, respectively, roughly one fifth and one tenth of all board members.

Second, we use the database managed by the *Cerved Group* which gathers balance sheet information of the universe of the Italian limited liability firms. The dataset includes the value added and the revenues of the firm, its productive inputs and other anagraphic information such as firm's age, sector of economic activity and the municipality where the headquarter is located.[13] We use balance sheet information to compute the TFP using the Levinsohn and Petrin (2003) estimator with the Ackerberg et al. (2015) correction. Our main sample comprises all the firms included in the intersection of the *Infocamere* and *Cerved* databases for the years from 2005 to 2017 (the longest available panel for both datasets) for which there are available data to compute measures of firm performance. We consider firms in the private-non financial sector and we exclude from the analysis the micro-firms (i.e. firms with less than 10 employees).[14]

Third, 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 for a representative sample of firms with at least 20 employees. In particular, it includes granular

[12]Director appointments are essentially unregulated - there are no restrictions regarding directors' independence, their stock ownership, previous experience or education.

[13]For obtaining information about firms' employees, we have also used firm-level data drawn from the *INPS* dataset, which contains the distinction between (middle) managers, white- and blue-collar workers and their corresponding monthly wages. This enable us to construct also efficiency units as alternative to total employment at the firm level, giving different weights to (middle) managers, white- and blu-collar, with weights being proportional to the relative wage premia.

[14]Micro-firms are nevertheless exploited in the estimation of the directors fixed effects insofar they are connected via a manager with any of larger companies.

measures of a firm's productive inputs (i.e., the composition of the workforce) and firm's forecast about future performance. Moreover, the 2010 wave contains several questions on the share of the workforce with a college degree and on the adoption of managerial practices within the firm (i.e., the presence of team work, performance pay, and employees' involvement in the decision-making within the firm). Finally, the 2017 wave contains a special section on the adoption of advanced technology and, in particular, artificial intelligence and big data, internet of things, robots, and 3D printing.

3 Our measure of managerial talent

Measuring managerial talent is crucial to our empirical analysis of what talented directors do. Good manager characteristics reflect observable (and, ideally, observed) personal traits such as education, qualifications or previous experience, but do likely comprise also those unobserved, such as ability, charisma or leadership skills. Throughout the paper, we define as talent the individual portable and time-invariant contribution that a director brings to the TFP of the firm that she/he runs. Given this definition, the talent can be captured by the director's fixed effect in a regression that explores the determinants of firms' TFP. The idea that the talent of prominent actors in an organization can be measured by fixed effects is present in the seminal work of Bertrand and Schoar (2003) on the role of top managers' identities on corporate policies of U.S. largest companies. More recently, it has been exploited in other settings by Graham et al. (2012), Lazear et al. (2015), Best et al. (2019) and Fenizia (2019).

3.1 Connected set of firms and directors' mobility

In our analysis, we attempt to estimate directors' and firms' fixed effects separately. As shown by Abowd et al. (1999) (AKM, henceforth), this can be done insofar as there are directors who hold a seat in multiple firms, either in the same year or over time.[15] The

[15]The AKM method was first 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

existence of such directors allows to separately estimate directors' and firms' fixed effects within each set of firms that are connected via directors' mobility and interlocking.

We observe more than 750,000 directors of nearly 300,000 limited liability companies in our panel. About one fifth of the directors in our sample are 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 or due to switching (i.e., the same manager moves from one firm to another over time). As shown in Figure 1, about 11% of the directors sit every year on boards of two different firms (9% in two firms, nearly 3% in three or more firms). Moreover, every year about 6% of the directors exit from or enter into the board of a firm. In our sample period, about 15% of the directors move at least once (more than 7% at least twice).[16]

In our analysis, we focus on the largest connected set of firms. This set includes more than 30% of the universe of the firms and almost 40% of the universe of directors. Table 1 displays the observable characteristics of directors, separately for movers and non-movers, in the universe of the Italian limited liability companies (columns 1-2) and in the largest connected set of firms (columns 4-5). Columns 3 and 6 show whether differences between movers and non-movers within each of the two samples are statistically significant or not. Among the directors, nearly 80% are male and the corresponding figure is even larger among movers, indicating that men are more often involved in managing more than one firm. Furthermore, directors in the movers sample appear to be more often native Italians, born outside the province in which the firm is located and slightly older. The differences between mover and non-mover directors in the largest connected set are similar to those in the entire sample for most of the variables.

Table 2, columns 1 and 2 display the observable characteristics of firms in the largest connected set and other firms, respectively, while column 3 shows the test of statistical

method to explain the drivers of the increasing wage inequality observed in West Germany.

[16]We provide additional information on the labour market of corporate directors in Appendix A.1.

significance of the difference between the two samples. Firms in the largest connected set are larger: the average size is 66 employees against 20 in other firms. Figure 2 illustrates the distribution of firms by their size. The left panel shows that the majority of firms in the largest connected set are small, representing 79% of the total (medium-sized and large firms, respectively, correspond to nearly 18% and 4% of the total). Importantly, the right panel shows that the largest connected set is more representative of the universe for medium-sized and large firms, as it contains 61% and 85% of the total in these categories. Moreover, Table 2 reveals that firms in the largest connected set are also older and less likely to be located in Southern Italy, suggesting that firms' networks, defined in terms of their directors' linkages, are seemingly more dense in Northern and Central Italy. Finally, firms in the largest connected set are more often managed by a board of directors, whose average size is around three.

3.2 Estimation

The largest connected set consists of N firms and each firm i is observed over T_i years. We have therefore an unbalanced panel of $T = \sum_{i=1}^{i=N} T_i$ firm-year observations. In each year t a firm i is run by one or some among J directors, whose identities are known to us. This allows us to estimate the following high-dimensional two-way fixed effect model:

$$y = F\alpha + D\psi + X\beta + \varepsilon \tag{1}$$

y is a $T \times 1$ vector whose j-th element is the TFP of firm i in period t;[17] F is a $T \times N$ matrix that collects firm dummies; D is a $T \times J$ matrix that collects directors dummies; X is a $T \times K$ matrix of year dummies (with $K = 13$ in our setting); ε is the $T \times 1$ vector containing the error terms.

The OLS estimation of equation (1) provides a meaningful estimate of the coefficients ψ of interest as long as directors do not systematically sort into firms based on factors that are not observed by the econometricians and are thus included into the error term. As specification

[17]We use a measure of TFP that has been purged of sector-year and province-year fixed effects.

(1) features firm fixed effects, sorting based on companies time-invariant characteristics would not constitute a threat to identification. Following Card et al. (2013) we assume that the error term is composite and captures three forms of endogenous mobility: first, mobility patterns that depend on the idiosyncratic component of the firm-director match; second, mobility patterns based on the drift/trend component of firm TFP; third, mobility patterns that arise as a response to the transitory component of firm TFP. This amounts to assuming 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.

Figure 3 shows the distribution of directors' and firms' fixed effects, estimated based on specification (1). Both sets of fixed effect display a considerable dispersion, suggesting that there is substantial variation in directors' talent and firms' efficiency.[18] After estimating individual fixed effects, we derive our measure of time-varying managerial talent available to the firm q as the average of its director fixed effects in any given year. We therefore compute:

$$q_{it} = \sum_{j \in J_{it}} \psi_j \tag{2}$$

where J_{it} is the set of directors who run firm i in year t.

We then explore in Table 3 how much our measure of managerial talent available to the firm explains the variation in TFP. We begin by estimating a parsimonious model that only features sector-year and province-year fixed effects (column 1) and has a considerably low explanatory power. The model which adds firm fixed effects in column 2 has the adjusted R^2 equal to 0.53. In column 3 we further include the average observable board characteristics (i.e., gender, age, share of foreign-born and local-born director), but the explained variance of the model remains virtually unchanged. The inclusion of our measure of average managerial talent, in contrast, improves substantially the fit of the regression model (column 4): the

[18] Also the dependent variable, a firm TFP, is highly dispersed: in our data, the output of firms at the 90th percentile of TFP distribution is three times larger than that of firms at the 10th percentile (keeping constant the inputs).

adjusted R^2 goes up 0.63, corresponding to a 19% increase with respect to the previous specification. This finding suggests that variation in board talent explains a significant portion of variation of the firm TFP, with an elasticity of above 0.7.

