# The Right Director in the Right Firm

## Director Heterogeneity, Sorting and Firm Performance*

Maximilian Mayer†

April 2023

**Abstract**

This paper studies the role of the matching between firms and directors appointed to their boards in determining firm outcomes. I apply a finite-mixture random-effects model to estimate the contribution of unobserved firm and director heterogeneity while explicitly allowing for an interaction between the two to estimate the quality of the match between board members and firms. Results reveal that positive complementarities drive positive sorting between firms and their directors. Using hand-collected data and textual analysis to build a large dataset on directors' skills and qualifications, I find in particular directors with specialized skill sets to be associated with higher complementarities. In contrast, consistent with the idea of knowledge hierarchies in the firm, CEOs and CFOs tend to be generalists relying on directors' advice. Finally, I exploit unexpected deaths of directors to establish that boards, where productivity is concentrated to a few highly complementary directors, have a positive causal effect on firm value and firm performance. The paper thereby offers new evidence on the organizational structure within the firm and its impact on firm performance.

**Keywords:** Sorting, Board of Directors, Complementarities, Skills and Qualifications, Productivity Concentration

* I would like to thank my advisor Ester Faia for her patient guidance, support and invaluable advice as well as Michalis Haliassos, Chiara Lacava, Guido Lenz, Gianmarco Ottaviano, Vincenzo Pezone, and Ferdinand von Siemens for helpful comments. I thank the Fritz Thyssen Foundation (project 10.17.2.025WW) and DFG (project 415866087) for financial support.

† IWH; maximilian.mayer@iwh-halle.de

# 1. Introduction

How the composition of the board of directors affects firm outcomes is a question that is widely studied. Increasing interest is placed on the role of the board of directors in advising and providing information to executives and management.[1] Similarly, the focus shifted to study directors as individuals rather than the board as a whole (Adams et al., 2010) and how individual characteristics of board members are best combined to ensure that firms create value for their shareholders.[2]

This paper studies the matching between firms and directors appointed to their boards and asks whether directors sort into firms where they are a *good fit* creating positive complementarities with the firm, how these complementarities between directors and firms arise, and how they affect firm value and contribute to firm performance. While most of the literature focuses either on the matching of CEOs or the role of observable characteristics of directors, I explicitly study the *quality of fit* between directors and firms in terms of their unobservable heterogeneity, such as latent director productivity.

The paper exploits a finite-mixture random-effects model recently proposed by Bonhomme et al. (2019) to disentangle the contribution of unobserved heterogeneity from the *quality of fit* of a given director. I thereby decompose directors' compensation into the differences attributable to unobserved firm characteristics and director productivity but importantly allow for an interaction between the two to explicitly account for the existence of complementarities between firms and their directors. The presence of positive complementarities implies that a given director might be not very productive in many firms but very productive on the board where she is the *right director for the job.*

Results reveal positive sorting of directors and firms, *i.e.*, directors are predominantly appointed to boards where they are a good fit and document the salience of complementarities between all members of the board, not just CEOs, and firms. Using extensive hand-collected data on directors' skills and qualifications, I provide novel evidence that complementarities arise in particular for directors with specialized skills, while the opposite is true for CEOs and CFOs as the top decision-makers in the firm. At the same time, I establish causal evidence that boards, where individual productivity is more concentrated to just a few directors, have

1 See Adams and Ferreira (2007), and the reviews by Adams et al. (2010), and more recently Adams (2017).

2 A large part of the literature is focused on differences of CEOs in terms of managerial styles (Bertrand and Schoar, 2003), personality traits (Kaplan et al., 2012; Kaplan and Sorensen, 2021; Hansen et al., 2021), overconfidence of the CEO (Malmendier and Tate, 2005, 2008) and CFO (Malmendier et al., 2020), general skills (Custódio et al., 2013; Custódio et al., 2019) or talent (Falato et al., 2010) among others. For directors the effect of past experiences has been studied in terms of past industry experience (Dass et al., 2014), financial (Güner et al., 2008) or legal (Krishnan et al., 2011) expertise and political connections (Goldman et al., 2009) or gender diversity (Ahern and Dittmar, 2012). More related, Hansen et al. (2021), Kaplan et al. (2012) and Kaplan and Sorensen (2021) study find evidence for increased importance of social and interpersonal skills for CEOs and Adams et al. (2018) is the first to study skills of directors.

a positive effect on firm value and performance. Taken together, these results imply that directors, horizontally differentiated by specialized skills, qualifications, and experiences, are appointed to the boards of the firms where they best complement the firms' need for advice. Knowledge hierarchies within the firm imply that the top-decision makers, *i.e.* CEOs or CFOs, instead tend to be generalists (Ferreira and Sah, 2012) relying on directors' advice. Higher concentration of productivity at the board level improves the decision-making of top executives and consequently firm performance. This provides new evidence on the organizational structure within the firm and its effects on firm performance.

To reach these conclusions, I estimate a finite-mixture random-effects model that identifies director and firm heterogeneity and complementarities between them using the method recently proposed by Bonhomme et al. (2019). The estimation follows in two steps: First, I group firms together into a finite number of *firm classes* based on a number of observable firm characteristics using a simple, so-called *k-means*, clustering approach. Second, conditional on these firm classes, I estimate a random-effects model of directors' compensation that restricts unobserved heterogeneity to a limited number of different *director types* modeled as random effects. Doing so allows moments of the estimated earnings distribution to differ across firm classes for each director type and thereby directly identifies complementarities between firms and directors appointed to their boards. This approach departs from the previous literature that relies on linear two-way fixed effects models that identify unobserved heterogeneity at the director (or primarily CEO) and firm-level while ignoring potential interactions between them. Limiting the heterogeneity to a smaller number of firm classes and director types additionally alleviates concerns about potential bias in the estimation of the fixed effects in the previous literature.[3,4]

I estimate the finite-mixture model using data on total compensation for all board members in the Execucomp database from 2010-2019 and find evidence of moderately positive sorting of 14% indicated by the correlation of director and firm heterogeneity. Interestingly, I find strong negative sorting of $-43\%$ when using a standard linear-additive two-way fixed effects approach. This confirms existing concerns about the identification strategy in the previous literature and highlights the value of the estimation approach employed in this paper.

In addition, the positive sorting signals the importance of appointing the right director to the board (Adams and Ferreira, 2008). The moderate effect likely reflects the trade-off between an increased workload (Fahlenbrach et al., 2017), litigation risk (Brochet and Srinivasan,

3 See, e.g., Bertrand and Schoar (2003) studying managers' influence on firm policies, or Graham et al. (2012) studying the effect of heterogeneity on compensation.

4 Bias arises from an incidental parameter problem and the so-called limited mobility bias. Limiting the number of director types and firm classes eliminates the incidental parameter problem by reducing the number of parameters (*i.e.* fixed effects) that need to be estimated and similarly requires less restrictive assumptions about the mobility of director types between firm classes compared to the mobility of directors across individual firms necessary in previous literature.

2014), or reputation damage (Fich and Shivdasani, 2007) for productive directors that sort negatively into unproductive firms on the one side and the possibility for a productive director to fill leadership positions and build a reputation in poorly performing firms on the other side (Dou and Zhang, forthcoming). These arguments are corroborated by cross-sectional tests of sorting patterns that reveal that more complex firms consisting of many business units, firms with high intangible capital, and more innovative firms drive the observed positive sorting as they potentially rely more on directors in their role as advisors and information providers (Coles et al., 2008). On the contrary, firms with high markups and high profitability display lower levels of sorting in line with reputation building.

Naturally, the question of what determines a good match and whether match quality has a positive impact on firm performance arises. I tackle this question by analyzing the role of directors' skill sets for determining complementarities and positive sorting between directors and firms and then use exogenous variation in the composition of boards arising from unexpected deaths of directors to establish a causal relation between board-level measures of director productivity and firm performance.

In order to understand the role of directors' skills, specialized versus generalized, I hand-collect a comprehensive dataset on skills and qualifications of over $100,000$ directors from company proxy statements and use textual analysis to identify 20 different skill categories and qualifications (following the definitions in Adams et al., 2018) that firms use to justify the nomination of a given director to shareholders. Results reveal a robust positive association between estimated match-productivity and more specialized directors: I find that directors with more *Company/Business*, *Strategic*, or *Leadership Skills* and in particular directors that possess a skill that is not associated with any other director on the board display larger complementarities. Similar to Adams et al. (2018), I additionally compute the first factor of all 20 individual skills and qualifications as a proxy for the broadness of a director's skill set and find a negative association between broad skill sets and estimated complementarities.

Finally, I reinforce this finding by additionally constructing a *General Ability Index* from directors' previous employment experiences as defined in Custódio et al. (2013) for CEOs.[5] Consistent with the positive effects of skill specialization, the data shows that a director with more general ability is estimated to have lower complementarities with the firm. Specialized skills and general ability are, however, not substitutes but are independently associated with higher and lower complementarities, respectively. Strikingly, these results reverse when focusing only on the sample of CEOs and CFOs as the top decision-makers in the firm. While this confirms previous findings (Custódio et al., 2013), the positive effect of specialization

5 In particular I consider directors' experience in other firms, other industries, board tenure and the number of positions inside the firm. The *General Ability Index* is then defined as the principal factor of these four variables.

for directors complements evidence on the importance of certain characteristics for CEOs in Kaplan et al. (2012) and recent evidence of the increasing importance of social and interpersonal skills documented by Hansen et al. (2021) and Kaplan and Sorensen (2021). But while they focus on skills demanded by firms, I take an ex-post perspective by looking at complementarities of resulting matches. As long as shareholders appoint directors with specialized skills with their respective future tasks in mind, the findings of this paper are similarly consistent with extending the model of Guadalupe et al. (2012), who argue that executives specialize in performing their function-specific tasks.

Finally, to assess the causal impact of board-level productivity on firm value and firm performance, I hand-collect data on the cause of death of directors from obituaries and news reports and follow the classification of Nguyen and Nielsen (2010) to identify unexpected deaths of directors. These events then allow to isolate plausibly exogenous variation in board composition and board-level productivity. Next, I use the market response to exogenous changes in board-level statistics of estimated director productivity in the days following the death of a director as an agnostic test of how investors value board composition in terms of productivity. I find a small and insignificant market response to predicted changes, attributed to an unexpected death of a director, in either average or total board productivity, measured as the average or total of the estimated complementarities across directors sitting on a given board, respectively. In contrast, markets react strongly to predicted changes, due to an unexpected death, in the concentration of productivity at the board level measured by the Herfindahl index of the estimated complementarities: a one-standard-deviation increase in concentration causes a 95 basis-point increase in excess stock returns. This effect is robust to different controls, risk-adjustments of returns and appears persistent over time. I reinforce these findings by adopting an instrumental variable strategy that exploits the unexpected deaths of directors to generate exogenous variation in the board-level productivity measures and find a strong and positive causal effect of productivity concentration on firm performance measured by their return on assets.

This finding indicates that board hierarchies in terms of productivity matter. Consistent with the idea of optimal hierarchies in a knowledge economy (Garicano and Rossi-Hansberg, 2006, 2015), results, therefore, indicate the presence of knowledge hierarchies within the board of directors. This complements the findings of Hansen et al. (2021), who similarly relate the increasing importance of social and interpersonal skills for CEOs to the presence of hierarchies in a knowledge economy where facilitating communication to other layers in the hierarchy creates value. The result that boards, where productivity is concentrated to a few members, have a positive effect on firm performance complements these arguments. Furthermore, they indicate that advice from a few directors rather than similar advice from all directors creates more value. These positive effects of larger productivity concentration at the board level seemingly contrast Adams et al. (2018), who find that directors that are more similar in terms of skills provide *common ground* that facilitates decision making. However, concentration in match-level productivity does not exclude the presence of common ground to facilitate decision-making.

**Related Literature:** This paper is related to the literature documenting the contributions of managers to firm outcomes in the spirit of Lucas's (1978) span-of-control problem. Closely related, Bertrand and Schoar (2003) find evidence of the effects of *managerial styles*, *i.e.*, the difference in specific firm-level performance measures ascribed to unobserved managerial attributes. Similarly, Hagendorff et al. (2021) study the effects of unobserved characteristics of bank managers, Fenizia (2019) examines the impact of unobserved productivity of managers in the Italian public sector. Gabaix and Landier (2008) and Tervio (2008) formulate an assortative matching model based on unobservable CEO and firm characteristics to explain the observed increase in CEO compensation, and Graham et al. (2012) explicitly relate unobserved CEO characteristics to their compensation.[6] This paper complements this literature by departing from the typical linear-additive specification of unobserved heterogeneity and thereby overcomes several related identification issues. In addition, I extend the analysis from studying only CEOs to all board members. Furthermore, I estimate productivity at the firm-director match level rather than individual CEO and firm-level and more broadly contribute to the literature by applying the finite-mixture approach proposed by Bonhomme et al. (2019) to estimate director or CEO and firm heterogeneity.[7]

Further, by relating the estimated complementarities to granularly defined skills and qualifications, I add to the literature on CEO skill sets that finds more generalist CEOs to receive higher compensation (Custódio et al., 2013) and innovate more (Custódio et al., 2019). More recently, Kaplan and Sorensen (2021) and Hansen et al. (2021) show increasing demand for CEOs with social and interpersonal skills linking this to the increasing importance of lowering communication costs in knowledge economies (Garicano and Rossi-Hansberg, 2015). While this paper does not explicitly study the communication cost channel, I add to this literature by directly estimating the value a director or CEO can deliver to the firm she is matched with. While I confirm their findings that CEOs with a broader skill set and more general experience display higher complementarities, I document, more importantly, that the opposite is true for other directors and thereby offer a novel view on the organizational structure of the board of directors.[8]

6 See also Bennedsen et al. (2020) using hospitalization to provide causal evidence on the question of the impact of managers on firm outcomes.

7 This approach has previously been mainly used in labor economics; see Bonhomme et al. (2019) for an application to Swedish matched employer-employee data, and Bonhomme et al. (2020) for US data and other European countries. A notable exception is Alviarez et al. (2020) who apply the method to estimate brand value in the beverage market.

8 In that sense, this paper also contributes to the extensive literature surrounding the *World Management Survey* (see Scur et al., 2021, for a recent summary of this literature) and generally the idea of *management as a technology* (see Bloom et al., 2016).

This paper also contributes to the literature documenting positive direct effects of observable board diversity in terms of gender (Ahern and Dittmar, 2012), ethnicity (Carter et al., 2003) or demographics (Anderson et al., 2011) and, more related to this paper, mixed evidence on the indirect effects of group diversity on efficient decision making (Malenko, 2013; Jiang et al., 2015; Adams, 2017). Most closely related are the results in Adams et al. (2018), suggesting that skill-similarity of directors provides common ground among board members that facilitates efficient decision making. On the contrary, I find that more diversity regarding productivity resulting in a higher concentration of director productivity at the board-level positively affects firm performance beyond the direct effects of increased productivity.

Furthermore, by studying the sorting of directors, this paper also extends the view of the CEO labor market as a competitive labor market with positive assortativity established by Gabaix and Landier (2008) to all members of the board.[9] Nevertheless, my finding that parts of compensation remain unexplained by director and firm heterogeneity additionally allows for alternative explanations of executive pay like luck (Bertrand and Mullainathan, 2001).

This paper also contributes more laterally to the growing literature on teams (see Bonhomme, 2021; Devereux, 2018; Weidmann and Deming, 2020; Herkenhoff et al., 2018) and recent evidence that highlights the role of team formation and sorting under information frictions (Chade and Eeckhout, 2018) and for the emergence of market power (Chade and Eeckhout, 2019). In particular, Chade and Eeckhout (2018) show that while team diversity can be optimal, this rules out positive sorting. In contrast, I document positive sorting while at the same time I find evidence that concentration of productivity improves firm performance.