Does our measure of average managerial talent meaningfully capture the portable and time-invariant ability of directors? To provide a first answer to this question, we test the plausibility of the assumptions underlying the additive model of firms' efficiency and managerial ability postulated in equation (1). We find 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 our setting. The largest departure from these assumptions, in contrast, is related to sorting based on the trend component of productivity, i.e., more (less) talented directors appear to sort into firms whose performance is improving (deteriorating) over time. This might lead to somewhat overestimated (in levels) measure of managerial talent.[19]

3.3 Alternative definitions and heterogeneity analysis

In Table 4 we explore other measures of board talent, going beyond the simple average of directors' fixed effects. In particular, column 1 replicates the baseline result, while column 2 indicates that a more homogeneous distribution of the talent within the board positively affects the TFP. Column 3 shows that the overall level of talent matters more than just the talent of the most capable manager. In column 4 we examine the role of the executives. We observe this information only for a subset of firms. In order to overcome this data limitation, we attempt to identify executives within the board using their observable characteristics.[20] Then, instead of the simple average (as for the board talent), we use a weighted average of the directors fixed effect giving more weight to those who are more likely to be executives on the basis of the observables. The impact of executives on the firm TFP has an order of

[19]See Appendix A.2 for more details on the validity checks of the AKM assumptions.

[20]We examine characteristics of the executives in the subsample of firms for which we are able to make this distinction within the board of directors. Executives are more likely male, natives, older, local and holding a share of the equity of the firm. The results are available upon request.

magnitude that is comparable to that of the overall board talent. This is likely due to the fact that the average board size is relatively small - nearly half of the firms have at most two directors and typically both of them have executive powers.

Table 5 explores heterogeneous effects of management talent. 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 1) and firm age (column 2). Column 3 shows that board talent has a stronger impact on firms in Northern Italy, while it decreases as we move to the Central and Southern parts of the country. Finally, columns 4 and 5, using a different and complementary perspective, show that managerial talent matters more in more competitive environments. Indeed, the impact on the firm TFP is higher in urban and metropolitan areas than in rural ones - i.e., where agglomeration forces impose a thougher local competition - and in sectors more exposed to international trade. These findings mirror those obtained by Bloom and Van Reenen (2010), who show that product market competition is positively associated with the quality of management practices.

4 What managers do

This section sheds light on what talented managers do to boost firm productivity, under the assumption that, as a matter of fact, crucial drivers of productivity within the firm are under the control of the management (Syverson, 2011). To this end, we combine the administrative *Infocamere-Cerved* data with the *Invind* survey data, which contains additional information on firms' practices and strategies. About 5,500 firms contained in the *Infocamere-Cerved* largest connected set are also present in the *Invind* survey (Table 2, column 4). Matched firms are relatively older and larger; nearly two thirds of them operate in manufacturing and one forth are located in the South of the country.

4.1 Managerial forecasting error

Being accurately informed about the company and the environment in which it operates is an essential prerequisite for making optimal decisions on the use of production factors and on the organization of the production process. A growing literature, for example, has emphasized the importance of systematic errors in managerial forecasting in terms of investments decisions and firm performance Malmendier and Tate, 2005; Ben-David et al., 2013. Using our survey data, we examine whether talented managers are better able to accurately assess the current and future firm performance. We define the forecasting error as the absolute difference between the predicted firms' revenues in the current year for the following year and the realized firm revenues in the following year (Ma et al., 2019). We estimate the following regression specification:

$$forecast_{it} = \alpha + \beta q_{it} + \rho x_{it} + \theta_i + \tau_t + \varepsilon_{it} \tag{3}$$

where $forecast_{it}$ is the absolute value of the prediction error; q_{it} is the managerial talent; x_{it} include firms (time-varying) controls; θ_i and τ_t are firm and year fixed effects, respectively, to control for time-invariant firm characteristics and common time trends.

Table 6 shows that our measure of managerial talent is negatively associated with forecasting errors made. The effect is sizeable since a one standard deviation change in managerial talent is associated to more than a one fifth standard deviation change in the forecasting error (column 1). The estimated impact is confirmed if we control for sectoral and local economic cycles (column 2) and for firm-specific demand shocks (column 3).

This exercise reassures about the informational content of our managerial talent measure. Most important, it does suggest that talented managers possess a more accurate set of information regarding the performance of the firm they lead, providing grounds for implementation of more suitable, and potentially efficiency-boosting, corporate decisions, which we study in the following subsections.

4.2 Characteristics of the workforce

Talented managers may boost firm productivity by using different production inputs. Our data contains, in particular, information on the level and composition of the workforce, which are available at the firm-year level. Therefore, we estimate the following panel regressions:

$$y_{it} = \alpha + \beta q_{it} + \rho x_{it-1} + \theta_i + \tau_t + \varepsilon_{it} \tag{4}$$

where y_{it} is the firm's outcome of interest; the right-hand side variables are the same as those included in specification (3).

We start by examining the choice of labor inputs in firms led by talented managers in Table 7. More precisely, Panel A investigates the choice of workforce size and its composition. Column 1 shows that an increase in the managerial talent is associated with an increase in the total number of employees in the firm. The impact is, however, small in magnitude - moving from the 25th to the 75th percentile of the board talent distribution is associated to a 0.2% increase in the number of employees - and weakly significant. Interestingly, we detect a change in the composition of the workforce and, namely, a reduction of the fraction of middle-level managers. This suggests that talented leadership is associated with a horizontal firm organization and a higher efficiency of middle-management.

Panel B studies directors' role in managing their workforce skill composition, which we proxy by their wages. We find that talented managers seem to retain better paid (and likely more skilled) workers on average (column 1). This effect is present for workers at all organization levels - middle-level managers (column 2), white-collar workers (column 3) and blue-collar workers (column 4). All in all, firms undergo the so-called "skill-upgrading" whereby the production process involves more able employees, at the expense of low-skilled ones, especially among those not directly involved in output production.

Table 8 provides further support to the positive association between managerial talent and skills of the workforce. Namely, we exploit the 2010 wave of the *Invind* survey on the share of firms' employees with a college degree, both in total and separately for white-collar and blue-collar workers. We use this cross-sectional information on formal education as an alternative proxy of workforce ability/productivity. The analysis shows that the schooling level of the workforce, on average, is positively correlated with the managerial talent, measured in the previous three years to guarantee that is pre-determined with respect to the outcome variable. Interestingly, the positive association is present only for white-collar workers, but not for blue-collar ones. The latter result provides a "falsification" test reassuring that the effects do not stem from firm-level reporting differences. As formal education is likely a weak proxy for blue-collars' skills, one would not expect university graduates to perform better in blue-collar tasks, in which other factors, such as firm-specific human capital (acquired, e.g., during on-the-job-training), may be instead more important. Overall, these results mirror those by Bender et al. (2018) and Cornwell et al. (2019) who document an important role of managerial practices in determining workforce skill-composition.[21]

4.3 Managerial practices and technology adoption

In this subsection we exploit further information on firm's organization and strategies drawn from two special waves of the *Invind*. Namely, the 2010 wave contains questions on managerial practices adopted within the firm, while the 2017 wave includes information on adoption of advanced technologies. In order to measure conditional correlations between managerial talent and these firm features, we estimate the following cross-sectional regression specifications:

$$y_i = \alpha + \beta q_i + \rho x_i + \varepsilon_i \tag{5}$$

where y_i is the firm's outcome of interest and q_i is the managerial talent, with the latter computed as the lagged three-year average, predetermined with respect to the dependent variable; x_i is a set of control variables at the firm level: among these, we include firm fixed effects as estimated in the two-way fixed effect model in specification (1), as a measure of time-invariant firm characteristics.

Concerning managerial practices, the 2010 *Invind* survey includes a set of questions on the (i) extent of use of team work, (ii) adoption of performance-based incentive pay and (iii) participation of employees at a lower hierarchical level in the decision-making. The

[21] Namely, 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. Cornwell et al. (2019) link firm-level information on (survey-based) management practices with employee records in Brazil and find that firms using structured management practices consistently hire and retain better workers, and fire more selectively.

potential answers to these questions were none, low, moderate and high. We use 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.[22] We use the first principal component as the main 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. In addition, for a richer interpretation of the results, we also replicate the analysis using the three single items separately.

Table 9 shows that board talent is positively associated with managerial score and with each its component (the coefficient is statistically significant for two of the three components, i.e., the use of team work and for the involvement of lower hierarchical level in decision-making). These results are consistent with Bender et al. (2018) who show that the skills (measured as the individual fixed effects in a two-way fixed effects model) of the top quartile of plant employees – to which the authors refer to as managers – are positively correlated with plant-level productivity and with higher management practice scores. Interestingly, we document a positive association between our composite index of managerial practices' quality and several firms' characteristics. Namely, larger and more productive firms (and those belonging to more export oriented sectors) have significantly higher managerial practices scores, while family-owned firms are significantly lagging behind. We also find that a highly-educated workforce is positively associated with higher 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 (2010).

Concerning the adoption of advanced technologies, the 2017 *Invind* survey includes a set of questions on the firm-level use of (i) artificial intelligence and big data, (ii) internet of things, (iii) robots and (iv) 3D printing. These different items are also summarized in a synthetic indicator that is equal to 1 if at least one of these technologies is adopted (and 0

[22]See Table A.1 for more details on the principal component analysis.

otherwise). Table 10 shows the variables correlated with the adoption of advanced technologies. Managerial talent is positively associated with the adoption of advanced technologies and, in particular, robots and internet of things. Moving from the 25th to the 75th percentile of managerial talent distribution, the likelihood of adopting these two technologies rises by 1.1 percentage points (with respect to sample means that are equal to 23% and 14%, respectively). Moreover, as expected, larger and more productive firms are more likely to invest in new technologies, while family firms enter with a negative sign.

Overall, exploiting the unique information contained in specific waves of the *Invind* survey, in this subsection we have shown that managerial quality is positively correlated with the adoption of modern management practices and advanced technologies.

5 Complementarities

Complementarities exist if the output produced by combining two or more economic factors in a production process exceeds that would have been otherwise generated through the use of the same factors in isolation (Brynjolfsson and Milgrom, 2013). We explore complementarities between managerial talent and human capital of the workforce (subsection 5.1); managerial practices (subsection 5.2); and advanced technology (subsection 5.3).

We use the following cross-sectional regression specifications:

$$TFP_i = \alpha + \beta q_i + \gamma z_i + \theta q_i z_i + \rho x_i + \epsilon_i \tag{6}$$

where TFP_i is the firm's total factor productivity; q_i is the managerial talent; z_i is one of the productivity levers discussed in the previous section which are under the control of the management; x_i include controls at the firm level. The dependent variable and the key explanatory variables are all standardized, in order to guarantee an easier comparison of the relative size of the estimated effect and improve the readibility of the results.

5.1 Managerial talent and workforce education

The level of human capital of the workforce, proxied by the fraction of employees with a college degree, is arguably a strong predictor of firm's TFP. Moreover, talented managers might be better able to hire and retain those that better match the firm's skills demand, to exploit the workers' competences, and to allocate them more efficiently across the different tasks, therefore improving their efficacy within the firm.

Table 11 examines the contribution of managerial talent and workforce education to firm's TFP. 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 double of that of workforce schooling (column 1). Interestingly, the interaction between the two variables is also positive and statistically significant (column 2). According to these findings, the positive impact of the share of workforce with a college degree more than doubles moving from a firm at the 25th to one at the 75th percentile of board talent distribution. In columns 3-6 we distinguish between white- and blue-collar workers and find that complementarities are entirely driven by the former.

5.2 Managerial talent and managerial practices

There is extensive evidence that differences in firm- and country-level productivity partly reflect variation in management practices (Bloom and Van Reenen, 2010). However, 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).

Table 12 investigates the joint role of the board talent and the adoption of managerial practices in determining firms' TFP. Column 1 shows that both managerial talent and managerial score contribute positively to firms' efficiency, on average. Most important, the positive effect of the managerial score doubles for firms led by talented directors. In other words, managerial practices and management talent appear as complements, as these practices matter more for firm productivity if they are adopted by talented managers. Columns 3-5 show that such complementarity is present for performance-pay and involvement of lower hierarchical levels in decision-making, while it is absent for the team-work. In fact, the presence of good managers enhances the efficiency of those practices which require the direct involvement of top management of the company. For example, performance-pay is more effective in firms where top managers deciding on the employee' objectives and performance are talented. Similarly, higher workforce inclusion in decision-making delivers better results in firms where different opinions are aggregated and translated into corporate strategies by talented management.

5.3 Managerial talent and technology

Innovation and adoption of new technologies are among key drivers of efficiency gains (Syverson, 2011). Moreover, the effectiveness of such investments may strongly depend on the presence of complement factors, such as appropriate human capital or organization structures (Brynjolfsson and Milgrom, 2013). We examine whether talented managers are not only more prone to adopt advanced technologies, but also more able to exploit their effects in the production process. Since a more talented management tends to make smaller forecast errors (as shown in subsection 4.1), better directors may be more able to gauge the best timing for the adoption of a given technology.

Table 13 shows that not only management talent and technology adoption do boost firm productivity separately (column 1), but they also complement each other. In particular, the interaction term is positive and statistically significant for the overall index (column 1) and for artificial intelligence and big data adoption (column 2). The effect remains positive, yet lacking statistical significance for the other single items in columns 3-5, possibly due to the small sample we work with.

6 Concluding remarks

This paper attempts to open the black-box of managerial talent. The analysis exploits a novel and rich dataset on Italian privately-held limited liability companies to derive a measure of time-invariant and portable component of talent for individuals responsible for the key corporate decisions. We then rely on detailed survey data on a wide set of firm strategies to better understand the role of managerial talent in determining firm performance.

Importantly, talented managers operate under a more accurate set of information when leading their businesses. Therefore, and unsurprisingly, lower incidence of managerial forecasting bias allows them to adopt efficiency-increasing practices within the firm. Firms led by talented individuals improve the efficiency of their middle-management layers and move towards high-skill workers at all organization levels. The presence of talented managers is also related with the adoption of good managerial practices and advanced technology.

Most importantly, the data reveals synergies between managerial ability and other key internal drivers of productivity. While the workforce human capital, the use of good managerial practices and the adoption of new technologies do boost firm productivity on their own, there is evidence of complementarities between each of them and the presence of talented management in the firm. Overall, our results indicate that able leaders are valuable to the firm not only because of good decisions they make, but also because of how such decisions are put in practice.

References

Abowd, J. M., F. Kramarz, and D. N. Margolis (1999). High wage workers and high wage firms. *Econometrica 67*(2), 251–333.

Ackerberg, D. A., K. Caves, and G. Frazer (2015). Identification properties of recent production function estimators. *Econometrica 83*(6), 2411–2451.

Adams, R. B., A. C. Akyol, and P. Verwijmeren (2018). Director skill sets. *Journal of Financial Economics 130*(3), 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) 171*(3), 673–697.

Aral, S., E. Brynjolfsson, and L. Wu (2012). Complementarities: performance pay, human resource analytics, and information technology. *Management Science 58*(5), 913–931.

Baltrunaite, A., E. Brodi, and S. Mocetti (2019). Assetti proprietari e di governance delle imprese italiane: nuove evidenze e effetti sulla performance delle imprese. *Bank of Italy Occasional Paper* (514).

Bandiera, O., S. Hansen, A. Prat, and R. Sadun (2020). Ceo behavior and firm performance. *Journal of Political Economy*.