**Roadmap:** The paper proceeds as follows: Section 2 introduces the estimation strategy and Section 3 describes the data. Section 4 contains the empirical results and Section 5 concludes.

# 2. Empirical Methodology

To fix ideas, consider the following model for directors' compensation:

$$Y_{ik(i)t} = \psi_{k(i)} + b_{k(i)}\gamma_i + cX'_{it} + \epsilon_{it}, \tag{1}$$

where $Y_{ik(i)t}$ denotes compensation of director $i$ employed in a firm $k(i)$ at time $t$, where $k$ can denote individual firms or a *firm class* where multiple firms can belong to the same class or group. The parameters $\psi_{k(i)}$ and $\gamma_i$ denote firm and director specific heterogeneity of compensation, respectively. Importantly note that the formulation in equation (1) allows the effect of director heterogeneity to have a possibly differential effect across different firms $k$

9 See Edmans and Gabaix (2016) for an extensive review.

($i.e.$ $b_{k(i)} \neq 1$) and thus explicitly allows for positive and negative complementarities between directors and firms. $\epsilon_{it}$ is the residual and $X'_{it}$ is a vector of controls. Throughout I abstract without loss of generality from including control variables.

## 2.1. Two-way fixed effects

While this paper aims to estimate a parameter similar to $b_{k(i)}$, typical applications in labor economics and finance estimate a model like equation (1) under the restriction $b_{k(i)} = 1$ by estimating a two-way fixed effects model with separate parameters for each director and firm. Identification in these models relies on observing directors appointed to boards in different firms. Otherwise, firm and director fixed effects for firms without any director turnover would be perfectly co-linear. Bertrand and Schoar (2003) for example, estimate a two-way fixed effects model to study the effect of managerial styles on firm policies for a sample of CEOs that are observed to be CEO in at least two different firms. This so-called *mover-dummy variable* approach is, however, very restrictive as it only identifies fixed effects for those CEOs moving between firms and firms employing a CEO who is observed in at least one other firm in the sample period. Abowd et al. (1999) (hereafter AKM) propose a less restrictive approach that is widely used in the labor literature (see, e.g. Card et al., 2013; Song et al., 2019), but has also been applied in the context of executive compensation (Graham et al., 2012).

The AKM model still estimates a linear model like equation (1) under the restriction $b_{k(i)} = 1$, but identifies fixed effect for all firms and directors in the so-called *connected set* of firms that have appointed at least one director that is also observed on the board of at least one other company in the connected set.[10] In contrast to the mover-dummy variable approach, fixed effects can be estimated for all directors in firms belonging to the connected set regardless of whether they are observed in other firms or not. Intuitively, observations of directors that move between two firms identify the firm fixed effect in the connected set of firms as the average pay differential observed for directors moving between firms. Once the firm fixed effects are identified, it is straightforward to back out the fixed effect for all directors observed in these firms. Consequently, AKM can identify fixed effects not only for firms connected by directors and directors connecting these firms but also for all directors in firms belonging to the connected set.

While overcoming these sample restrictions, the AKM approach suffers from two established

10 The *connected set* can accordingly be identified by a simple iterative procedure initialized with all firms begin in the connected set: first, keep all firms in the connected set. Secondly, drop all firms from the connected set without a director observed at any other firm in the connected set. Repeating these steps until no firm is dropped yields the connected set of firms and directors. This idea can also be cast in terms of graph theory: The director firm network is a bipartite network, where the connected set, in the sense of AKM, is simply the largest component of the one-mode projection of the bipartite network. The sample selection issue and potential bias when estimating the AKM model then depend on the density of the network resulting from the one-mode projection.

shortcomings: The limited mobility bias and the exogenous mobility assumption. Andrews et al. (2008) have shown that even if the connected set of firms is large, but we observe only a few directors moving between firms, estimates are biased. This incidental parameter problem arise since as the connected set grows, the number of parameters (*i.e.*, director and firm fixed effects) proliferates relative to the number of observations of actual moves between firms. Secondly, identification requires that director mobility between firms is exogenous conditional on firm fixed effects. This assumption is violated if directors sort into firms based on firm-director specific components of productivity, *i.e.*, the comparative advantage of directors would violate the linearity assumption $b_{k(i)} \neq 1$.[11]

A third concern exists about identifying sorting patterns based on these linear specifications, which I want to identify in this paper. Eeckhout and Kircher (2011) argue that the correlation of worker and firm fixed effects, typically used as a measure of sorting (Card et al., 2013; Song et al., 2019), can identify complementarities in production even if the output is linear in the firm and worker heterogeneity. They show in a setting of search frictions and assortative matching that the matching region results in a non-monotonic relation between wages and worker types as workers both with more or fewer skills than the perfect match would accept the job under search frictions. Hence, even in linear settings, wage data alone is not always sufficient to identify the complementarities by estimating a linear fixed effect model.

## 2.2. Finite-mixture models

The goal of this paper is to identify the complementarities between directors and firms akin to the parameter $b_{k(i)}$ in Equation (1). Generally, this is possible relying only on directors moving between firms $k$ and $k'$ to identify the interaction term (up to labeling):

$$\frac{\mathbb{E}_{kk'}(Y_{i,t}) - \mathbb{E}_{k'k}(Y_{i,t-1})}{\mathbb{E}_{kk'}(Y_{i,t-1}) - \mathbb{E}_{k'k}(Y_{i,t})} = \frac{b(k')}{b(k)} \frac{[\mathbb{E}_{kk'}(\alpha_i) - \mathbb{E}_{k'k}(\alpha_i)]}{[\mathbb{E}_{kk'}(\alpha_i) - \mathbb{E}_{k'k}(\alpha_i)]} = \frac{b_{k'(i)}}{b_{k(i)}}, \tag{2}$$

where $\mathbb{E}_{kk'}(x) = \mathbb{E}(x|k(i,t-1) = k, k(i,t) = k')$ is the expected compensation of a director moving from firm $k$ to firm $k'$. $\frac{b_{k'(i)}}{b_{k(i)}}$ is identified using mean restrictions as long as $\mathbb{E}_{kk'}(\alpha_i) \neq \mathbb{E}_{k'k}(\alpha_i)$; *i.e.* the share of different directors moving between firms $k$ and $k'$ is different. Again the issue is that this requires to estimate a large number of parameters using only a limited number of directors transitioning between firms.

This paper follows Bonhomme et al. (2019) (hereafter BLM) to identify the parameters in equation (1) using a finite-mixture random-effects model. Their approach follows two steps: first, I classify firms into a smaller number of groups using k-means clustering to overcome the limited mobility bias. Secondly, conditional on firm classes, I estimate a random-effects

11 Similarly, exogeneity requires that better directors do not systemically sort into firms with declining productivity or in response to a transitory firm-level productivity shock.

model with a finite number of director types.

The approach of BLM offers two significant advantages. First, it allows to directly estimate the complementarities between different director types and firm classes corresponding to $b_{k(i)}$, which previous research restricted to be one. Secondly, I can estimate all parameters of interest using panel data with only a short time dimension. Thus, it is possible to test the effects of complementarities on firm performance while avoiding any forward-looking bias in estimating director types and firm classes.

**Classification:** The critical step to the estimation is to first reduce the number of parameters by grouping firms into classes. While before in Equation (1) $k$ denoted individual firms, I now use $k$ to denote firm classes, each consisting of multiple individual firms. These firm classes are estimated as *discrete fixed effects* in the classification step. As the number of firm classes $k$ is much smaller than the number of firms in the sample, we naturally observe more transitions between firm classes compared to transitions between individual firms, mitigating the bias arising from the limited mobility of directors.

Classifying firms into a discrete number of classes reduces the number of parameters that need to be estimated. The dimension reduction effectively mitigates the bias arising from the limited mobility of directors. As the number of firm classes $k$ is much smaller than the number of firms in the sample, we naturally observe more transitions between firm classes compared to transitions between individual firms.

The k-means clustering algorithm works as follows: assume we have $J$ firms with $n_j$ observations for each firm and want to assign each firm to a cluster $k(j)$ so as to minimize the distance between $G$ different firm characteristics $h_{j,g}$ and firm class-specific location $H_{k(j),g}$:

$$\min_{k(1),\ldots,k(J);H_1,\ldots,H_k} \sum_{j=1}^{J} n_j \sum_{g=1}^{G} \left(h_{j,g} - H_{k(j),g}\right)^2 . \tag{3}$$

For most of the paper, I follow BLM and use $G = 4$ moments of the firms' empirical CDF of directors' log compensation to form $K = 8$ clusters. However, I will show that sorting patterns are similar for different choices of $K$ (see Table 5).[12]

**Estimation:** Conditional on firm classes $k$, I proceed to estimate the parameters of interest and recover director types by leveraging a random-effects approach with a finite number of director types as proposed in BLM. Throughout I assume to observe compensation data for a given director for at least two consecutive years $t-1$ and $t$. Let $F_{k,\alpha}(y_{i,,t-1})$ denote the cumulative distribution function of log earnings in period $t-1$ for directors of type $\alpha$ and

12 Note the difference to equation (2) where restrictions of one moment of the wage distribution, *i.e.*, the mean, identify the parameters. However, relying on several moments allows identifying the parameters even if the means are identical across firms.

firm class $k$. Next, define $m_{it} = 1$ if director $i$ moves from firm class $k$ to any other firm class $k'$ between $t-1$ and $t$. For a director transitioning between firm classes, I denote the earnings distribution in period $t$ as $F^m_{k',\alpha}(y_t)$ and denote the probability distribution of directors of type $\alpha$ moving between a firm of class $k$ to class $k'$ as $p_{kk'}(\alpha)$. The bivariate log-earnings distribution then reads:

$$\Pr\left[Y_{i,t-1} \leq y_{t-1}, Y_{i,t} \leq y_t | k_{i,t-1} = k, k_{i,t} = k', m_{i,t-1} = 1\right] = \sum_{\alpha=1}^{L} F_{k\alpha}(y_{t-1}) F^m_{k',\alpha}(y_t) p_{kk'}(\alpha) \tag{4}$$

and similarly the earnings of a director in period $t-1$ that does not move:

$$\Pr\left[Y_{i,t-1} \leq y_{t-1} | k_{i,t-1} = k\right] = \sum_{\alpha=1}^{L} F_{k\alpha}(y_{t-1}) q_k(\alpha). \tag{5}$$

Throughout I follow BLM and maintain the following assumptions to identify the parameters in Equation (4) and Equation (5) (see Appendix A and BLM for additional details and a proof of identification):

(i) **Mobility Determinants:** Conditional on the director type and firm class, mobility between firms and the firm class of new board appointments are independent of earnings in the first period; *i.e.* $m_{it}$, $k_{i,t+1}$ are independent of $Y_{it}$ conditional on $\alpha_i$, $k_{i,t}$ and $m_{i,t-1}$.

(ii) **Serial Dependence:** A director's compensation in the second period is independent of compensation and firm class in the first period conditional on director type and firm class in the second period and the fact that he is observed on both boards; $Y_{i,t+1}$ is independent of $Y_{it}$,$k_{it}$ and $m_{i,t-1}$ conditional on $\alpha_i$, $k_{i,t+1}$ and $m_{i,t}$.

(iii) **Connecting Cycle:** For every director type $\alpha$, any two firm classes $k$ and $k'$ belong to a connecting cycle.

(iv) **Heterogeneity:** Director types are sufficiently different such that transition probabilities between any two firm classes are different across director types.

(v) **Full Rank:** Director types are sufficiently different so that they draw from different distributions for each firm class.

Assumption (i) imposes strict exogeneity on transitions of directors between different boards. At the same time, appointments to other boards might depend on directors' previous and current type and firm class, but not directly on earnings. Secondly, assumption (ii) maintains that, unlike mobility, earnings in the second period are not allowed to depend on previous firm classes or earnings conditional on director type and the firm class of his new appointment. This assumption is necessary to distinguish whether earnings are high because of the director type or persistently high wage draws. However, I observe that roughly 90% of directors in the Execucomp database receive some form of option or equity awards that introduce idiosyncratic fluctuations to earnings conditional on types. The more restrictive part of assumption (ii) lies in the fact that compensation in the second period cannot depend on the firm classes of other board appointments. This is in line with the view that the compensation of CEOs is the result of a competitive labor market between firms and CEOs as postulated in Gabaix and Landier (2008) and Tervio (2008). It also accommodates the finding in Custódio et al. (2013) that CEOs are paid a premium for general managerial skills as long as the general ability is only a function of director types. Previous work experience in various industries or positions results from her innate director type allowing her to be productive in many different firms rather than vice versa the ability resulting from past experiences.[13]

Assumptions (iii)-(v) bear little economic meaning but impose conditions on the data. Note that conditions (iii) and (iv) require mobility between firm classes to be sufficiently high.[14] Importantly, I only impose connectedness at the firm-class level rather than the individual firm level and do not require every director type to move between every firm class bilaterally. Instead, identification only requires that for every director type, transitions between firm classes are such that they connect all firm classes in a connecting cycle. This assumption is less demanding than the stronger assumptions necessary for identifying the AKM two-way fixed effects model. Condition (v) is a standard rank condition similar to the mean restrictions necessary to identify the parameters in Equation (2). Choosing the number of firm classes and director types balances the need for enough heterogeneity to satisfy (iv) and enough transitions between firm classes for each director type to satisfy (iii). For the baseline estimates, I choose eight director types and firm classes, respectively. Results show that this ensures relatively high graph connectedness. Furthermore, I show that varying the number of types and classes does not significantly affect the estimates.

The fulfilled assumptions allow me to estimate the model using the following simple two-step likelihood estimator, where aggregating over all individuals then yields the following likelihood function:

$$\sum_{i=1}^{N_m}\sum_{k=1}^{K}\sum_{k'=1}^{K}\mathbf{1}\{\hat{k}_{i,t-1}=k\}\mathbf{1}\{\hat{k}_{i,t}=k'\}\ln\left(\sum_{\alpha=1}^{L}p_{kk'}\left(\alpha;\theta_p\right)f_{k\alpha}\left(Y_{i,t-1};\theta_f\right)f_{k'\alpha}\left(Y_{i,t};\theta_{f^m}\right)\right). \quad (6)$$

The multiplication of type probabilities and densities follows from the independence assumption conditional on firm classes and director types. The log-likelihood of all directors

13 Note that assumption (i) and (ii) are satisfied in the linear setting imposed by the AKM model.

14 This is effectively the same assumption about graph connectedness in AKM.

in period 1 is given by:

$$\sum_{i=1}^{N}\sum_{k=1}^{K}\mathbf{1}\{\hat{k}_{i,t-1}=k\}ln\left(\sum_{\alpha=1}^{L}q_k\left(\alpha;\theta_q\right)f_{k\alpha}\left(Y_{i,t-1};\hat{\theta}_f\right)\right). \tag{7}$$

I follow BLM and model the earnings densities to be log-normal. I estimate director-type and firm-class specific means and variances indexed by the parameter vector $\theta_f$ and $\theta_{f^m}$ for first and second-period earnings densities, respectively. I allow the mean and variance of log earnings to differ for all combinations of director types and firm classes and estimate the director-type proportions $q_k(\alpha)$ for proportions for job-movers $p_{kk'}(\alpha)$ as unrestricted parameters. Having estimated all parameters in Equation (6) and Equation (7), I assign each director to one of the eight director types depending on which type maximizes the likelihood of the directors observed wage draws:

$$\alpha^* = \arg\max_{\alpha}\frac{q_k(\alpha,\hat{\theta^f})f_{k\alpha}\left(Y_{i,t-1};\theta_f\right)}{\sum_{\alpha'=1}^{L}q_k(\alpha',\hat{\theta^f})f_{k\alpha'}\left(Y_{i,t-1};\theta_f\right)}. \tag{8}$$

Based on the assigned type and conditional on the classification of firms, I then define the complementarities between firms and directors appoint to their boards or, in other words, the director fixed effect at a firm of class $k$ as $\hat{\theta}_k^{\alpha^*}$.

**Implementation:** I estimate the model based on annual data on directors' compensation. Throughout, I use residualized log total compensation obtained from regressing total compensation on age, age squared, gender, tenure, highest level of education, a dummy whether the director is an executive director, and firm-level determinants of compensation (log of total assets, log of market valuation and log of sales) as well as a set of year and industry fixed effects defined at the 2-digit SIC industry level.

Furthermore, I only consider board appointments in two consecutive years[15] and estimate the model first for each overlapping two-year interval from 2010 to 2019 separately and secondly on the full sample by using all observations from two consecutive years while treating observations from the same director in two overlapping two-year intervals as independent observations; *i.e.*, allowing director types to vary unrestrictedly over time.

In comparison to other matched employer-employee data, directors can hold multiple directorships simultaneously. I exploit the variation in compensation across multiple directorships in the same year in the same fashion as observations from a director transitioning between firms between periods $t$ and $t+1$ to identify the parameters of interest. Suppose a director

15 Bonhomme et al. (2019) present additional results based on five years of compensation that in return allow relaxing some assumptions. In the setting of this paper, focusing only on directors present for five consecutive years imposes, however, substantial restrictions on the sample.

holds more than two directorships at the same time. In that case, I construct all possible unique combinations of firms and consider each as a single observation.

# 3. Sample and Data Description

The sample consists of a panel of 163,330 director-firm-year observations from 2010-2019. I combine data on board composition and director characteristics from BoardEx with data on annual director compensation from Execucomp and firm-level financial data from Compustat and CRSP.

I first match firms across databases on CIK identifiers and firm names. Then, for each firm, I match directors between BoardEx and Execucomp based on first and last names checking imperfect matches manually for accuracy. The matched sample consists of observations for 2,229 unique firms and 24,972 unique directors.[16] Table 1 Panel A reports summary statistics on total compensation for the entire sample and average compensation by estimated *director types*, sorted from one to eight according to average compensation. *High-type* directors, *i.e.*, directors that obtain higher compensation on average, are younger and predominantly male, although within one standard deviation of the corresponding full sample average. Interestingly, there is no strong relationship between education and director types. While BoardEx reports almost all directors to have obtained an undergraduate degree, higher director types are not strongly associated with having obtained either a Masters' degree, MBA, or Ph.D.

**Director Skills, Qualifications and Experiences** To address the question which director characteristics eventually drive heterogeneity in the estimated director fixed effects, I collect data on directors' skill sets and qualifications from companies' proxy statements. From 2010 onwards, public companies are required to report experiences, qualifications, attributes, and skills that led to the nomination of a given director in their annual proxy statement.[17] I obtain proxy statements for 2,171 unique firms and identify relevant paragraphs describing the skill set of a nominated director for 23,616 unique directors resulting in a sample of 146,221 firm-director-year observations. Using these paragraphs, I use textual analysis to decompose reported skills and qualifications of directors into the following 20 different categories using the dictionary developed in Adams et al. (2018): *Academic*, *Company Business*, *Compensation*, *Entrepreneurial*, *Finance and Accounting*, *Governance*, *Government and Policy*, *International*, *Leadership*, *Legal*, *Management*, *Manufacturing*, *Marketing*, *Outside Board*, *Outside*, *Executive*, *Risk Management*, *Scientific*, *Strategic Planning* and *Sustainability* (see Table A1 for exact definitions and word lists associated with each skill).

16 Note that the sample is effectively restricted by the number of firms in the Execucomp database used to obtain directors' compensation. The sample, therefore, consists mainly of large companies in the S&P 1500.

17 See Adams et al. (2018) for additional details around the legislation.

Table 1 Panel B provides summary statistics for each skill category. Column 1 reports the average probability that a director is associated with a given skill by her firm. Firms most commonly associate their directors with *Management* and *Finance/Accounting* skills or *International Experience*. In contrast, directors are least likely to have *Entrepreneurial* skills or qualifications associated with *Sustainability*. On average, firms report between four and five different skills and qualifications for each director. I also compute the number of unique skills, *i.e.*, the number of skills not reported for any other director sitting on the same board. On average, every second director has one unique skill. Column 2 reports the percentage of firms that employ at least one director with a given skill or qualification. Almost all firms employ a director with *Finance/Accounting* skills, and a large percentage reports their directors to have *Compensation* or *Governance* qualifications in line with the fact that these skills overlap with specific board committees present in most firms. On average, roughly four skills are associated with only a single board member, and boards consist on average of directors with 34 potentially overlapping skills.

To reduce the dimensionality of the skill vector to a single variable, I follow Adams et al. (2018) and perform a factor analysis on all 20 skill categories. The first factor accounts for roughly 50% of the observed variation (compared to 56% in Adams et al., 2018) and associated factor loadings are in column 3. Since all skill categories load positively on the first factor, I label this factor as *Skill Set*, where higher values are associated with directors having a broader skill set and more qualifications. The remaining columns in Panel A again report the average probability for each estimated director type. Again strikingly, no clear pattern emerges, and neither *low* nor *high* director types are associated with more total skills, more unique skills, or any individual category in particular.

I complement the data on director characteristics by additionally collecting data on directors' professional careers from BoardEx to construct a proxy for directors' general managerial ability similar to Custódio et al. (2013). I collect information on directors' board tenure, the number of firms where a director previously held a position, the number of previous positions held outside the firm, previous appointments inside the firm as well as the number of industries at the 4-digit SIC level in which a director was previously employed.[18] I combine these five variables into a single measure of directors' general managerial ability using factor analysis as in Custódio et al. (2013) [19]. Summary statistics are in Panel C of Table 1, with averages in column 1 and factor loadings in column 2. While board tenure and inside positions likely reflect higher firm-specific knowledge, directors with more general managerial ability,

18 Note that the sample in Custódio et al. (2013) only contains CEOs, and therefore I drop the variable CEO experience used in their analysis. Instead, I additionally consider the firm-specific information on previous positions inside the board and board tenure.

19 The first factor explains around 65% which again is similar to Custódio et al. (2013) who report 59% for their sample of CEOs

either innate or acquired through previous experience, are associated with higher values of the remaining variables. This is also reflected in the factor loadings being positive for all variable except board tenure and the number of inside positions. Board tenure and previous positions held inside the firm are the only variables with a negative loading and hence indicate firm-specific knowledge rather than general ability.

**Firm-Level Characteristics** Throughout, I explore potential channels of my main findings, *i.e.*, positive sorting patterns and skill specialization, by exploiting heterogeneity in characteristics across firms. First, I obtain data on firms' balance sheets from Compustat and combine this with data on equity prices from CRSP. Then, following De Loecker et al. (2020) and Baqaee and Farhi (2020), I compute firm-level markups as the ratio of sales to costs of goods sold multiplied by the output elasticity concerning variable capital inputs, where I obtain the elasticity by estimating a production function at the industry-year level, using 2-digit NAICS industries.[20] From Peters and Taylor (2017), I further obtain data on firms' intangible capital and total Q from Peters and Taylor (2017) as a measure of Tobin's Q adjusted for intangible capital and collect data on the inflation-adjusted value of firms' patents as estimated by Kogan et al. (2017). Finally, I obtain data on the number of firms' business segments from Compustat and define a firm to be diversified if the number of business units exceeds the sample median of business units reported per firm. Summary statistics are displayed in Table 2 for the full sample (columns 1 and 2) and each estimated firm class (ordered by average total compensation) in columns 3 through 10. *Higher* firm classes tend to have lower ROA, innovate less successfully, display higher markups, and Tobin's Q. In contrast, the middle firm classes are slightly larger and have more intangible capital.

# 4. Results

## 4.1. Model Estimates and Sorting

Table 3 shows the results of decomposing variation of residual log wages into the components explained by either firm ($\theta$) and director ($\gamma$) heterogeneity and sorting of director types to firm classes. For comparison, results in the first row are based on estimates of director and firm heterogeneity from a standard AKM two-way fixed effects model, where sorting is defined as the correlation of director and firm fixed effects. Results indicate that in the linear model about two-thirds of the variation in compensation is explained by director heterogeneity and unobservable firm characteristics explain about 40% while the error term accounts for a similar

20 This is motivated by the fact that the firm's first-order condition generally equates the output elasticity of a variable input to the expenditure share of total costs. By doing so, I avoid having to estimate the firm's total cost.

share of the observed variation. Interestingly, sorting appears to be strongly negative. The correlation between the firm and director fixed effects is estimated to be around -40%.[21] However, as discussed before, limited mobility bias and associated measurement error likely attenuate the estimated correlation and potentially lead to a spurious estimate of negative sorting.[22]

Addressing these concerns, the remaining rows display the corresponding variance decomposition after estimating the non-linear model in equation (6) and equation (7). Throughout estimates are based on eight director types and firm classes. The second row of Table 3 shows estimates based on the full sample and are therefore directly comparable to the estimates of the AKM model. Importantly, results indicate a moderate degree of positive sorting of 14%. This difference is likely the result of resolving the limited mobility bias by estimating only a finite number of firm classes and director types. Finally, the last column reports a measure of how well the graph is connected,[23] where the value of 0.54 indicates a high level of connectivity. Although not directly testable, this gives confidence that the assumption of director transitions between different firm types forming a connecting cycle is satisfied in this setting.

Figure 2 provides a graphical illustration of the positive sorting patterns. It plots the estimated productivity $\widehat{\theta}$ that materializes for each observed match against the counterfactual average productivity of that director across all firm classes. The size of each dot scales with the number of matches, and the dashed grey line is the 45-degree line. The fact that most matches are located to the left or close to the 45-degree line illustrates that directors are more productive at the firm they eventually match with relative to their average productivity at all other firms. These positive complementarities between certain director types and firm classes drive the observed positive sorting. These positive sorting patterns are also apparent in the estimated director-type proportions $\hat{q}_k(\alpha)$, *i.e.*, the estimated share of director type $\alpha$ appointed to the board of a firm belonging to firm class $k$, displayed in Figure 1.

Overall estimated director and firm heterogeneity explain only about a quarter of the observed variation in residual compensation. Nevertheless, similar to the AKM estimates, director heterogeneity accounts for a larger share of the observed variation. It explains about three times as much as the variation across firm classes. Even though director and firm heterogeneity explain only about a quarter of the variation and unobserved components

21 For comparison, Card et al. (2013) find a correlation between 3% and 24% for German matched employer-employee data, and Bonhomme et al. (2019) document a correlation of 48% when applying their method to Swedish data.

22 Interestingly, when estimating the correlation of director and firm fixed effects only for the sub-sample of directors who sit on more than one board, the estimated degree of sorting becomes less negative corroborating that the limited mobility creates a spurious negative correlation.

23 A graph's Laplacian is a continuous measure of how well a graph is connected. Generally speaking, it is based on the second eigenvalue of $L = D - A$, where $D$ is a diagonal matrix whose entries are the degree of each node and $A$ is the adjacency matrix. In this setting, each node represents a firm class, with the degree being the number of directors and entries in the adjacency matrix reflect the number of directors moving from one firm class to another.

account for the majority of the variation in residual compensation, the estimated model fits the data well as the following finding shows: Table 4 compares the first two moments of log compensation imputed from the estimated model (columns 1 and 3) to the respective moments observed in the data (columns 2 and 4) across the estimated firm classes. Overall, the model performs well and can replicate average compensation very closely and similarly produces wage variation closely resembling the real-world data.

As before, full-sample results in the second row of Table 3 are obtained by pooling all overlapping two-year windows, thereby allowing director types to vary over time while restricting firm classes and parameters to be time-invariant. The remaining rows display the variance decomposition after estimating the BLM model on each two-year overlapping window separately. While the contribution of director types and firm heterogeneity is remarkably stable over time, estimating the model for every 2-year window individually reveals considerable heterogeneity in sorting patterns over time. Averaging across years delivers a much lower degree of positive sorting of 4%, and although sorting appears to be positive for earlier years, it decreases over time. This seems to be a secular feature of the data rather than the naturally smaller samples being again subject to the limited mobility bias; throughout, connectivity is high and comparable to that reported for the full sample.[24]

An essential choice for estimating equation (6) and equation (7) is the number of firm types estimated in the random-effects model and the number of firm classes chosen for the classification step. Table 5, therefore, replicates the baseline results from Table 3 using ten firm clusters and director types in Panel A and alternatively ten director types and six firm classes in Panel B. For both specifications sorting is estimated to be somewhat stronger (26% or 27% vs. 14%); hence estimates in Table 3 are likely a conservative estimate of the true degree of sorting. The share of variation in director compensation explained by either director or firm heterogeneity is similar. Mobility between firm classes and director types remains high despite the increased number of types. As before, estimating the model on each two-year subsample separately allows parameter estimates, director types and firm classes to vary over time. This again reveals substantial heterogeneity in sorting patterns. But differences in the other components of the variance decomposition are minor compared to the baseline results.

Results illustrate two important points: firstly, allowing for interaction between unobserved director and firm heterogeneity is essential. The standard two-way fixed effects approach appears to be biased and indicates negative sorting between directors and firms. Secondly, allowing for such interactions and complementarities between firms and members of their boards instead reveals positive sorting, *i.e.*, directors are predominantly observed to be

24 Note that although sorting is estimated to be negative for a few years, once I run robustness checks that vary the number of discrete firm classes and director types, only results for 2015 are consistently negative across specifications but small in magnitude.

appointed to boards where they are more productive relative to other boards. This result is crucial as it extends the widely accepted view of positive assortativity in the matching between CEOs and companies (see Gabaix and Landier, 2008; Edmans and Gabaix, 2016) to directors who similarly match positively with the board where their ability best complements the needs of the firm.

## 4.2. Heterogeneity in Sorting

To shed light on potential mechanisms that drive the positive sorting of directors to firms, I next explore differences in sorting behavior across firms with different characteristics. Following the literature highlighting the role of directors as advisors to the firm, I hypothesize that matching with the right director is more important for firms with higher need for advise and hence display more positive pattern. Similarly, growth firms or firms with low performance or facing high competition might benefit from appointing directors with higher complementarities. I borrow from the literature to identify firms that benefit more from a higher quality of fit. In particular I hypothesize that more complex firm, as measured by the number of their business units, and firms whose value depends more on firm-specific knowledge, as measured by the intangible capital and the value of innovations, benefit from matching with the right directors. On the contrary, firms characterised by lower markups, ROA and Tobin's Q might benefit from the advice of a better director simply because they face though market competition.

Then I follow the literature on discrete fixed effects (Bonhomme et al., 2017) to estimate the following linear specification with OLS:

$$Y_{ik(i)t} = \psi_k + \gamma_\alpha + \epsilon_{it}, \tag{9}$$

where $\psi_k$ and $\gamma_\alpha$ denote director-type and firm-class fixed effects, respectively. Rather than estimating a fixed effect for each firm and director in the sample, I use the estimates from the full model in equation (6) and equation (7) to group directors into eight groups according to their estimated type as defined in equation (8) and group firms into the eight classes identified by the k-means classification. While parameter estimates for assigning directors to groups allow for the unrestricted interaction of director types and firm classes, I impose a parsimonious additive linear structure in equation (9) and restrict heterogeneity to vary across different director types rather than individual directors (and similarly for firm classes). However, in turn, I only need to estimate a small number of fixed effects. This reduces the limited mobility bias as identification comes from a director with the same type moving across different firm classes. This allows to flexibly estimate the degree of sorting for different samples of firms.