Bartel, A., C. Ichniowski, and K. Shaw (2007). How does information technology affect productivity? plant-level comparisons of product innovation, process improvement, and worker skills. *Quarterly Journal of Economics 122*(4), 1721–1758.

Ben-David, I., J. R. Graham, and C. R. Harvey (2013). Managerial miscalibration. *Quarterly Journal of Economics 128*(4), 1547–1584.

Bender, S., N. Bloom, D. Card, J. Van Reenen, and S. Wolter (2018). Management practices, workforce selection, and productivity. *Journal of Labor Economics 36*(S1), S371–S409.

Bennedsen, M., K. M. Nielsen, F. Pérez-González, and D. Wolfenzon (2007). Inside the family firm: The role of families in succession decisions and performance. *Quarterly Journal of Economics 122*(2), 647–691.

Bernile, G., V. Bhagwat, and S. Yonker (2018). Board diversity, firm risk, and corporate policies. *Journal of Financial Economics 127*(3), 588–612.

Bertrand, M. and A. Schoar (2003). Managing with style: The effect of managers on firm policies. *Quarterly Journal of Economics 118*(4), 1169–1208.

Best, M., J. Hjort, and D. Szakonyi (2019). Individuals and organizations as sources of state effectiveness. *working paper*.

Black, S. E. and L. M. Lynch (2001). How to compete: the impact of workplace practices and information technology on productivity. *Review of Economics and Statistics 83*(3), 434–445.

Bloom, N., B. Eifert, A. Mahajan, D. McKenzie, and J. Roberts (2013). Does management matter? evidence from india. *Quarterly Journal of Economics 128*(1), 1–51.

Bloom, N., R. Sadun, and J. Van Reenen (2012). Americans do it better: Us multinationals and the productivity miracle. *American Economic Review 102*(1), 167–201.

Bloom, N. and J. Van Reenen (2007). Measuring and explaining management practices across firms and countries. *Quarterly Journal of Economics 122*(4), 1351–1408.

Bloom, N. and J. Van Reenen (2010). Why do management practices differ across firms and countries? *Journal of Economic Perspectives 24*(1), 203–24.

Brynjolfsson, E. and L. M. Hitt (2000). Beyond computation: information technology, organizational transformation and business performance. *Journal of Economic Perspectives 14*(4), 23–48.

Brynjolfsson, E. and P. Milgrom (2013). Complementarity in organizations. In R. Gibbons and J. Roberts (Eds.), *Handbook of Organizational Economics*. Princeton University Press.

Bugamelli, M., F. Lotti, M. Amici, E. Ciapanna, F. Colonna, F. D'Amuri, S. Giacomelli, A. Linarello, F. Manaresi, G. Palumbo, F. Soccianti, and E. Sette (2018). Productivity growth in italy: a tale of a slow-motion change. *Bank of Italy Occasional Paper* (422).

Card, D., J. Heining, and P. Kline (2013). Workplace heterogeneity and the rise of west german wage inequality. *Quarterly Journal of Economics 128*(3), 967–1015.

Cornwell, C., I. M. Schmutte, and S. Daniela (2019). Building a productive workforce: the role of structured management practices. *working paper*.

Fenizia, A. (2019). Managers and productivity in the public sector. *working paper*.

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.), *Handbook of Organizational Economics*. Princeton University Press.

Graham, J. R., S. Li, and J. Qiu (2012). Managerial attributes and executive compensation. *Review of Financial Studies 25*(1), 144–186.

Ichniowski, C., K. Shaw, and G. Prennushi (1997). The effects of human resource practices on manufacturing performance: A study of steel finishing lines. *American Economic Review 87*(3), 291–313.

Kaplan, S. N., M. M. Klebanov, and M. Sorensen (2012). Which ceo characteristics and abilities matter? *Journal of Finance 67*(3), 973–1007.

Lazear, E. P., K. L. Shaw, and C. T. Stanton (2015). The value of bosses. *Journal of Labor Economics 33*(4), 823–861.

Levinsohn, J. and A. Petrin (2003). Estimating production functions using inputs to control for unobservables. *Review of Economic Studies 70*(2), 317–341.

Lieberman, M. B., L. J. Lau, and M. D. Williams (1990). Firm-level productivity and management influence: A comparison of us and japanese automobile producers. *Management Science 36*(10), 1193–1215.

Ma, Y., T. Ropele, D. Sraer, and D. Thesmar (2019). A quantitative analysis of distortions in managerial forecasts. *working paper*.

Malmendier, U. and G. Tate (2005). Ceo overconfidence and corporate investment. *Journal of Finance 60*(6), 2661–2700.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica 71*(6), 1695–1725.

Syverson, C. (2004). Product substitutability and productivity dispersion. *Review of Economics and Statistics 86*(2), 534–550.

Syverson, C. (2011). What determines productivity? *Journal of Economic Literature 49*(2), 326–65.

Tables and figures

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

	(1)	(2)	(3)	(4)	(5)	(6)
	universe of firms			connected set		
	Non-movers	Movers	Δ	Non-movers	Movers	Δ
Female	0.260	0.151	0.109***	0.237	0.134	0.102***
Foreign-born	0.090	0.072	0.018***	0.101	0.072	0.029***
Age	48.701	50.431	-1.730***	49.624	51.110	-1.485***
Local	0.722	0.658	0.064***	0.676	0.628	0.048***
Shareholder	0.356	0.278	0.078***	0.200	0.204	-0.004***
Share	0.811	0.189	0.000	0.303	0.303	0.000
N	752,597			275,811		

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 largest connected set; Δ indicates 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 largest *connected* set

	(1)	(2)	(3)	(4)
	other firms	connected set	Δ	*Invind* sample
# employees	19.620	66.467	-46.847***	404
Firm age	12.686	16.286	-3.601***	33.1
# directors	1.692	3.097	-1.405***	4.753
% manufacturing	0.318	0.285	0.032***	0.613
% South	0.302	0.145	0.157***	0.251
Share	0.684	0.316		
N	297,354			5,557

Notes: Data are drawn from the combined *Infocamere-Cerved* sample in the first two columns and from the combined *Infocamere-Cerved-Invind* sample in the last column. Columns (1) and (2) report mean values for firms outside the largest connected set and within it, respectively; Δ indicates the corresponding difference in means; N represents the total number of firms in the period considered.

Table 3: Board talent and firm productivity: analysis of the variance

Dependent variable:	Total factor productivity					
	(1)	(2)	(3)	(4)	(5)	(6)
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		Yes	Yes	Yes	Yes	Yes
Board characteristics			Yes	Yes	Yes	Yes
Board talent				0.765***		
				(0.004)		
Board FE					Yes	Yes
Board FE × Firm FE						Yes
Adj-R^2	0.017	0.532	0.533	0.632	0.651	0.620
N	755,169	750,018	750,018	750,018	750,018	657,751

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: industry- and province-year FEs (column 1); firm FEs (column 2); the observable characteristics of the board of directors (column 3); the talent of the board (measured as the average of director fixed effects at the firm-year level), both as a continuous variable (column 4) and as a set of fixed effects corresponding to its centiles (column 5). Standard errors clustered at the firm level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Board talent and firm productivity: various measures of board talent

Dependent variable:	Total factor productivity			
	(1)	(2)	(3)	(4)
Board talent (mean)	0.765***	0.765***		
	(0.004)	(0.004)		
Board talent (sd)		−0.015***		
		(0.003)		
Board talent (max)			0.461***	
			(0.005)	
Executives talent (mean)				0.762***
				(0.004)
Firm FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Province × Year FE	Yes	Yes	Yes	Yes
Firm age × Year FE	Yes	Yes	Yes	Yes
Board characteristics	Yes	Yes	Yes	Yes
Adj-R^2	0.632	0.632	0.570	0.629
N	750,018	750,018	750,018	750,018

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 industry- and province-year FEs, firm FEs, the observable characteristics of the board of directors and the talent of the board. In column 1 board talent is the average of directors fixed effect at the firm-year level; in column 2 it is captured by both the average and the standard deviation of directors fixed effects; in column 3 board talent is the highest among directors' fixed effects; in column 4 it is the average of executive fixed effects. Standard errors clustered at the firm level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Heterogeneous effects

Dependent variable:	Total factor productivity				
	(1)	(2)	(3)	(4)	(5)
Board talent (BT)	0.756***	0.758***	0.820***	0.749***	0.735***
	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)
BT × medium	0.054***				
	(0.007)				
BT × large	0.142***				
	(0.022)				
BT × age 10-30		−0.001			
		(0.005)			
BT × age 30+		0.017***			
		(0.005)			
BT × Centre			−0.099***		
			(0.009)		
BT × South			−0.148***		
			(0.009)		
BT × urban area				0.028***	
				(0.009)	
BT × metropolitan area				0.020**	
				(0.010)	
BT × mid export					0.032***
					(0.009)
BT × high export					0.058***
					(0.011)
Firm FE	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes
Province × Year FE	Yes	Yes	Yes	Yes	Yes
R^2	0.676	0.676	0.677	0.676	0.676
N	750,018	750,018	750,018	750,018	750,018

Notes: Data are drawn from the combined *Infocamere-Cerved* sample. Panel with fixed effects. The dependent variable is firm TFP. Board talent is interacted with various firm characteristics. The residual categories are small firm (column 1), aged less than 10 (column 2), North (column 3), rural area (column 4) and low export sectors (column 5). Standard errors clustered at the firm level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Managerial information

Dependent variable:	Forecasting error		
	(1)	(2)	(3)
Board talent	-0.227^{***}	-0.220^{***}	-0.156^{***}
	(0.025)	(0.024)	(0.023)
Log of revenues			-0.492^{***}
			(0.049)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry × Year FE		Yes	Yes
Region × Year FE		Yes	Yes
R^2	0.386	0.412	0.426
N	23,556	23,547	23,547

Notes: Data are drawn from the combined *Infocamere-Cerved-Invind* sample. Panel with fixed effects. The dependent variable is the managerial forecast error defined as the absolute value of the percentage difference between the predicted revenues in the current year for the subsequent year and realized revenues in the subsequent year. Standard errors clustered at the sector×region level in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Workforce composition and wages

	Panel A			
Dependent variable:	log	share of:		
	employees	managers	white-collar	blue-collar
	(1)	(2)	(3)	(4)
Board talent	0.015*	−0.064**	−0.126	0.234
	(0.008)	(0.029)	(0.148)	(0.163)
Firm FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
R^2	0.980	0.912	0.979	0.978
N	31,039	31,039	31,039	31,039

	Panel B			
Dependent variable:	log wages			
	total	managers	white-collar	blue-collar
	(1)	(2)	(3)	(4)
Board talent	0.029***	0.025***	0.025***	0.034***
	(0.003)	(0.005)	(0.004)	(0.004)
Firm FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes
Region × Year FE	Yes	Yes	Yes	Yes
R^2	0.955	0.816	0.920	0.902
N	31,039	19,913	30,971	28,982

Notes: Data are drawn from the combined *Infocamere-Cerved-Invind* sample. Panel with fixed effects. Dependent variables are in logarithms in Panel A column 1, Panel B columns 1-4 and in shares in Panel A columns 2-3. Standard errors clustered at the sector×region level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Workforce education

Dependent variable:	share of college degree		
	total	white-collar	blue-collar
	(1)	(2)	(3)
Board talent (lagged)	0.078**	0.096**	0.013
	(0.030)	(0.042)	(0.028)
Firm FE	0.157***	0.189**	0.015
	(0.058)	(0.073)	(0.068)
Log employees	0.095***	0.101***	0.073**
	(0.025)	(0.028)	(0.029)
Firm age	−0.030	−0.066*	−0.026
	(0.030)	(0.035)	(0.038)
Family-firm	−0.148***	−0.159**	−0.097**
	(0.051)	(0.069)	(0.046)
Industry FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
R^2	0.254	0.117	0.169
N	1,776	1,526	1,399

Notes: Data are drawn from the combined *Infocamere-Cerved-Invind* sample, using the 2010 wave. OLS cross-section regression. The dependent variable is the share of employees with a college degree. Board talent is lagged and measured as an average in the previous three years. Firm FEs are those estimated using the two-way fixed effect model described in specification (1). Standard errors clustered at the sector×region level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Adoption of managerial practices

Dependent variable:	Managerial score	Team work	Performance-pay	Decision-making
	(1)	(2)	(3)	(4)
Board talent (lagged)	0.092**	0.045**	0.030	0.042*
	(0.045)	(0.021)	(0.021)	(0.023)
Firm FE	0.154*	0.092**	0.014	0.113**
	(0.085)	(0.041)	(0.042)	(0.050)
Log employees	0.268***	0.096***	0.145***	0.033*
	(0.041)	(0.015)	(0.016)	(0.020)
Firm age	−0.090**	−0.021	−0.034	−0.051**
	(0.045)	(0.023)	(0.026)	(0.023)
Family-firm	−0.268***	−0.048	−0.122***	−0.076
	(0.081)	(0.046)	(0.039)	(0.050)
% college	0.147***	0.042*	0.087***	0.029
	(0.049)	(0.024)	(0.023)	(0.027)
Industry FE	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
R^2	0.292	0.153	0.271	0.112
N	661	661	661	661

Notes: Data are drawn from the combined *Infocamere-Cerved-Invind* sample, using the 2010 wave. OLS cross-section regression. Board talent is lagged and measured as an average in the previous three years. The dependent variable is the managerial practice score obtained with the principal component analysis (and corresponding to the first component) and items referring to specific managerial practices. Firm FEs are those estimated using the two-way fixed effect model described in specification (1). Standard errors clustered at the sector×region level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Adoption of advanced technology

Technology:	At least one	AI&Big data	Internet of things	Robots	3D print
	(1)	(2)	(3)	(4)	(5)
Board talent (lagged)	0.067***	0.015	0.044**	0.055**	0.043
	(0.024)	(0.021)	(0.022)	(0.024)	(0.033)
Firm FE	0.152***	0.059	0.119**	0.065	0.132*
	(0.051)	(0.049)	(0.052)	(0.039)	(0.073)
Log employees	0.230***	0.277***	0.203***	0.171***	0.121***
	(0.018)	(0.024)	(0.020)	(0.025)	(0.025)
Firm age	−0.034	−0.022	−0.006	−0.006	−0.068*
	(0.025)	(0.035)	(0.031)	(0.030)	(0.036)
Family-firm	−0.567***	−0.244***	−0.389***	−0.503***	−0.332***
	(0.057)	(0.073)	(0.038)	(0.092)	(0.091)
Industry FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
R^2	0.159	0.124	0.101	0.112	0.094
N	2,299	2,289	2,286	2,287	2,286

Notes: Data are drawn from the combined *Infocamere-Cerved-Invind* sample, using the 2017 wave. OLS cross-section regression. Board talent is lagged and measured as an average in the previous three years. The dependent variables are indicators for adoption of different types of technology adopted within the firm in the last three years. Firm FEs are those estimated using the two-way fixed effect model described in specification (1). Standard errors clustered at the sector×region level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Complementarities: management talent and workforce education

Dependent variable:	TFP				
	(1)	(2)	(3)	(4)	(5)
Board talent (BT)	0.255***	0.259***	0.255***	0.234***	0.253***
	(0.047)	(0.046)	(0.045)	(0.046)	(0.047)
% college total (CO)	0.089**	0.083**			
	(0.036)	(0.037)			
BT × CO		0.110*			
		(0.056)			
% college white collars (WC)			0.072**		0.049
			(0.028)		(0.032)
BT × WC			0.093***		0.109***
			(0.035)		(0.040)
% college blue collars (BC)				0.003	−0.013
				(0.028)	(0.028)
BT × BC				0.037	0.001
				(0.052)	(0.050)
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
R^2	0.106	0.114	0.112	0.102	0.113
N	1,776	1,444	1,526	1,399	1,390