Table 6 reports the estimated degree of sorting obtained by projecting standardized estimated director on standardized estimated firm fixed effects obtained from estimating equation (9). Standard errors are double clustered at the firm and director level. The baseline estimate in Table 6 using the full sample is reassuringly positive compared to the negative estimate obtained from estimating equation (1) with fixed effects for each director and firm (and setting $b_{k(i)} = 1$) reported in Table 3.

The remaining columns report results from re-estimating equation (9) separately for firms in the lowest and highest quartile of each of the different firm characteristics.[25] I find that more diversified companies, companies with more intangible capital, and firms producing more valuable innovations drive the positive sorting. The coefficients of interest are 13.2%, 18.6%, and 13.6% and between three and six times as large as their counterpart estimated for the subsample of firms in the lowest quartile. Estimated correlations are statistically significantly different from zero for both the high and low samples.

On the contrary, firms with higher markups and more profitable firms display lower degrees of sorting. Here the coefficients of interest, estimated in the lowest quartile, are 10.5%, 10% and 11.9% and roughly twice as large compared to coefficients estimated in the highest quartile.

These results show that complementarities arise in particular in firms that have greater advising requirements. Firms with low markups and low performance seem to hire directors that are more complementary which corroborates evidence that better-matched directors are perceived as a strategy to improve firm performance. Primarily these firms might depend more on the advice provided by their directors. This is line with findings in Coles et al. (2008) that indicate that more complex firms indeed appoint certain directors in order to meet their increased need for outside advice. Similarly, firms whose value depends more on firm-specific knowledge (*i.e.*, high intangible assets or valuable innovations) find it particularly beneficial to appoint directors that best complement the existing firm-specific knowledge. How specific skill-sets of directors complement firms' need for advice is the central question for the remainder of the paper.

## 4.3. What makes a good director?

The arguments above predicate that higher complementarities between directors and firms indeed influence firm outcomes. To shed light on this Figure 3 plots firms' ROA against the sum of estimated productivities of all board members. Total board productivity is standardized to have zero mean and unit standard deviation. The dashed red line is the linear fit. There is a strong positive association between board productivity and firm performance: a one standard deviation increase in board productivity increases firms' ROA by around 0.7 percentage points. This is reassuring as this indicates that appointing directors with a *better fit*, or higher comple-

25 Estimating equation (9) anew for each subsample is the most flexible specification as I allow unobserved firm-class heterogeneity to additionally vary across firm samples

mentarities for that matter, is in turn also associated with positive effects for firm performance.

### 4.3.1. Skills and Qualifications

Naturally, this positive association raises the question of what makes a director a *good match* or, in other words, particularly valuable for a firm. From an organizational perspective, the question is how directors with different skills and business experience act in monitoring and advising the firm's executives and creating value for shareholders and has implications for how to best design the search for new board nominees as well as potential governance mechanisms for the selection of suitable directors. I explore this question by asking whether directors' skills, qualifications, and experiences can explain variation in estimated productivity at the level of a director-firm match, $\widehat{\theta}$. Figure 4 illustrates the distribution of estimated complementarities by plotting the histogram of $\hat{\theta}$ of all director-firm matches estimated on the overlapping 2-year windows.

I begin by documenting the correlation between the 20 skills and qualifications identified from the firms' proxy statements. Figure 5 plots estimated coefficients and associated 95% confidence intervals from univariate regressions of $\widehat{\theta}$ on each skill. In particular, directors with *Company and Business* skills or *Legal*, *Leadership*, and *Strategic Planning* skills are associated with larger complementarities; *i.e.* directors associated with these skills tend to be a better match as indicated by the estimated productivity. On the contrary, directors with *Outside Board Experience*, *Outside Executive Experience*, or *International Experience* and with a *Finance/Accounting*, *Academia*, or *Government Background* are associated with lower complementarities.

Rather than thinking about each skill in isolation, I next consider each director to have a vector of skills and qualifications that matter to the firm directly and indirectly in relation to the skills offered by all other board members. Table 7 shows results from regressing estimated complementarities on several statistics derived from the reported skill set of directors. I include firm-year fixed effects to control for firm-specific variation, and standard errors in parentheses are double-clustered at the firm and director level. In column 1, I define a director to have a unique skill if they are reported to have a skill that no other member of his board possesses; a unique skill does not significantly impact the director's complementarities with a firm directly (column 1). Once I control the total number of skills of a given director in column 2, possessing a unique skill positively affects complementarities, significant at the 5% level. On the contrary having more skills is associated with lower productivity. In column 3, I summarise a director's skill set using the first factor obtained from a factor analysis on all twenty skills (see Table A1 for details); as each skill loads positively on the first factor (Table 1 column 3), larger values are associated with a broader skill set. The coefficient in column 3 is estimated to be negative and significant at the 10% level. Including the number of unique skills in column 4 yields comparable results. Overall, this suggests that directors that offer a unique skill to the board and are more specialized, *i.e.*, have a narrow skill set, are more productive for their respective firms. The effects are also economically large: taking, e.g., estimates from column 4, an additional unique skill is associated with an increase in the estimated $\hat{\theta}$ of around 8% relative to the sample average. An increases in the broadness of skills corresponding to a one-standard-deviation increase in the skill set factor implies a similar drop in the estimated complementarity by around 8%.

Interestingly, the sign and significance changes when focusing only on CEOs and CFOs as the top decision-makers in a company in columns 5 to 7. While a unique skill does not translate into higher productivity, the effect of a broader skill set as measured by the first factor is associated with higher complementarities. The estimated coefficients in columns 6 and 7 are 0.938 and 1.193 and significant at the 5% level. This finding is in line with previous evidence by Custódio et al. (2013); Custódio et al. (2019) and complements evidence on CEOs having different skills than other managers (Kaplan et al., 2012) and recent evidence documenting that social and interpersonal skills have become more important (Hansen et al., 2021; Kaplan and Sorensen, 2021) indicating the presence of knowledge hierarchies as in Garicano and Rossi-Hansberg (2006).

#### 4.3.2. General Abilities

I complement these findings by examining the effect of general abilities on complementarities of directors. I infer general abilities from directors' employment history; in particular, I associate directors that previously worked at other firms, held more different positions, and had appointments to firms in different industries (all measured before the current board appointment) with having more general abilities. In contrast, directors with longer board tenure and more previous positions inside the firm have more firm-specific than general abilities. Table 8 shows results from regressing estimated complementarities on these indicators of directors' general abilities where I include as before firm-year fixed effects and standard errors in parentheses are double-clustered at the firm and director level.

In line with previous results, estimated coefficients on the number of prior firms ($-0.133$) and different industries ($-0.771$) are negatively associated with complementarities and statistically significant. The effect of the number of previous positions is insignificant. In particular, the effect of experience in other industries is economically large, where having worked in another industry is associated with a decrease in $\widehat{\theta}$ by around 25% relative to the average.

In contrast, experiences associated with firm-specific knowledge, *i.e.*, board tenure and the number of inside positions, are estimated to be positive, highly significant, and economically large. For example, one additional previous position inside the firm corresponds to an increase in complementarities by around 30% relative to the average.

As these variables are highly correlated, I report in column 7 of Table 8 estimates using the first factor of the five variables. Higher values of the *General Ability* factor are associated with a director having more general skills as loadings are positive for experiences associated with more general skills (*i.e.*, number of previous firms, previous industries, and positions) while the number of previous positions inside the firm and board tenure load negatively on the first factor (see Table 1 column 3). In line with previous results, the coefficient on *General Ability* is estimated to be negative and highly significant. In column 8, I additionally control for directors' skill sets.[26] As before, having a broad skill set or more general abilities is associated with lower complementarities. The coefficient on the general ability factor is about three times as large as the corresponding effect of a broader skill set, but both are highly significant. Results remain qualitatively similar when additionally including director fixed effects in column 9 (albeit the effect of general abilities being almost five times as large) or controlling for industry-year fixed effects instead of firm-fixed effects in column 10.

Column 11 is again estimated using only CEOs and CFOs. Mirroring results in Table 7, top executives with more general abilities and a broader skill set are associated with higher complementarities. Increasing either factor by one standard deviation is related to an increase in $\widehat{\theta}$ between 35% and 50% relative to the average.

#### 4.3.3. Specialisation in the Cross-Section of Firms

These findings show that directors differentiated by specialized skills, qualifications, and experiences are appointed to the firms' boards where they best complement the firms' need for advice. I corroborate this channel by further testing the importance of specialized skills relative to a broader skill set or general abilities in the cross-section of firms. In particular, I hypothesize that more diverse as well as larger, more complex firms are more likely to benefit more from advice from directors with a broader skill set and more general abilities (see Coles et al., 2008, for a similar argument).

I use the number of business segments and firm size measured as the log of total sales to proxy for the complexity and scope of firms' operations (see, e.g. Coles et al., 2008; Custódio et al., 2013). I then estimate the effect of directors' skill sets and general ability on director-firm complementarities separately for firms above and below the sample median for each of the two measures. Table 9 shows the results.

Matches with less complex firms drive the negative effect of a broader skill set on complementarities. The coefficient is $-0.35$ and statistically significant, while the effect is small and insignificant in more complex firms. There is no similar difference between more or less complex firms for the *General Ability* factor with coefficients estimated to be similar across

26 Both factors are orthogonalized to isolate variation unique to each one. See El-Khatib et al. (2015) for a similar approach.

both sub-samples ($-0.594$ vs. $-0.587$) and both statistically significant.

On the contrary, the effect of a less specialized director (in terms of skills and general abilities) is estimated to be significantly negative in larger firms (columns 7 and 8). The evidence for smaller firms is mixed and insignificant (columns 5 and 6). Surprising at first, this reflects that larger firms tend to have larger boards. Consequently, directors in larger firms are only responsible for a particular topic such that appointed directors are, in comparison to smaller firms, responsible for a narrower range of issues and require potentially more specialized skills. This would be consistent with the model of Guadalupe et al. (2012) who argue that executives specialize in performing their function-specific tasks.

To this end, columns 9 through 12 split the sample of larger firms into firms with below- (column 9 and 10) and above-median (column 11 and 12) number of business segments. In line with the previous argument, a broader skill set is also associated with lower complementarities in larger firms as long as the large firms have few business segments. The coefficient of $-0.755$ is highly significant and almost twice as large as the insignificant estimate of $-0.357$ for more complex firms in column 11. General abilities, although more negative for less complex firms, are estimated to be negative and highly significant regardless of firms' complexity. This difference additionally reveals an interesting distinction between the effects of broader skill sets compared to more general ability in firms with different levels of complexity.

To summarize, results document that the quality of fit between firms and directors appointed to their boards is particularly good for directors with a specialized skill set and less general ability. On the opposite top decision-makers in the firm, *i.e.*, CEOs and CFOs, tend to be more valuable to the firm if they have a broad skill set and more general ability. The fact that these findings are driven by matching with more complex firms highlights the importance of directors giving valuable advice. This conclusion is further validated by the previous finding that sorting is also more positive in more complex firms and firms whose value depends on more firm-specific knowledge. For exactly these kinds of firms, finding the right director to advise on the firm-specific issues and policies is particularly valuable.

## 4.4. Board Productivity and Firm Performance

Previous evidence focused on the complementarities and skills of each director individually, directors are not operating in isolation but rather together with all other board members. While Figure 3 offers some first graphical evidence on the positive effect of more productive directors on firm performance, this section aims to establish a causal relation between board-level productivity and firm outcomes. I do so by examining changes in firm value and performance following the unexpected death of directors.

### 4.4.1. Agnostic Test of Market Reaction

I collect data on the date of directors' death provided by BoardEx and manually search news sources, obituaries, press releases, and company reports to identify the cause of death for each director. I follow Nguyen and Nielsen (2010) to classify deaths as sudden if the stated cause of death is a heart attack, stroke, or accident.[27] In total, 376 directors in the sample died while serving as a board member. Out of these events, I can identify the cause of death for 362 cases, and 25% are classified as sudden.[28]

I begin by estimating the reaction of stock returns to changes in board productivity around the sudden death of directors. I isolate exogenous changes in the productivity of the board of directors using the plausibly exogenous departures of directors that die unexpectedly. To fix ideas, suppose director $i$ in firm $k$ dies unexpectedly in 2014. I then use data from 2012 and 2013 to obtain estimates of the productivity of all board members by estimating the nonlinear model in equation (6) and equation (7) as before and predict the effect of director $i$'s departure on overall board productivity by recomputing board productivity excluding director $i$. The predicted change in board productivity is then defined as:

$$\Delta_{kt} = \overline{\text{Board Productivity}}_{kt} - \text{Board Productivity}_{kt}, \tag{10}$$

where $\overline{\text{Board Productivity}}_{kt}$ is the predicted and Board Productivity$_{kt}$ is the actual board productivity. The novel feature of this paper is that BLM allows to estimate the director-firm specific productivities based on only two years of observations thereby avoiding forward-looking bias. Using AKM would typically require to use longer panel data, thereby introducing forward-looking bias in the estimation of firm fixed effects.

I remain agnostic about how exactly the productivities of individual directors combine to form a productive board overall. Therefore, I consider the total and average productivity as well as the concentration of productivity on the board by computing the Herfindahl index of directors' estimated productivity. In particular, the latter is an interesting dimension to consider in light of recent evidence by Adams et al. (2018) documenting that less dispersion in directors' skills provide common ground between directors that facilities decision making and similarly connects to evidence on the effects of board diversity (Ahern and Dittmar, 2012; Carter et al., 2003; Anderson et al., 2011) on firm performance. Different from these studies, I focus here on board-level heterogeneity in estimated productivities.

I test for the market response to the predicted change in each of the three measures around

27 If the reason is undisclosed, I classify deaths as sudden only if the source explicitly states the death to be *unexpected* or occurring suddenly. See Appendix C for additional details on the data collection.

28 Figure A1 provides details on the exact cause of death for both sudden and non-sudden deaths.

an unexpected death of a director by estimating the following regression:

$$CAR_k = \beta \times \Delta_k + \gamma X_i + \epsilon_k, \tag{11}$$

where $CAR$ is defined as the cumulative abnormal return of firm $k$ on the day and the day after a director's death. Daily abnormal returns are risk-adjusted using the market model. $\Delta$ represents either one of the three measures of board productivity (total or average productivity or productivity concentration), and $\beta$ is the coefficient of interest that captures the impact of changes in board productivity on firm value. The vector of controls $X$ includes size, defined as the log of total assets, ROA, the log of the market value of equity, and a set of industry fixed effects defined at the broad 17 Fama-French industries given the small sample size.[29]

Table 10 presents the main results of regressing the cumulative abnormal return on the predicted change in each of the three board-level productivity measures (demeaned and standardized). Results in columns 1 and 2 indicate that markets do not respond in a sizeable and statistically significant way to exogenous changes in the total or the average productivity across directors, *i.e.*, $\Delta$. In contrast, the estimated coefficient on the predicted change in the concentration of productivity in column 3 is economically large: a one standard deviation increase in concentration induces a 95 basis points increase in stock returns. The effect is statistically significant at the 10%-level with a corresponding t-statistic of 1.92, which is relatively high given the small sample. The remaining columns in Table 10 then test the robustness of the market response to changes in concentration by excluding controls (column 4), using the Fama-French 3-factor model (column 5) to adjust for risk or using raw returns (column 5). Throughout, the estimated reaction remains significant at the 10%-level and economically large, with coefficients ranging from 0.968 to 0.788.

Next, I check that results are not driven by any pre-trends by regressing productivity concentration on the predicted change $\Delta$ interacted with time dummies and omitting the coefficient corresponding to the year before a given death. The resulting coefficients in Figure 6 are small and insignificant for years before a death. At the same time, the positive and significant response of concentration afterward indicates that firms were unable to immediately recover in the first two years following an unexpected death by hiring a similar director.