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 while the explanatory variables are workforce skill composition and their interaction with board talent. Standard errors clustered at the sector×region level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 12: Complementarities: management talent and managerial practices

Dependent variable:	TFP				
	(1)	(2)	(3)	(4)	(5)
Board talent (BT)	0.232***	0.247***	0.254*	−0.032	0.068
	(0.070)	(0.061)	(0.139)	(0.112)	(0.112)
Managerial score (MS)	0.082**	0.082**			
	(0.036)	(0.036)			
MS × BT		0.083*			
		(0.042)			
Team work (TW)			0.054*		
			(0.031)		
TW × BT			−0.010		
			(0.046)		
Performance-pay (PP)				0.066*	
				(0.037)	
PP × BT				0.146***	
				(0.046)	
Decision-making (DM)					0.048
					(0.036)
DM × BT					0.081*
					(0.045)
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
R^2	0.170	0.177	0.169	0.192	0.174
N	661	661	661	661	661

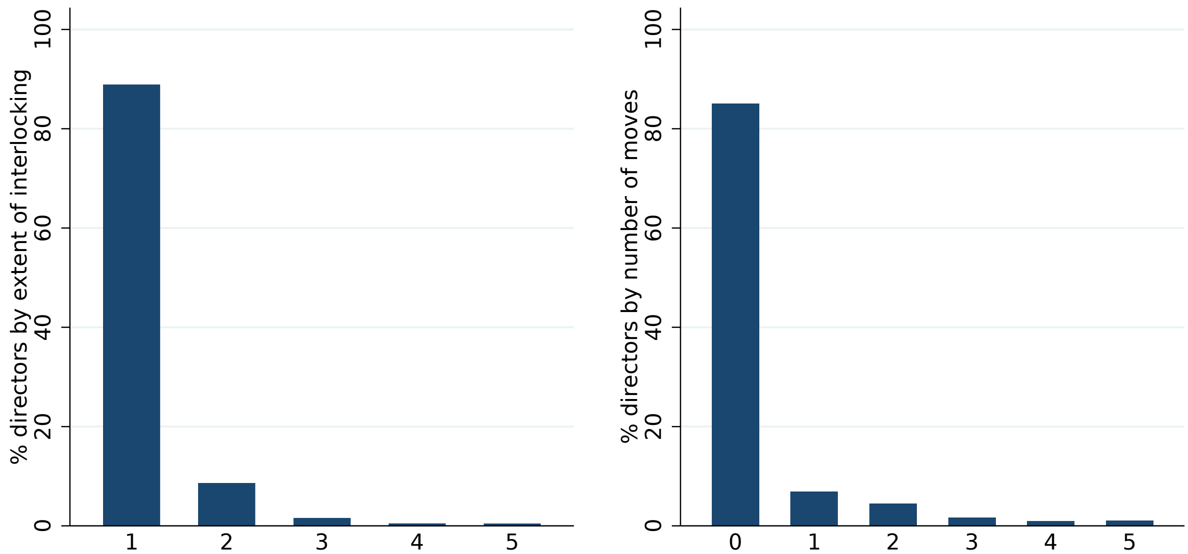
Notes: Data are drawn from the combined *Infocamere-Cerved-Invind* sample, using the 2010 wave. OLS cross-section regression. The dependent variable is firm TFP while the explanatory variables the managerial practices score and its interaction with board talent. Standard errors clustered at the sector×region level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 13: Complementarities: management talent and technology

Dependent variable:	TFP					
	(1)	(2)	(3)	(4)	(5)	(6)
Board talent (BT)	0.827***	0.837***	0.834***	0.829***	0.824***	0.829***
	(0.046)	(0.044)	(0.044)	(0.045)	(0.046)	(0.045)
Advanced technology (TECH)	0.040**	0.037*				
	(0.020)	(0.020)				
TECH × BT		0.075**				
		(0.035)				
AI and big data (T1)			0.026*			
			(0.015)			
T1 × BT			0.077**			
			(0.031)			
Internet of things (T2)				0.018		
				(0.019)		
T2 × BT				0.033		
				(0.033)		
Robot (T3)					0.079***	
					(0.012)	
T3 × BT					0.004	
					(0.033)	
3D printing (T4)						0.004
						(0.012)
T4 × BT						0.013
						(0.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.473	0.478	0.477	0.472	0.477	0.471
N	2,261	2,261	2,251	2,248	2,249	2,248

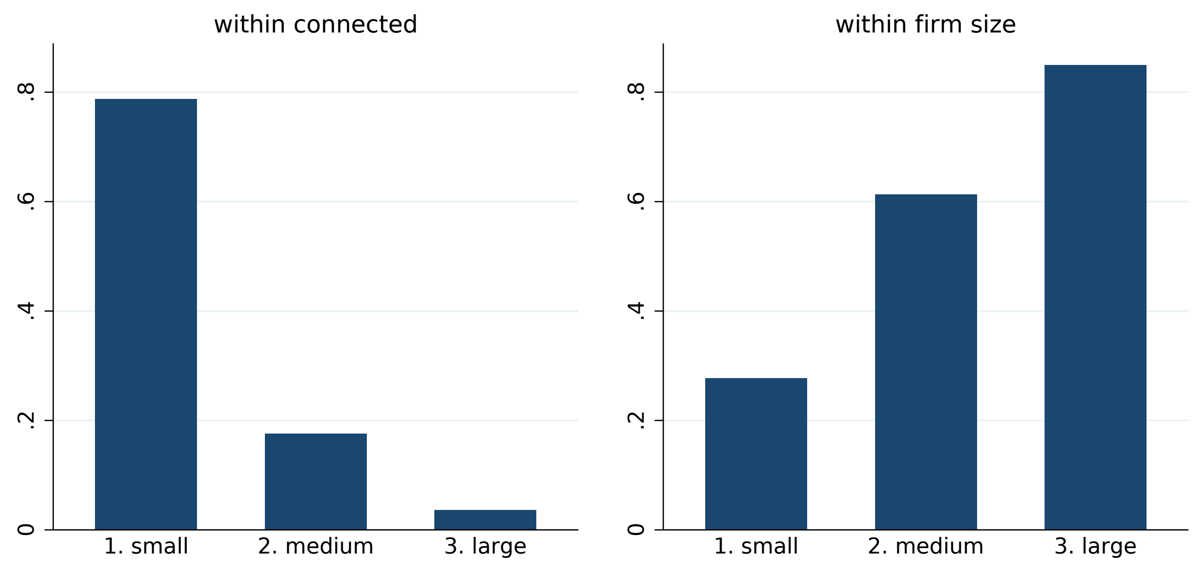
Notes. Data are drawn from the combined *Infocamere-Cerved-Invind* sample, using the 2017 wave. OLS cross-section regression. The dependent variable is firm TFP while the explanatory variables are indicators for adoption of different types of technology and their interaction with board talent. Standard errors clustered at the sector×region level in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Extent of interlocking and switching among directors



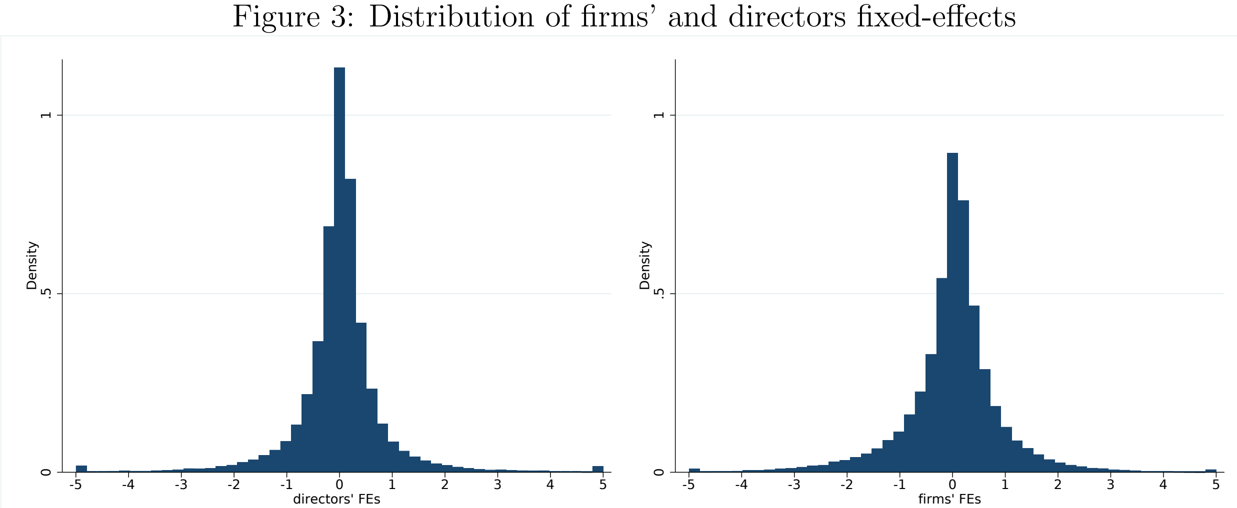
Notes: Data are drawn from the combined *Infocamere-Cerved* sample. The left panel shows the extent of interlocking, i.e. the distribution of directors by the number of boards (of different firms) on which they seat in the same year; the right panel shows the extent of switching, i.e. the distribution of directors by the number of switch (from one firm to another across time) over the period 2005-2017.

Figure 2: 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, small firms have from 10 to 50 employees, medium-sized firms have up to 250 employees while large firms have more than 250 employees. Micro firms

Figure 3: 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.

Appendix

A.1 Stylized facts on the labour market of directors

As shown in Section 3, many directors sit on the board of multiple firms over the period 2005-2017. Directors tend to move across firms that are "close" from both a geographical and sectoral point of view (Figure A.1).[23] On average interlocking and/or switching occur between firms that are less than 50 kilometers away from each other. In particular, 44% of these moves occur within the same municipality, while around 20% of the moves occur between firms more than 100 kilometers away. Similarly, directors tend to sit on the boards of firms belonging to the same sector of activity: the likelihood that the two firms belong to the same section (alphabetical classification), division (2 digit numerical classification) or group (3 digit numerical classification) of the NACE classification of economic activities are, respectively, around 56%, 39% and 32%. These probabilities are significantly larger than those that would be recorded by observing a random shift from one sector to another.[24]

A.2 Validity checks on the AKM model

As explained in Section 3, specification (1) relies on the assumption that directors do not systematically sort into firms based on factors that enter in the error term. In this section, we test three patterns of endogenous mobility that would violate this assumption. To this end, we perform the validity checks proposed in Card et al. (2013).

[23] 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).

[24] 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 11% for the moves that we observe, 6 times larger than the simple average obtained from a random move.

First, we consider sorting 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 our baseline model. To test this, in column 6 of Table 3 we regress a firm TFP on the interaction between fixed effects for the average managerial talent q (obtained after discretizing the continuous measure into centiles) and firm fixed effects.[25] The R^2 of this model is not larger than that of the additive model in column 5, suggesting that match-specific effects should not have a first-order relevance in determining the sorting of directors into companies.

Moreover, if match-specific effects are not relevant the additive model should not deliver abnormally large residuals. Figure A.2 plots 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 and never exceeding the rule-of-thumb value of 0.02.

Furthermore, if this form of endogenous mobility 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 of similar extent in managerial talent.[26] To check for this, we focus on a balanced panel of firms that (i) change at least one director in year-to-event 0 and (ii) do not experience any other significant change - in terms of management quality - in the 3 years before the event and in the 3 years following it. We classify these companies into 9 groups, based on the terciles of managerial talent of the old board and the new board. Figure A.3 plots the evolution of TFP from year-to-event -2 to year-to-event 1 for firms whose old director/board belongs to the bottom or top tercile of managerial talent. The figure shows no change in TFP 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 to 1

[25]In column 5 we estimate the same model as in column 4, substituting the continuous measure of board talent with indicators for each centile of the corresponding discretized measure. Although the discrete variable has less informative value than the continuous variable, the use of fixed effects allows capturing potential non-linearities in the relationship between board talent and firm TFP. The fit of the model is however only marginally affected by this change.

[26]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.

or 3 to 3). Focusing on changes of intermediate intensity (i.e., for transitions of the type 1 to 2 and 3 to 2), TFP is fairly flat before year-to-event 0, while it starts to increase (decrease) when a higher (lower) talented board takes over. Extreme changes in the managerial talent available to the firm (i.e., for transition of the type 1 to 3 and 3 to 1) are associated with larger changes in TFP from year 0, although these positive (negative) extreme changes are also preceded by increasing (declining) trends in TFP. However, these (mild) pre-trend do not seem to explain the jump observed when extreme changes in board talent occurs, as shown in Figure A.4 that plots the observed pattern of the TFP and that predicted extrapolating from the trend observed before the change in the board quality. Finally, Figure A.5 plots the overall change in TFP (between year-to-event -2 and year-to-event 1) for downward movers against that of upward movers making the opposite change in managerial talents.[27] Dots are close to the the -45 degree line, indicating that TFP gains and losses for companies that experience opposite changes in board talent are roughly symmetric.

Second, we turn our attention to endogenous mobility based on the trend component of TFP. If sorting based on trends was not important, TFP should display a flat dynamic before a director leaves or joins the firm. As commented in the above paragraph, this appears to be the case when considering board changes that involve little or medium changes in the level of managerial talent available to the firm. On the other hand, this assumption seems less plausible when larger changes in managerial talent occur. A consequence of this is that we could be overstating the impact of managerial quality on TFP. However, Figure A.3 also shows that, even in these types of transitions, the changes in TFP 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.

Third, we examine endogenous mobility related to the transitory component of TFP. If this type of sorting was relevant, we should observe dips or spikes in TFP just before the

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

change in the composition of the board. Such patterns do not emerge from Figure A.3, suggesting that this type of endogenous mobility is likely not of first-order relevance.

Last, more talented directors tend to be in more productive firms, as shown in Figure A.6. 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 (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.

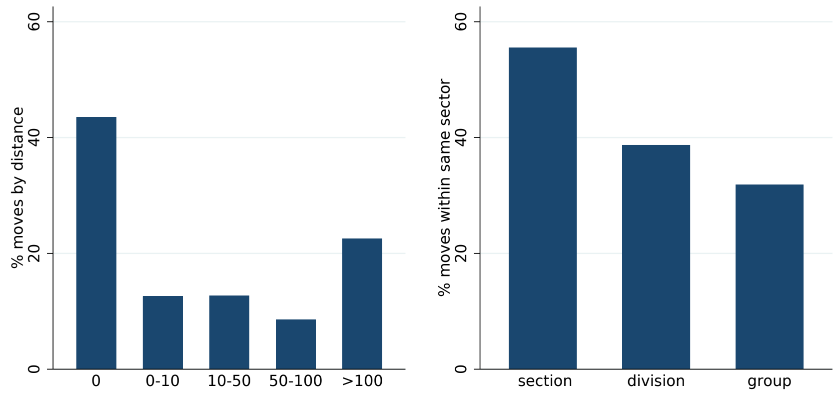
A.2.1 Supplementary figures and tables

Table A.1: Managerial practices: principal component analysis

	(1)	(2)	(3)
	1st component	2nd component	3rd component
Eigenvalue	1.966	0.554	0.480
Proportion	0.655	0.185	0.160
Cumulative	0.655	0.840	1.000
	use of team works	performance-based incentive pay firm	extent of participation in decision-making
Correlation with 1st PC	0.822	0.788	0.818

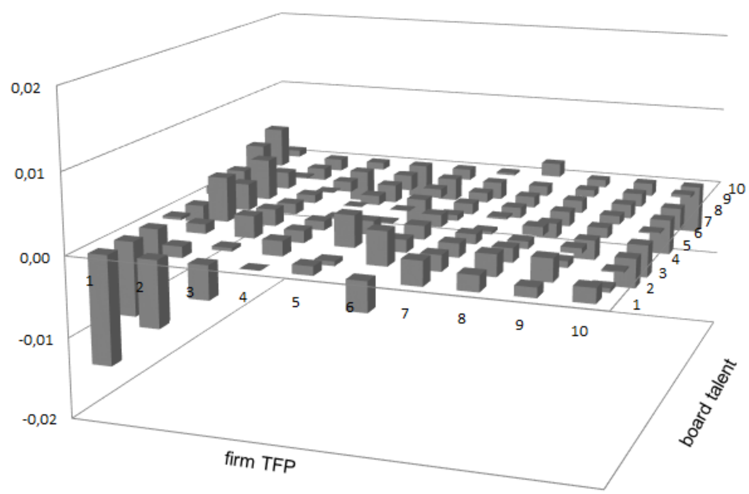
Notes: Data are drawn from the *Invind* sample, using the 2010 wave. Results of the first principal component analysis. For each managerial practice, the firms is required to answer the extent of the use of each of them (none, poor, moderate, high).