Next, I verify that these results are not driven by pre-trends in stock returns and illustrate that the effects are persistent. I re-estimate equation (11) replacing the cumulative return with the buy-and-hold return between day $t - 7$ and $t + \tau$ for $\tau = -7, ..., 5$ and plot the resulting coefficients along with 90% confidence intervals in Figure 7. Coefficients are close to zero before an unexpected death and remain elevated after a death.

29 As I need to observe a director in the two years before his death, the sample of death due to sudden causes reduces to only 55 observations.

#### 4.4.2. Concentration and Firm Performance

The agnostic test using market reactions to changes in board-level productivity indicates the importance of productivity concentration for firm outcomes. I again exploit the exogenous variation caused by the unexpected death of directors to identify the causal effect of productivity concentration on ROA using an instrumental variable approach. I estimate the following equation:

$$ROA_{kt} = Productivity \quad Concentration_{kt} + cX_{jt} + \eta_k + \delta_t + \epsilon_{k,t} \tag{12}$$

where the dependent variable is the return on assets of firm $k$ in year $t$, and $\eta$ and $\delta$ are firm and year fixed effects, respectively. The vector of controls $X$ includes the log of total assets, market value of equity and log of total sales. $\epsilon$ is the error term. I establish a causal effect of board concentration on firms' ROA by using the predicted change in concentration following a director's death defined in equation (10) as an instrument for *Productivity Concentration* in equation (12).

Table 11 presents results of both IV estimates and corresponding OLS estimates for comparison to indicate the extent of endogeneity. Standard errors are clustered at the firm level. Column 1 shows that a one-standard-deviation increase in productivity concentration increases ROA by around 0.24 percentage points but is interestingly statistically insignificant. Column 2 addresses the endogeneity of board composition using the IV strategy. The estimated coefficient is statistically significant at the 5% level and economically large: a one-standard-deviation increase in concentration increases ROA by roughly 3.6 percentage points. The F-statistic is equal to 19.691, above the suggested values of 16.38 when using clustered standard errors, suggesting that the instrument is strong. Interestingly, bias in the OLS estimates causes the effect of concentration to be underestimated. This is in line with the evidence in Table 6 that positive sorting is more prevalent in firms with lower ROA, as long as low productivity boards are associated with low ROA (see Figure 3) and begin to gradually replace low productivity directors with high productivity ones. Consequently, the high concentration would be associated with lower ROA.

One concern is that the results might simply be driven by firms with very productive top executives and other board members play no role in determining firm performance. To this end, columns 3 and 4 repeat the previous exercise, only now the Herfindahl index of productivity concentration is computed excluding CEOs and CFOs as top executives on the board. Results reveal that the positive effect of concentration is not simply driven by the top executives. The OLS estimate is slightly larger than its counterpart in column 1 and significant at the 10% level. Estimates using the predicted change in concentration as an IV are in column 4. The estimated coefficient remains economically large and significant at the

5% level. The first-stage F-statistic remains reasonably high; however, it drops below the threshold of 16.38 for a 10% size bias. This finding indicates that board hierarchies in terms of productivity matter. This complements findings of Hansen et al. (2021) and Kaplan and Sorensen (2021) documenting the increasing importance of social and interpersonal skills for CEOs and show that this is consistent with the idea of hierarchies in a knowledge economy (Garicano and Rossi-Hansberg, 2015) where facilitating communication to other layers in the hierarchy create value. The result that boards, where productivity is concentrated to a few members, have a positive effect on firm performance complements these arguments in that the results indicate that advice from a few directors rather than similar advice from all directors create more value.

# 5. Conclusion

This paper studies the role of sorting of directors. To this end, I introduce a novel finite-mixture random-effects model following Bonhomme et al. (2019) to the literature studying the role of director and firm heterogeneity in firm outcomes. Unlike previous literature, this estimation technique allows me to directly estimate complementarities between firms and directors appointed to their firms.

Results reveal that complementarities induce positive sorting; *i.e.*, directors are appointed to the board where their respective attributes best complement the firm. Using hand-collected data and textual analysis to identify directors' skills and qualifications from firms' proxy statements. I show that complementarities arise especially when firms appoint directors with specialized skill sets and less general abilities. Strikingly, the opposite is true for CEOs and CFOs. These findings indicate that directors with a specialized skill set best complement the firms' need for advice, while CEOs or CFOs tend to be generalists relying on directors' advice. This evidence is also corroborated by exploiting heterogeneity across firms that show that there is more positive sorting in more complex firms and firms whose value depends on firm-specific knowledge. At the same time, these firms also seem to benefit more from directors with specialized skills.

Finally, I use unexpected deaths of directors to establish causal evidence that boards, where productivity is concentrated to few directors, improve firm value and firm performance.

These findings offer an interesting new perspective on the organizational structure between the board of directors as advisors to top executives in the firm. It also raises interesting questions for future research. One exciting avenue would be to use the estimated complementarities along with director skills and qualifications and apply the machine learning approach of Erel et al. (2021) to study optimal board composition.

# References

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High Wage Workers and High Wage Firms. *Econometrica*, 67(2):251–333.

Adams, R. B. (2017). Boards, and the Directors Who Sit on Them. In *The Handbook of the Economics of Corporate Governance*, volume 1, pages 291–382. Elsevier.

Adams, R. B., Akyol, A. C., and Verwijmeren, P. (2018). Director Skill Sets. *Journal of Financial Economics*, 130(3):641–662.

Adams, R. B. and Ferreira, D. (2007). A Theory of Friendly Boards. *The Journal of Finance*, 62(1):217–250.

Adams, R. B. and Ferreira, D. (2008). Do Directors Perform for Pay? *Journal of Accounting and Economics*, 46(1):154–171.

Adams, R. B., Hermalin, B. E., and Weisbach, M. S. (2010). The Role of Boards of Directors in Corporate Governance: A Conceptual Framework and Survey. *Journal of Economic Literature*, 48(1):58–107.

Ahern, K. R. and Dittmar, A. K. (2012). The Changing of the Boards: The Impact on Firm Valuation of Mandated Female Board Representation. *The Quarterly Journal of Economics*, 127(1):137–197.

Alviarez, V., Head, K., and Mayer, T. (2020). Global giants and local stars: How changes in brand ownership affect competition.

Anderson, R. C., Reeb, D. M., Upadhyay, A., and Zhao, W. (2011). The economics of director heterogeneity. *Financial Management*, 40(1):5–38.

Andrews, M. J., Gill, L., Schank, T., and Upward, R. (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.

Baqaee, D. and Farhi, E. (2020). Productivity and Misallocation in General Equilibrium. *Quarterly Journal of Economics*.

Bennedsen, M., Perez-Gonzalez, F., and Wolfenzon, D. (2020). Do CEOs Matter? Evidence from Hospitalization Events. *The Journal of Finance*, 75(4):1877–1911.

Bertrand, M. and Mullainathan, S. (2001). Are CEOs Rewarded for Luck? The Ones Without Principals Are*. *The Quarterly Journal of Economics*, 116(3):901–932.

Bertrand, M. and Schoar, A. (2003). Managing with Style: The Effect of Managers on Firm Policies. *The Quarterly Journal of Economics*, 118(4):1169–1208.

Bloom, N., Sadun, R., and Van Reenen, J. (2016). Management as a technology? Working Paper 22327, National Bureau of Economic Research.

Bonhomme, S. (2021). Teams: Heterogeneity, sorting, and complementarity. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2021-15).

Bonhomme, S., Holzheu, K., Lamadon, T., Manresa, E., Mogstad, M., and Setzler, B. (2020). How much should we trust estimates of firm effects and worker sorting? Technical report, National Bureau of Economic Research.

Bonhomme, S., Lamadon, T., and Manresa, E. (2017). Discretizing Unobserved Heterogeneity. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2019-16).

Bonhomme, S., Lamadon, T., and Manresa, E. (2019). A Distributional Framework for Matched Employer Employee Data. *Econometrica*, 87(3):699–739.

Brochet, F. and Srinivasan, S. (2014). Accountability of Independent Directors: Evidence from Firms Subject to Securities Litigation. *Journal of Financial Economics*, 111(2):430–449.

Card, D., Heining, J., and Kline, P. (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *The Quarterly Journal of Economics*, 128(3):967–1015.

Carter, D. A., Simkins, B. J., and Simpson, W. G. (2003). Corporate governance, board diversity, and firm value. *Financial Review*, 38(1):33–53.

Chade, H. and Eeckhout, J. (2018). Matching Information. *Theoretical Economics*, 13(1):377–414.

Chade, H. and Eeckhout, J. (2019). Competing Teams. *The Review of Economic Studies*, 87(3):1134–1173.

Cohen, L., Frazzini, A., and Malloy, C. (2008). The small world of investing: Board connections and mutual fund returns. *Journal of Political Economy*, 116(5):951–979.

Coles, J. L., Daniel, N. D., and Naveen, L. (2008). Boards: Does one size fit all? *Journal of Financial Economics*, 87(2):329–356.

Custódio, C., Ferreira, M. A., and Matos, P. (2019). Do General Managerial Skills Spur Innovation? *Management Science*, 65(2):459–476.

Custódio, C., Ferreira, M. A., and Matos, P. (2013). Generalists versus specialists: Lifetime work experience and chief executive officer pay. *Journal of Financial Economics*, 108(2):471–492.

Dass, N., Kini, O., Nanda, V., Onal, B., and Wang, J. (2014). Board Expertise: Do Directors from Related Industries Help Bridge the Information Gap? *The Review of Financial Studies*, 27(5):1533–1592.

De Loecker, J., Eeckhout, J., and Unger, G. (2020). The Rise of Market Power and the Macroeconomic Implications. *The Quarterly Journal of Economics*, 135(2):561–644.

Devereux, K. (2018). Identifying the value of teamwork: Application to professional tennis. Technical report, Working Paper Series.

Dou, Y. and Zhang, E. J. (forthcoming). Why do Directors Join Poorly Performing Firms? *Journal of Financial and Quantitative Analysis*.

Edmans, A. and Gabaix, X. (2016). Executive Compensation: A Modern Primer. *Journal of Economic Literature*, 54(4):1232–87.

Eeckhout, J. and Kircher, P. (2011). Identifying Sorting—in Theory. *The Review of Economic Studies*, 78(3):872–906.

El-Khatib, R., Fogel, K., and Jandik, T. (2015). CEO network centrality and merger performance. *Journal of Financial Economics*, 116(2):349–382.

Erel, I., Stern, L. H., Tan, C., and Weisbach, M. S. (2021). Selecting Directors Using Machine Learning. *The Review of Financial Studies*, 34(7):3226–3264.

Fahlenbrach, R., Low, A., and Stulz, R. M. (2017). Do Independent Director Departures Predict Future Bad Events? *The Review of Financial Studies*, 30(7):2313–2358.

Falato, A., Li, D., and Milbourn, T. (2010). To Each According to His Ability? The Returns to CEO Talent. *Washington University in St Louis working paper*.

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

Ferreira, D. and Sah, R. K. (2012). Who Gets to the Top? Generalists versus Specialists in Managerial Organizations. *The RAND Journal of Economics*, 43(4):577–601.

Fich, E. M. and Shivdasani, A. (2007). Financial Fraud, Director Reputation, and Shareholder Wealth. *Journal of Financial Economics*, 86(2):306–336.

Gabaix, X. and Landier, A. (2008). Why has CEO Pay Increased so Much? *The Quarterly Journal of Economics*, 123(1):49–100.

Garicano, L. and Rossi-Hansberg, E. (2006). Organization and Inequality in a Knowledge Economy. *The Quarterly Journal of Economics*, 121(4):1383–1435.

Garicano, L. and Rossi-Hansberg, E. (2015). Knowledge-based hierarchies: Using organizations to understand the economy. *economics*, 7(1):1–30.

Goldman, E., Rocholl, J., and So, J. (2009). Do Politically Connected Boards Affect Firm Value? *The Review of Financial Studies*, 22(6):2331–2360.

Graham, J. R., Li, S., and Qiu, J. (2012). Managerial Attributes and Executive Compensation. *The Review of Financial Studies*, 25(1):144–186.

Guadalupe, M., Wulf, J., and Li, H. (2012). The rise of the functional manager. *European Business Review*.

Güner, A. B., Malmendier, U., and Tate, G. (2008). Financial Expertise of Directors. *Journal of Financial Economics*, 88(2):323–354.

Hagendorff, J., Saunders, A., Steffen, S., and Vallascas, F. (2021). The wolves of wall street? managerial attributes and bank risk. *Journal of Financial Intermediation*, 47:100921.

Hansen, S., Ramdas, T., Sadun, R., and Fuller, J. (2021). The Demand for Executive Skills. Technical report, National Bureau of Economic Research.

Herkenhoff, K., Lise, J., Menzio, G., and Phillips, G. M. (2018). Production and learning in teams. Working Paper 25179, National Bureau of Economic Research.

Jiang, W., Wan, H., and Zhao, S. (2015). Reputation Concerns of Independent Directors: Evidence from Individual Director Voting. *The Review of Financial Studies*, 29(3):655–696.

Kaplan, S. N., Klebanov, M. M., and Sorensen, M. (2012). Which CEO Characteristics and Abilities Matter? *The Journal of Finance*, 67(3):973–1007.

Kaplan, S. N. and Sorensen, M. (2021). Are CEOs Different? *The Journal of Finance*, 76(4):1773–1811.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological Innovation, Resource Allocation, and Growth. *The Quarterly Journal of Economics*, 132(2):665–712.

Krishnan, J., Wen, Y., and Zhao, W. (2011). Legal Expertise on Corporate Audit Committees and Financial Reporting Quality. *The Accounting Review*, 86(6):2099–2130.

Lucas, R. E. (1978). On the Size Distribution of Business Firms. *The Bell Journal of Economics*, 9(2):508–523.

Malenko, N. (2013). Communication and Decision-Making in Corporate Boards. *The Review of Financial Studies*, 27(5):1486–1532.

Malmendier, U., Pezone, V., and Zheng, H. (2020). Managerial Duties and Managerial Biases. *CEPR Discussion Paper No.*, DP14929.

Malmendier, U. and Tate, G. (2005). CEO Overconfidence and Corporate Investment. *The Journal of Finance*, 60(6):2661–2700.

Malmendier, U. and Tate, G. (2008). Who Makes Acquisitions? CEO Overconfidence and the Market's Reaction. *Journal of Financial Economics*, 89(1):20–43.

Nguyen, B. D. and Nielsen, K. M. (2010). The Value of Independent Directors: Evidence from Sudden Deaths. *Journal of Financial Economics*, 98(3):550–567.

Peters, R. H. and Taylor, L. A. (2017). Intangible Capital and the Investment-Q Relation. *Journal of Financial Economics*, 123(2):251–272.

Scur, D., Sadun, R., Van Reenen, J., Lemos, R., and Bloom, N. (2021). The world management survey at 18: lessons and the way forward. Working Paper 28524, National Bureau of Economic Research.

Song, J., Price, D. J., Guvenen, F., Bloom, N., and Von Wachter, T. (2019). Firming Up Inequality. *The Quarterly Journal of Economics*, 134(1):1–50.

Tervio, M. (2008). The Difference That CEOs Make: An Assignment Model Approach. *American Economic Review*, 98(3):642–68.

Weidmann, B. and Deming, D. J. (2020). Team players: How social skills improve group performance. Working Paper 27071, National Bureau of Economic Research.

# 6. Figures

**Figure 1**
**Type Proportions**

Figure 1 plots estimated director-type proportions $q_k(\alpha)$, i.e. the estimated share of director type $\alpha$ appointed to the board of a firm belonging to firm class $k$, for each firm class k obtained from estimating equation (6) and equation (7).