Figure A.1: Geographical and sectorial distance of "moves" between firms



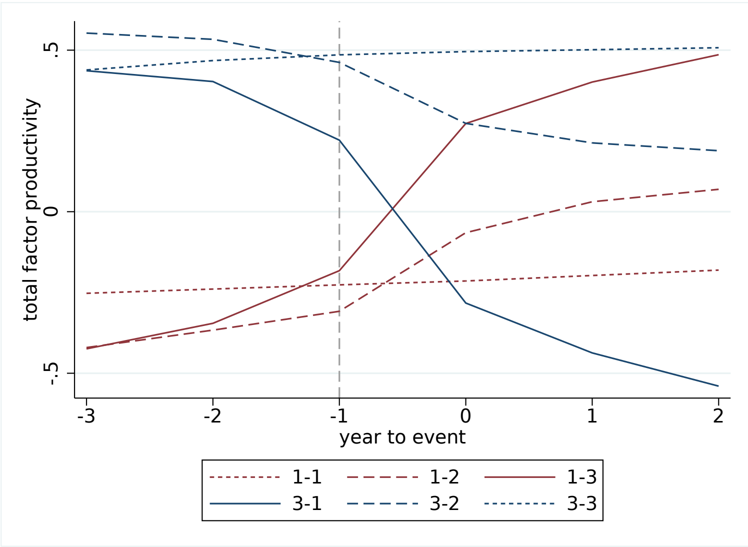
Notes: Data are drawn from the combined *Infocamere-Cerved* sample. We consider as moves both the presence in the board of two different firms in the same year and the switch from one firm to another across time.

Figure A.2: Residuals



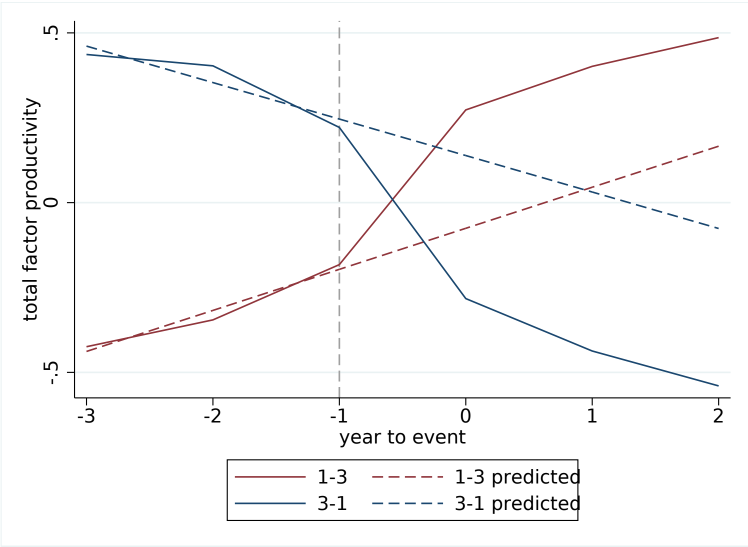
Notes: Data are drawn from the combined *Infocamere-Cerved* sample. Figure shows mean residuals from model (1) on the largest connected set with cells defined by deciles of board talent, interacted with deciles of estimated firm fixed effects.

Figure A.3: Evolution of TFP following a change in board talent



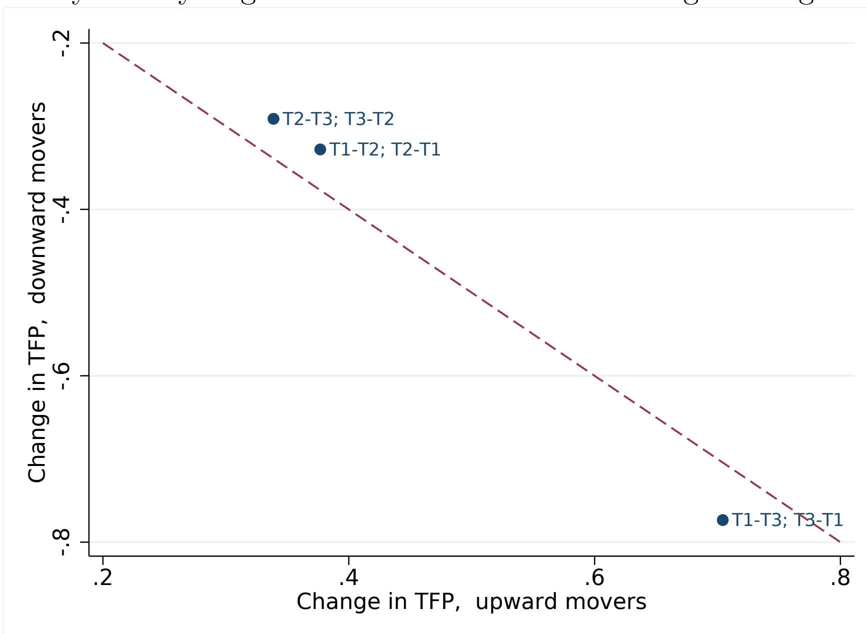
Notes: The figure plots the evolution of TFP from year-to-event -3 to year-to-event 2 on a balanced subset of firms that (i) change at least one director in year-to-event 0 and (ii) remain in the same tercile of board talent both in the 3 years before the event and in the following 3 years.

Figure A.4: Predicted and observed evolution of TFP following a change in board talent



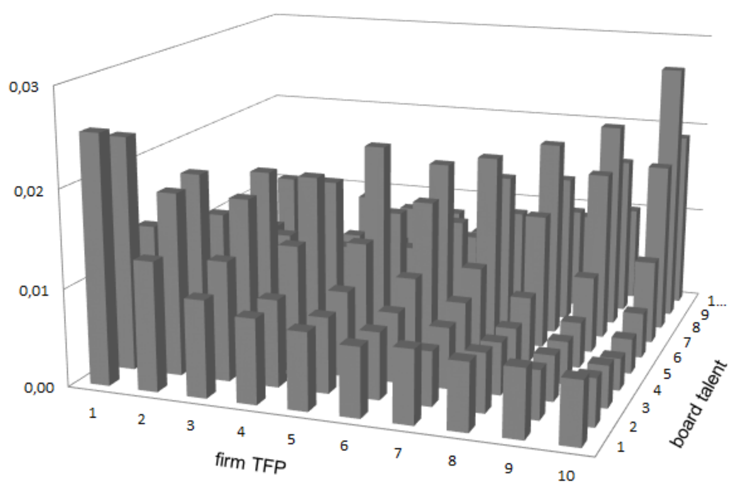
Notes: The figure plots the evolution of TFP from year-to-event -3 to year-to-event 2 on a balanced subset of firms that (i) change at least one director in year-to-event 0 and (ii) remain in the same tercile of board talent both in the 3 years before the event and in the following 3 years.

Figure A.5: Symmetry of gains and losses in TFP following a change in directors



Notes: The figure plots the change in TFP between the years preeceding and following the event.

Figure A.6: Assortative matching



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