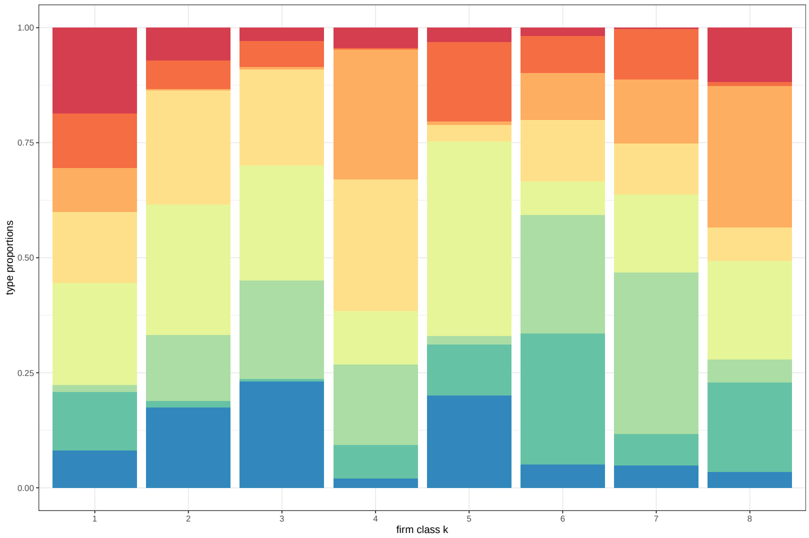
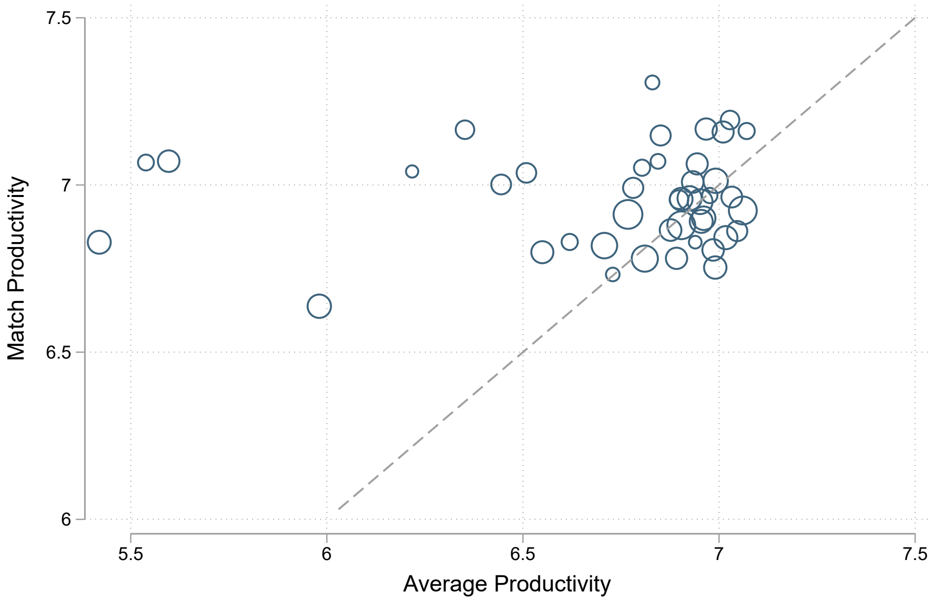


**Figure 2**

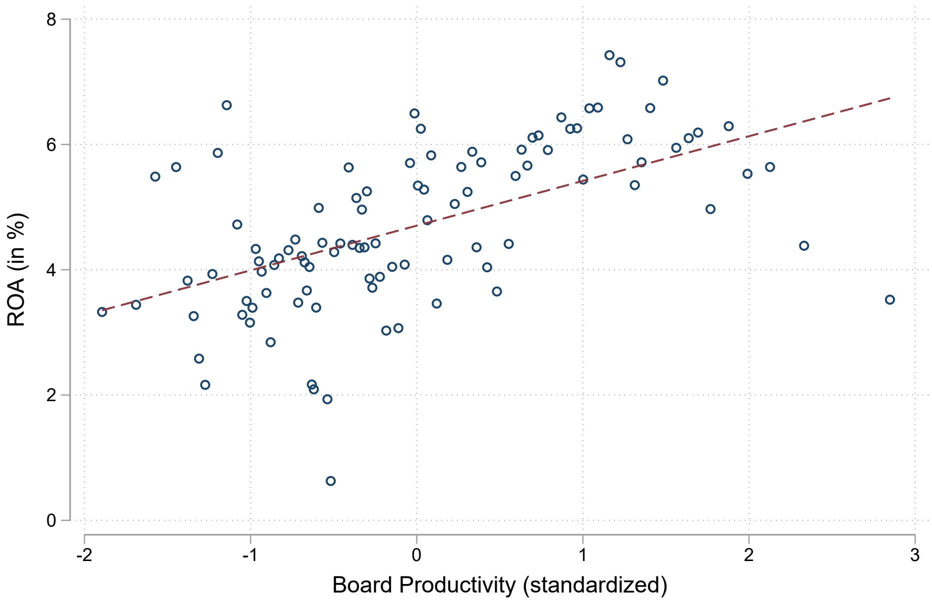
**Sorting — Match Productivity and Average Productivity**

Figure 2 plots director-firm match productivity against counterfactual average director productivity across firm-classes obtained from estimating equation (6) and equation (7). Match productivity is defined for each director-firm match as the estimated complementary, while average productivity is the average estimated complementarities of a director across all firm classes. Variables are binned into 100 bins where the size of each circle reflects the relative size of each bin. The dashed grey line represents the 45 degree line.



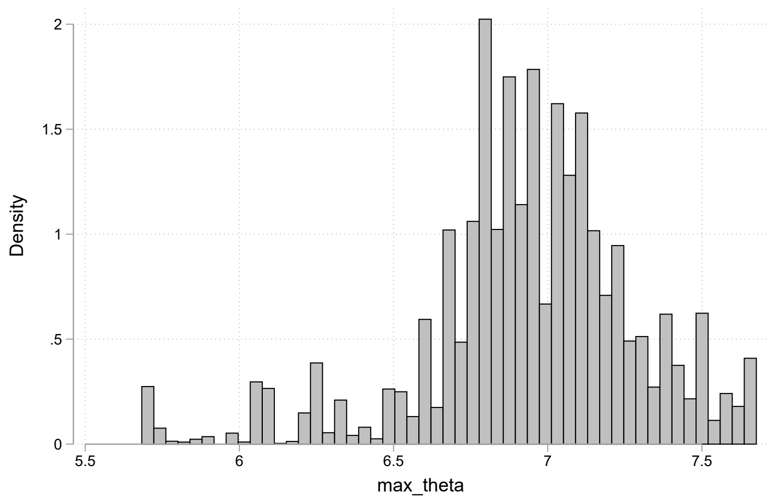
## Figure 3
## Board Productivity and Firm Performance

Figure 3 plots firms' ROA against the sum of estimated productivities of all board members grouped into 100 bins. Total board productivity is standardized to have zero mean and unit standard deviation. The dashed red line is the linear fit.



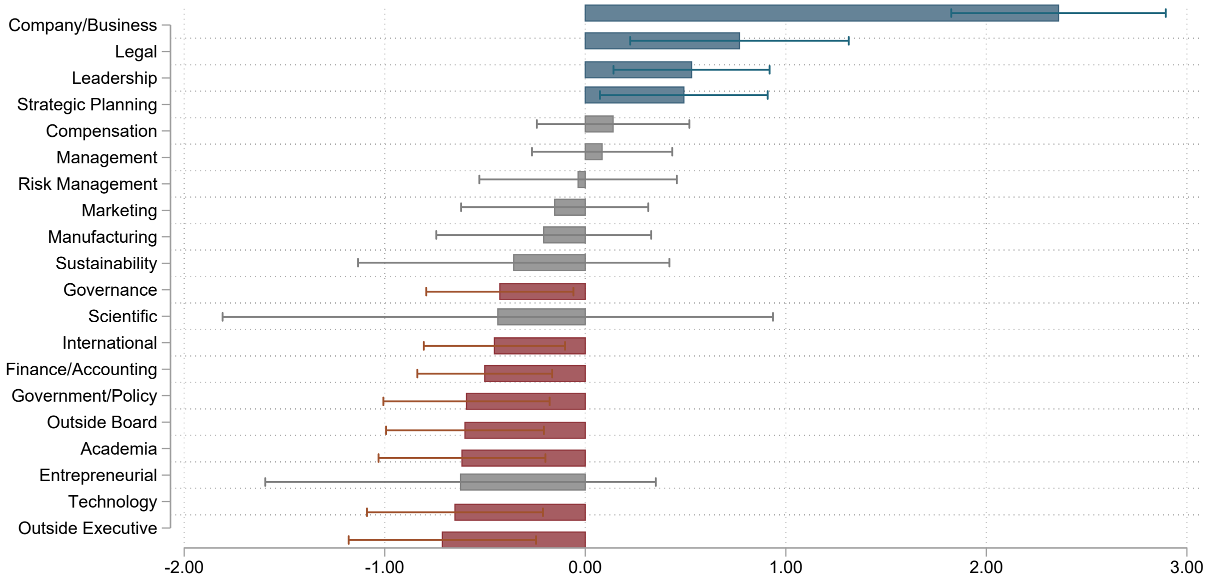

## Figure 4
## Distribution of Estimated Complementarities

Figure 4 plots the distribution of estimated complementarities between firms and directors appointed to their board obtained from estimating equation (6) and equation (7).



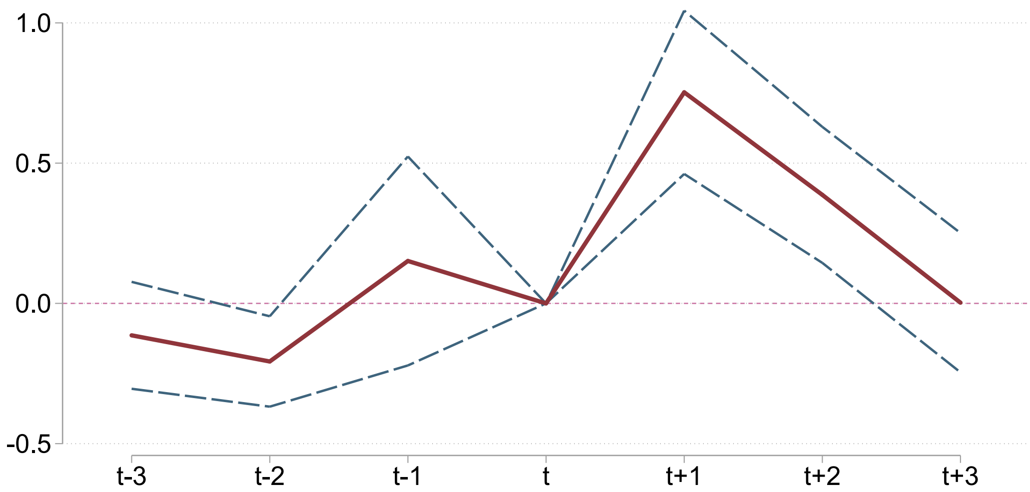
## Figure 5
## Complementarities and Director Skills & Qualifications

Figure 5 plots estimated coefficients and associated 95% confidence intervals from univariate regressions of each of the 20 director skills obtained from companies' proxy statements (see Table A1 for definitions) on estimated complementarities.



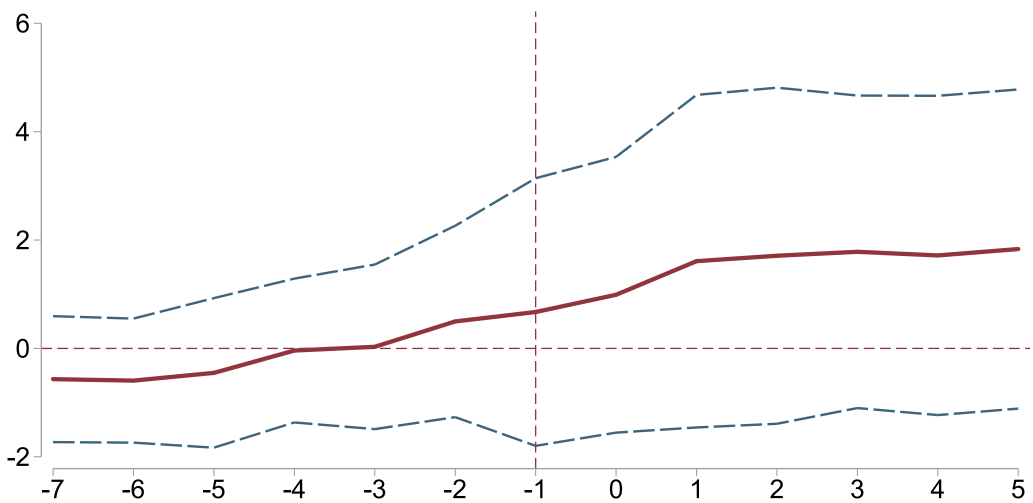
## Figure 6
## Event-Study: Productivity Concentration

Figure 6 shows coefficients from regressing productivity concentration defined as the Herfindahl index of estimated complementarities across all board members on time dummies multiplied by the predicted change in concentration $\Delta$. The predicted change in concentration $\Delta$ is the productivity concentration computed excluding observations on directors that died unexpectedly (see Appendix C for details). For each company, time dummies are centered around the year before a board member suddenly dies. The coefficients associated with the year dummies interacted with $\Delta$ are plotted together with the 95% confidence intervals. Regressions include firm fixed effects and standard errors are clustered at the firm level.




## Figure 7
## Cumulative Returns

Figure 6 shows coefficients from regressing compounded abnormal returns using the market model for risk adjustment on the predicted change in productivity concentration, $\Delta$. The coefficients $\beta_j$ associated with the cross-sectional regression of returns compounded from $t-7$ to $t=j$ on $\Delta$ are plotted together with 90% confidence intervals. All the regressions include industry fixed effects.



# 7. Tables

## Table 1
## Summary Statistics - Director Level

Table 1 presents descriptive statistics for the main variables used in the paper; director types denote each director's type as defined in equation (8) and ordered according to their average compensation. log(Total Compensation) is the log of total compensation as reported by Execucomp, age and gender is directors' age and gender, respectively. Data on education is obtained from BoardEx following the classification in Cohen et al. (2008). Panel B presents the average share of twenty skills and qualifications collected from companies' proxy statements (see Table A1 for details) at the director level (column 1) and board level (column 2), column 3 reports factor loadings of each skill on the first factor obtained from a factor analysis on all 20 skill categories. The number of unique skills is defined as the number of a given director's skills not reported for any other board member. The total number of skills is the sum of all skills and qualifications reported for a director. Panel C reports summary statistics for directors' previous employment experience. Board tenure is the number of years a director has served on a board, number of previous firms counts previous board appointments, number of previous industries counts the number of distinct industries at the 4-digit SIC level in which a director was previously employed, number of previous positions and inside positions counts the number of distinct positions previously held in other firms and the same firm, respectively.

**Panel A:** Director Characteristics

| | | | Director Type | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| log(Total Compensation) | 5.87 | 1.40 | 5.61 | 5.66 | 5.80 | 5.91 | 6.02 | 6.21 | 6.46 | 6.71 |
| Age | 61.36 | 8.81 | 63.15 | 63.22 | 62.52 | 61.84 | 61.38 | 60.67 | 60.49 | 59.72 |
| Female | 0.16 | 0.37 | 0.18 | 0.17 | 0.18 | 0.16 | 0.15 | 0.13 | 0.14 | 0.12 |
| Undergraduate Degree | 0.95 | 0.22 | 0.95 | 0.95 | 0.95 | 0.94 | 0.94 | 0.94 | 0.95 | 0.95 |
| Masters Degree | 0.19 | 0.39 | 0.20 | 0.20 | 0.20 | 0.19 | 0.19 | 0.18 | 0.18 | 0.17 |
| MBA | 0.38 | 0.49 | 0.39 | 0.39 | 0.38 | 0.37 | 0.38 | 0.37 | 0.39 | 0.38 |
| PhD | 0.13 | 0.33 | 0.13 | 0.12 | 0.13 | 0.13 | 0.14 | 0.12 | 0.13 | 0.13 |
| Law Degree | 0.09 | 0.28 | 0.09 | 0.10 | 0.09 | 0.08 | 0.09 | 0.08 | 0.07 | 0.07 |

**Panel B:** Director Skills and Qualifications

| | | | | Director Type | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Director | Board | Factor Loading | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Academia | 0.20 | 0.70 | 0.18 | 0.22 | 0.22 | 0.23 | 0.22 | 0.22 | 0.20 | 0.20 | 0.19 |
| Company/Business | 0.16 | 0.65 | 0.03 | 0.13 | 0.14 | 0.16 | 0.16 | 0.16 | 0.18 | 0.18 | 0.20 |
| Compensation | 0.29 | 0.80 | 0.38 | 0.31 | 0.30 | 0.30 | 0.28 | 0.29 | 0.26 | 0.29 | 0.27 |
| Entrepreneurial | 0.03 | 0.20 | 0.02 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 |
| Finance/Accounting | 0.51 | 0.99 | 0.19 | 0.54 | 0.53 | 0.53 | 0.51 | 0.52 | 0.48 | 0.48 | 0.46 |
| Governance | 0.36 | 0.88 | 0.49 | 0.40 | 0.39 | 0.39 | 0.36 | 0.37 | 0.34 | 0.35 | 0.34 |
| Government/Policy | 0.19 | 0.69 | 0.40 | 0.20 | 0.20 | 0.19 | 0.18 | 0.18 | 0.17 | 0.18 | 0.18 |
| International | 0.42 | 0.89 | 0.28 | 0.46 | 0.45 | 0.45 | 0.41 | 0.42 | 0.41 | 0.42 | 0.41 |
| Leadership | 0.35 | 0.83 | 0.27 | 0.36 | 0.37 | 0.36 | 0.35 | 0.34 | 0.36 | 0.37 | 0.38 |
| Legal | 0.10 | 0.53 | 0.25 | 0.10 | 0.09 | 0.11 | 0.10 | 0.10 | 0.09 | 0.10 | 0.11 |
| Management | 0.54 | 0.98 | 0.42 | 0.56 | 0.55 | 0.57 | 0.55 | 0.55 | 0.53 | 0.55 | 0.53 |
| Manufacturing | 0.13 | 0.53 | 0.10 | 0.14 | 0.13 | 0.13 | 0.12 | 0.12 | 0.12 | 0.13 | 0.12 |
| Marketing | 0.14 | 0.61 | 0.14 | 0.15 | 0.15 | 0.15 | 0.14 | 0.15 | 0.14 | 0.14 | 0.15 |
| Outside Board | 0.25 | 0.75 | 0.14 | 0.28 | 0.27 | 0.27 | 0.26 | 0.25 | 0.25 | 0.23 | 0.22 |

...continued from previous page

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Outside Executive | 0.15 | 0.62 | 0.05 | 0.16 | 0.16 | 0.16 | 0.15 | 0.15 | 0.15 | 0.14 | 0.15 |
| Risk Management | 0.15 | 0.56 | 0.43 | 0.17 | 0.17 | 0.16 | 0.16 | 0.15 | 0.14 | 0.15 | 0.15 |
| Scientific | 0.02 | 0.10 | 0.05 | 0.01 | 0.02 | 0.02 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 |
| Strategic Planning | 0.24 | 0.77 | 0.28 | 0.25 | 0.25 | 0.25 | 0.24 | 0.24 | 0.24 | 0.25 | 0.26 |
| Sustainability | 0.05 | 0.25 | 0.24 | 0.06 | 0.06 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Technology | 0.21 | 0.67 | 0.18 | 0.21 | 0.20 | 0.26 | 0.22 | 0.24 | 0.21 | 0.23 | 0.22 |
| Number of Unique Skills | 0.50 | 3.79 | | 0.48 | 0.47 | 0.52 | 0.49 | 0.52 | 0.49 | 0.48 | 0.49 |
| Total Number of Skills | 4.50 | 34.23 | | 4.74 | 4.68 | 4.77 | 4.52 | 4.56 | 4.36 | 4.47 | 4.44 |

**Panel C:** Director Experience and General Ability

| | Mean | Factor Loading | Director Type | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Board Tenure | 8.10 | -0.02 | 9.03 | 9.20 | 8.87 | 8.79 | 8.80 | 8.63 | 8.53 | 8.39 |
| # of Previous Firms | 8.44 | 0.87 | 9.40 | 9.22 | 9.43 | 8.72 | 8.67 | 8.24 | 8.06 | 7.89 |
| # of Previous Industries | 1.94 | 0.56 | 2.24 | 2.21 | 2.12 | 2.02 | 1.92 | 1.91 | 1.90 | 1.91 |
| # of Previous Positions | 8.60 | 0.83 | 9.15 | 9.18 | 9.06 | 8.85 | 8.74 | 8.70 | 8.81 | 8.92 |
| # of Previous Inside Positions | 1.99 | -0.04 | 1.82 | 1.92 | 1.89 | 2.10 | 2.15 | 2.42 | 2.64 | 2.84 |

**Table 2**

**Summary Statistics - Firm Level**

Table 2 presents descriptive statistics for the main firm-level variables used in the paper; firm types are defined following the k-means clustering as described in Section 2.2 and ordered according to average director compensation. Return on assets is defined as net income divided by lagged total assets, Tobins' Q is defined as total assets (at) plus market value of equity minus common value of equity (ceq) all divided by total assets. Market capitalization is the share price multiplied by common shares outstanding at the of the fiscal year and sales are total sales. Markups are estimated following De Loecker et al. (2020) and Baqaee and Farhi (2020), intangible capital is taken from Peters and Taylor (2017) and the value of innovations is taken from Kogan et al. (2017). The number of business units counts the number of a firm's business units as reported in Compustat's Segments data.

| | Mean | SD | Firm Class | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| Return on Assets | 4.43 | 12.59 | 5.36 | 4.57 | 4.30 | 4.76 | 4.86 | 4.59 | 4.33 | 3.85 |
| log(Assets) | 7.98 | 1.72 | 7.45 | 8.13 | 8.17 | 8.16 | 8.20 | 8.09 | 8.23 | 7.82 |
| log(Market Cap.) | 7.83 | 1.63 | 7.32 | 7.96 | 7.96 | 8.00 | 8.10 | 7.95 | 8.09 | 7.81 |
| log(Sales) | 7.41 | 1.59 | 6.83 | 7.59 | 7.63 | 7.59 | 7.70 | 7.52 | 7.61 | 7.18 |
| Firm Level Markups | 1.86 | 1.44 | 1.97 | 1.76 | 1.71 | 1.76 | 1.72 | 1.88 | 1.91 | 2.15 |
| Tobin's Q | 2.00 | 1.79 | 2.08 | 1.91 | 1.87 | 1.98 | 1.99 | 1.95 | 2.00 | 2.22 |
| Intangible Capital | 30.71 | 65.45 | 24.67 | 38.33 | 40.46 | 38.06 | 29.53 | 27.80 | 35.61 | 22.47 |
| Value of Innovations | 10.77 | 27.30 | 18.37 | 12.08 | 12.30 | 11.79 | 8.55 | 11.20 | 10.72 | 7.92 |
| # Business Units | 6.91 | 5.06 | 6.76 | 7.00 | 7.01 | 7.35 | 7.15 | 6.82 | 6.74 | 6.21 |

**Table 3**
**Variance Decomposition BLM Estimates (x 100)**

Table 3 presents the variance decomposition of total compensation obtained from a two-way fixed effects model (first row) or estimating equation (6) and equation (7) (remaining rows) based on the log of residualized annual total compensation obtained from regressing the log of total compensation on directors' age, age squared, tenure, highest level of education, an executive dummy as well as log of total assets, log of market capitalization and log of sales as well as year and industry fixed effects defined at the 2-digit SIC level. Sorting is defined as the correlation of director types and firm classes, where in the first row each director and each firm are defined to be an individual type and class, respectively. Director types and firm classes in the remaining rows are defined as in equation (6) and equation (7). $Var(y)$ is the total variation in residualized log compensation, $Var(\gamma)$ and $Var(\theta)$ are variation explained by director and firm heterogeneity and $Var(\epsilon)$ denotes unexplained variation. Connect. indicates connectivity between firm classes created by mobility of director types across different firm classes and is computed as the resulting graph's Laplacian.

| | Sorting | $\frac{Var(\gamma)}{Var(y)}$ | $\frac{Var(\theta)}{Var(y)}$ | $\frac{Var(\epsilon)}{Var(y)}$ | $\frac{Cov(\gamma,\theta)}{Var(y)}$ | Connect. |
|---|---|---|---|---|---|---|
| AKM | -43.28 | 65.04 | 40.56 | 39.95 | -45.56 | |
| Full Sample | 14.53 | 15.03 | 5.85 | 76.39 | 2.73 | 54.50 |
| 2011 | 4.76 | 25.16 | 3.22 | 70.76 | 0.86 | 57.60 |
| 2012 | 25.54 | 22.75 | 6.39 | 64.70 | 6.16 | 55.86 |
| 2013 | 12.57 | 26.80 | 2.86 | 68.13 | 2.20 | 62.81 |
| 2014 | 4.00 | 27.83 | 2.51 | 68.99 | 0.67 | 70.83 |
| 2015 | -3.27 | 28.04 | 2.22 | 70.26 | -0.52 | 68.90 |
| 2016 | -6.86 | 24.46 | 1.68 | 74.75 | -0.88 | 64.86 |
| 2017 | 1.45 | 23.50 | 1.80 | 74.51 | 0.19 | 65.97 |
| 2018 | -18.19 | 25.56 | 2.17 | 74.98 | -2.71 | 59.22 |
| 2019 | 17.57 | 20.58 | 2.62 | 74.23 | 2.58 | 64.98 |

**Table 4**
**Model Fit**

Table 4 presents statistics on model fit. For each firm class, mean and variances of the log total compensation implied by the model estimated in equation (6) and equation (7) are displayed in column 1 and 3 and compared with the corresponding mean and variance observed in the data (column 2 and 4).

| Firm Class | Mean | | Variance | |
|---|---|---|---|---|
| | Model | Data | Model | Data |
| 1 | 6.344 | 6.363 | 0.413 | 0.335 |
| 2 | 6.683 | 6.693 | 0.357 | 0.326 |
| 3 | 6.812 | 6.819 | 0.182 | 0.175 |
| 4 | 6.882 | 6.881 | 0.294 | 0.275 |
| 5 | 6.962 | 6.973 | 0.162 | 0.165 |
| 6 | 7.045 | 7.063 | 0.329 | 0.246 |
| 7 | 7.171 | 7.165 | 0.293 | 0.266 |
| 8 | 7.407 | 7.411 | 0.219 | 0.206 |

## Table 5
## Robustness - Choice of Number of Firm Classes and Director Types

Table 5 test the robustness of the main results to variations in the number of director types and firm classes. The variance decomposition of total compensation is obtained from estimating equation (6) and equation (7) based the log of residualized annual total compensation obtained from regressing the log of total compensation on directors' age, age squared, tenure, highest level of education, an executive dummy as well as log of total assets, log of market capitalization and log of sales as well as year and industry fixed effects defined at the 2-digit SIC level. Sorting is defined as the correlation of director types and firm classes. $Var(y)$ is the total variation in residualized log compensation, $Var(\gamma)$ and $Var(\theta)$ are variation explained by director and firm heterogeneity and $Var(\epsilon)$ denotes unexplained variation. Connect. indicates connectivity between firm classes created by mobility of director types across different firm classes and is computed as the resulting graph's Laplacian.

**Panel A:** BLM (No. of Firm Cluster = 10, No. of Director Types = 10)

| | Sorting | $\frac{Var(\gamma)}{Var(y)}$ | $\frac{Var(\theta)}{Var(y)}$ | $\frac{Var(\epsilon)}{Var(y)}$ | $\frac{Cov(\gamma,\theta)}{Var(y)}$ | Connect. |
|---|---|---|---|---|---|---|
| Full Sample | 26.52 | 14.06 | 3.67 | 78.46 | 3.81 | 61.82 |
| 2011 | 16.01 | 25.93 | 4.85 | 65.63 | 3.59 | 55.50 |
| 2012 | 25.92 | 22.53 | 8.01 | 62.49 | 6.97 | 50.58 |
| 2013 | 18.12 | 24.93 | 5.09 | 65.90 | 4.08 | 47.47 |
| 2014 | -1.36 | 28.94 | 5.07 | 66.32 | -0.33 | 54.80 |
| 2015 | -6.70 | 29.12 | 3.08 | 69.07 | -1.27 | 51.81 |
| 2016 | 15.50 | 22.91 | 1.71 | 73.44 | 1.94 | 60.29 |
| 2017 | 35.81 | 17.98 | 4.14 | 71.69 | 6.18 | 51.51 |
| 2018 | 17.03 | 20.50 | 4.27 | 72.04 | 3.19 | 51.94 |
| 2019 | 9.49 | 20.58 | 6.42 | 70.82 | 2.18 | 52.91 |

**Panel B:** BLM (No. of Firm Cluster = 6, No. of Director Types = 10)

| | Sorting | $\frac{Var(\gamma)}{Var(y)}$ | $\frac{Var(\theta)}{Var(y)}$ | $\frac{Var(\epsilon)}{Var(y)}$ | $\frac{Cov(\gamma,\theta)}{Var(y)}$ | Connect. |
|---|---|---|---|---|---|---|
| Full Sample | 27.57 | 12.85 | 3.15 | 80.49 | 3.51 | 60.02 |
| 2011 | 10.97 | 26.02 | 5.11 | 66.34 | 2.53 | 60.67 |
| 2012 | 11.72 | 25.00 | 2.97 | 70.01 | 2.02 | 60.01 |
| 2013 | 29.17 | 20.21 | 6.57 | 66.50 | 6.72 | 59.55 |
| 2014 | 27.33 | 23.29 | 3.47 | 68.33 | 4.91 | 76.35 |
| 2015 | -5.60 | 26.78 | 6.99 | 67.76 | -1.53 | 63.42 |
| 2016 | 16.25 | 20.40 | 2.53 | 74.74 | 2.34 | 54.17 |
| 2017 | 19.38 | 19.07 | 5.56 | 71.37 | 3.99 | 70.85 |
| 2018 | 8.64 | 21.17 | 2.24 | 75.39 | 1.19 | 61.54 |
| 2019 | 20.50 | 18.33 | 2.18 | 76.90 | 2.59 | 61.91 |

**Table 6**
**Sorting and Firm Characteristics**

Table 6 presents results from estimating equation (9). The reported coefficient *Sorting* is obtained by projecting standardized estimated director fixed effects on standardized estimated firm fixed effects obtained from estimating equation (9). Results in column 1 are estimated on the full sample. For the remaining columns firms are sorted according to seven variables: complexity (columns 2 and 3), intangible capital (columns 4 and 5), innovations (columns 6 and 7) as well as markups (columns 8 and 9), Tobin's Q (columns 10 and 11) and ROA (columns 12 and 13). Results are obtained by estimating equation (9) for firms in the "Low" or "High" subsample, where firms belong to the respective subsample if each measure is in the bottom or top quartile of the sample. Firm complexity is defined as the number of business units reported for each firm, intangible capital is taken from Peters and Taylor (2017) and the value of innovations is taken from Kogan et al. (2017). Markups are estimated following De Loecker et al. (2020) and Baqaee and Farhi (2020), Tobin's Q is defined as total assets plus market value of equity minus common value of equity all divided by total assets and ROA is defined as return divided by lagged total assets. Standard errors in parenthesis are double clustered at the firm and director level. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

| | Base-line | Firm Complexity | | Intangible Capital | | Value of Innovations | |
|---|---|---|---|---|---|---|---|
| | (1) | Low | High | Low | High | Low | High |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Sorting | 0.090*** | 0.052*** | 0.132*** | 0.035*** | 0.186*** | 0.065*** | 0.136*** |
| | (0.005) | (0.007) | (0.009) | (0.013) | (0.013) | (0.018) | (0.020) |
| $\beta^{High} - \beta^{Low}$ | | 0.081*** | | 0.151*** | | 0.071*** | |
| | | (0.011) | | (0.018) | | (0.027) | |
| Observations | 127,405 | 67,450 | 59,955 | 23,171 | 25,649 | 11,192 | 11,734 |
| $R^2$ | 0.008 | 0.003 | 0.017 | 0.001 | 0.035 | 0.004 | 0.018 |

| | Markup | | Tobin's Q | | ROA | |
|---|---|---|---|---|---|---|
| | Low | High | Low | High | Low | High |
| | (8) | (9) | (10) | (11) | (12) | (13) |
| Sorting | 0.105*** | 0.057*** | 0.100*** | 0.052*** | 0.119*** | 0.063*** |
| | (0.011) | (0.010) | (0.011) | (0.009) | (0.011) | (0.010) |
| $\beta^{High} - \beta^{Low}$ | -0.048*** | | -0.047 | | -0.057*** | |
| | (0.015) | | (0.015) | | (0.015) | |
| Observations | 31,274 | 31,582 | 27,066 | 28,226 | 30,444 | 31,593 |
| $R^2$ | 0.011 | 0.003 | 0.010 | 0.003 | 0.014 | 0.004 |

## Table 7
## Complementarities and Director Skills & Qualifications

Table 7 presents results from regressing complementarities estimated from equation (6) and equation (7) on directors' skills and qualifications obtained from companies' proxy filings as in Adams et al. (2018). The number of unique skills is defined as the number of a director's skills not reported for any other board member and total number of skills is the sum of all skills reported for a director. The *Skill Set Factor* is the first factor resulting from a factor analysis of all 20 reported skills. Estimated factor loadings are reported in column 3 in Panel A of Table 1. Columns 1 to 4 are estimated on the sample of all board members and include firm-year fixed effects, while columns 5 to 7 are estimated on the sample of CEOs and CFOs and include firm and year fixed effects. Standard errors in parenthesis are double clustered at the firm and director level. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

| | All Board Members | | | | only CEO & CFO | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Number of Unique Skills | 0.102 | 0.234** | | 0.243** | -0.078 | | -0.658 |
| | (0.103) | (0.119) | | (0.116) | (0.562) | | (0.612) |
| Total Number of Skills | | -0.096** | | | | | |
| | | (0.046) | | | | | |
| Skill Set Factor | | | -0.172* | -0.273** | | 0.938** | 1.193** |
| | | | (0.099) | (0.111) | | (0.434) | (0.472) |
| Firm-Year FE | Yes | Yes | Yes | Yes | No | No | No |
| Firm FE | No | No | No | No | Yes | Yes | Yes |
| Year FE | No | No | No | No | Yes | Yes | Yes |
| Observations | 104,812 | 104,812 | 104,812 | 104,812 | 11,882 | 11,882 | 11,882 |
| $R^2$ | 0.686 | 0.686 | 0.686 | 0.686 | 0.481 | 0.482 | 0.482 |

## Table 8
## Complementarities and Director Experiences

Table 8 presents results from regressing directors' complementarities estimated from equation (6) and equation (7) on employment experiences and skills. Board Tenure is the number of years a director has served on a board, number of previous firms counts previous board appointments, number of previous industries counts the number of distinct industries at the 4-digit SIC level in which a director was previously employed, number of previous positions and inside positions counts the number of distinct positions previously held in other firms and the same firm, respectively. The *General Ability Factor* is the first factor obtained from a factor analysis on the five individual experience variables. Estimated factor loadings are in column 3 in Panel C of Table 1. The *Skill Set Factor* is the first factor resulting from a factor analysis of all 20 reported skills obtained from companies' proxy filings. Estimated factor loadings are reported in column 3 in Panel A of Table 1. Columns 1 through 9 are estimated on the full sample of directors while column 10 uses only observations on CEOs and CFOs. Standard errors in parenthesis are double clustered at the firm and director level. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

| | All Board Members | | | | | | | | | only CEO & CFO |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Board Tenure | 0.145*** | | | | | | | | | |
| | (0.016) | | | | | | | | | |
| Number of Previous Firms | | -0.133*** | | | | | | | | |
| | | (0.017) | | | | | | | | |
| Number of Previous Positions | | | 0.004 | | | | | | | |
| | | | (0.023) | | | | | | | |
| Number of Previous Inside Positions | | | | 0.942*** | | | | | | |
| | | | | (0.060) | | | | | | |
| Number of Previous Industries | | | | | -0.771*** | | | | | |
| | | | | | (0.072) | | | | | |
| General Ability Factor | | | | | | -0.590*** | -0.533*** | -2.709*** | -4.823*** | 1.566* |
| | | | | | | (0.101) | (0.098) | (0.613) | (0.794) | (0.801) |
| Skill Set Factor | | | | | | | -0.182* | -0.616*** | -0.947*** | 1.127** |
| | | | | | | | (0.099) | (0.170) | (0.214) | (0.456) |
| Firm-Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | No | No |
| Industry-Year FE | No | No | No | No | No | No | No | No | Yes | No |
| Year FE | No | No | No | No | No | No | No | No | No | Yes |
| Director FE | No | No | No | No | No | No | No | Yes | Yes | No |
| BoardID | No | No | No | No | No | No | No | No | Yes | Yes |
| Observations | 127,401 | 127,161 | 127,161 | 127,161 | 127,161 | 127,039 | 104,453 | 101,481 | 101,697 | 11,850 |
| $R^2$ | 0.675 | 0.675 | 0.674 | 0.677 | 0.675 | 0.675 | 0.686 | 0.767 | 0.570 | 0.482 |

# Table 9
## Director Skills and Firm Complexity

Table 9 shows coefficients from a regression of estimated complementarities on directors' skills and experiences. Director skills are collected from companies proxy statements (see Table A1 for details). The *Skill Set Factor* is the first factor resulting from a factor analysis of all 20 reported skills. Estimated factor loadings are reported in column 3 in Panel A of Table 1. The *General Ability Factor* is the first factor obtained from a factor analysis on the five individual experience variables: board tenure, number of previous firms, number of previous positions and inside positions, number of previous industries. Estimated factor loadings are in column 3 in Panel C of Table 1. Firms are sorted according to their complexity and size. Firm complexity is defined as the number of business units reported for each firm (column 1 through 4) and size is defined as total sales (column 5 through 8). Firms belong to the "Low" or "High" sample if each measure is below or above the median. Columns 9 through 12 focus on the sample of large firms with sales above the sample median and sorts firms as before in low and high complexity firms according to their number of business units. Each regression includes firm-year fixed effects and standard errors are double clustered at the firm and director level. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

| | Firm Complexity | | | | Size | | | | Size – High | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | | High | | Low | | High | | Low Complexity | | High Complexity | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| Skill Set Factor | -0.350** | | -0.057 | | 0.182 | | -0.541*** | | -0.755*** | | -0.357 | |
| | (0.162) | | (0.177) | | (0.166) | | (0.169) | | (0.241) | | (0.233) | |
| General Ability Factor | | -0.594*** | | -0.587*** | | -0.159 | | -0.934*** | | -1.150*** | | -0.754*** |
| | | (0.142) | | (0.135) | | (0.146) | | (0.132) | | (0.206) | | (0.171) |
| $\beta^{High} - \beta^{Low}$ | | | 0.294 | 0.007 | | | -0.722*** | -0.774*** | | | 0.397 | 0.396 |
| | | | (0.294) | (0.191) | | | (0.235) | (0.194) | | | (0.331) | (0.268) |
| Firm-Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 55,529 | 67,298 | 49,283 | 59,741 | 54,198 | 63,214 | 50,610 | 63,819 | 23,192 | 29,475 | 27,418 | 34,344 |
| $R^2$ | 0.705 | 0.693 | 0.663 | 0.651 | 0.752 | 0.747 | 0.591 | 0.578 | 0.602 | 0.588 | 0.582 | 0.569 |

**Table 10**
**Complementarities and Stock Market Reaction**

Table 10 shows coefficients from a regression of cumulative abnormal returns on the predicted changes Δ in three board-level productivity measures: total productivity defined as the sum of estimated complementarities across all board members, mean skill productivity defined as the average of estimated complementarities across all board members and productivity concentration defined as the Herfindahl index of estimated complementarities across all board members. Complementarities are obainted from estimating equation (6) and equation (7). Cumulative abnormal returns are calculated over a two-day window of the day of an unexpected death of a director and the following day. Abnormal returns are risk-adjusted using the market model or risk adjusted using the Fama-French three factor model (column 5) or unadjusted (column 6). The vector of control variables includes size, defined as log(total assets), ROA, defined as net income divided by lagged total assets, and market capitalization. Column 4 is estimated without any controls. Each regression includes industry-fixed effects, following the Fama-French 17-industry classification. Standard errors, clustered at the firm level, are displayed in parentheses. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

| *Dep. Variable* | Excess Returns | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ Total Skill | 0.075 | | | | | |
| | (0.700) | | | | | |
| Δ Mean Skill | | 0.107 | | | | |
| | | (0.467) | | | | |
| Δ Productivity Concentration | | | 0.953* | 0.788* | 0.859* | 0.968* |
| | | | (0.496) | (0.456) | (0.505) | (0.547) |
| Observations | 55 | 55 | 55 | 55 | 55 | 55 |
| $R^2$ | 0.186 | 0.186 | 0.222 | 0.199 | 0.199 | 0.260 |
| Controls | X | X | X | | X | X |
| Window | [0,1] | [0,1] | [0,1] | [0,1] | [0,1] | [0,1] |
| Risk Adjustment | | Market Model | | | FF | Raw |

**Table 11**
**Skill Concentration and Firm Performance**

Table 11 presents results from testing the effect of productivity concentration on firms' ROA, defined as net income divided by lagged total assets. Productivity concentration is computed as the Herfindahl index of estimated complementarities across all board members (columns 1 and 2) and without the CEO and CFO (columns 3 and 4). The vector of controls includes firm size, measured as total assets, market value of equity and sales (all in logs) and all regressions include firm and year fixed effects. Coefficients in column 1 and 3 are estimated using OLS, while coefficients in column 2 and 4 are estimated using 2SLS, where concentration is instrumented by the change in concentration predicted using unexpected director deaths, $\Delta$. Standard errors are clustered at the firm level. ***, **, and * indicate statistically different from zero at the 1%, 5%, and 10% level of significance, respectively.

| | All Board Member | | w/o CEO & CFO | |
|---|---|---|---|---|
| | OLS | IV | OLS | IV |
| | (1) | (2) | (3) | (4) |
| Productivity Concentration | 0.240 | 3.590** | 0.346* | 2.144** |
| | (0.189) | (1.490) | (0.200) | (0.949) |
| Observations | 8,041 | 8,041 | 8,038 | 8,038 |
| $R^2$ | 0.717 | 0.094 | 0.708 | 0.132 |
| 1st Stage F-Stat | | 19.691 | | 13.135 |
| Controls | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

# Appendix

# A. Technical Details on Identification in BLM

**Assumption 1.** *1. $m_{i,t}$, $k_{i,t+1}$, and $X_i^{t+1}$ are independent of $Y_i^t$ conditional on $\alpha_i$, $k_i^t$, $m_i^{t-1}$ and $X_i^t$*

*2. $Y_{i,t+1}$ is independent of $Y_t^t$, $k_i^t$, $m_i^{t-1}$ and $X_i^t$ conditional on $\alpha_i$, $k_{i,t+1}$, $X_{i,t+1}$ and $m_{it} = 1$*

**Assumption 2.** *1. For any two firm classes $k \neq k'$ in $\{1, \ldots, K\}$, there exists a connecting cycle $(k_1, \ldots, k_R), (\tilde{k}_1, \ldots, \tilde{k}_R)$, such that $k_1 = k$ and $k_r = k'$ for some $r$, and such that the scalars $a(1), \ldots, a(L)$ are all distinct, where*

$$a(\alpha) = \frac{p_{k_1,\tilde{k}_1}(\alpha) p_{k_2,\tilde{k}_2}(\alpha) \cdots p_{k_R,\tilde{k}_R}(\alpha)}{p_{k_2,\tilde{k}_1}(\alpha) p_{k_3,\tilde{k}_2}(\alpha) \cdots p_{k_1,\tilde{k}_R}(\alpha)}. \tag{13}$$

*In addition, for all $k$, $k'$, possibly equal, there exists a connecting cycle $(k'_1, \ldots, k'_R)$, $(\tilde{k}'_1, \ldots, \tilde{k}'_R)$, such that $k'_1 = k$ and $\tilde{k}'_r = k'$ for some $r$.*

*2. There exist finite sets of $M$ values for $y_1$ and $y_2$ such that, for all $r$ in $\{1, \ldots, R\}$ the matrices $A\left(k_r, \tilde{k}_r\right)$ and $A\left(k_{r+1}, \tilde{k}_r\right)$ have rank $L$, where $A(k, k')$ has $(y_1, y_2)$ element*

$$Pr\left[Y_{i1} \leq y_1, Y_{i2} \leq y_2 | k_{i1} = k, k_{i2} = k', m_{i1} = 1\right]. \tag{14}$$

# B. Director Skills and Qualifications

The table below replicates the list of skills and qualifications and corresponding word list used to identify each skill and qualification from companies' proxy statements from Adams et al. (2018).

**Table A1**
**Director Skills & Qualifications**

| Variable | Description | Word List |
|---|---|---|
| Academic | The director is from academia or has a higher degree (such as a Ph.D.). | academia, academic, dean, doctorate, education, faculty, graduate, masters, Ph.D, PhD, professor, school environment |
| Company Business | The director is experienced in the firm's business or industry (or a closely related industry). | all aspects of our industry, chief executive officer of our, chief executive officer of the company, company's business, executive of our, executive of the company, experience with the company, historical insight, historical knowledge, history of the operation, history with our company, in-depth knowledge of, industry-specific perspective, industry experience, industry knowledge, inner workings, insider's perspective, internal operation, knowledge of all aspects of the company, knowledge of the, knowledge of the history, officer of our, officer of the company, president of our, president of the company, the company's chief, understanding of our business, working with the company |
| Compensation | The director has compensation and benefits experience. | compensation |
| Entrepreneurial | The director has entrepreneurial experience | entrepreneur, entrepreneurial, entrepreneurship, evaluating business, innovative idea |

...cont. from previous page

| Variable | Description | Word List |
|---|---|---|
| Finance and accounting | The director has experience in banking, finance, accounting, or economics related activities. | accountant, accounting and, accounting experience, accounting principles, and accounting, auditing, banking, capital markets, capital structure, corporate finance, experience in accounting, experience in finance, expertise in finance, finance experience, finance industry, finance matters, financial accounting, financial acumen, financial background, financial experience, financial expert, financial expertise, financial field, financial foundation, financial management, financial matters, financial reporting, financial services, investment, securities, understanding of finance |
| Governance | The director has corporate governance experience | governance |
| Government and policy | The director has governmental, policy, or regulatory experience | government, policy, politics, regulatory |
| International | The director has international experience. | global, international, multinational, worldwide |
| Leadership | The director is someone that has leadership skills/experience. | leadership |
| Legal | The director has legal expertise | attorney, lawyer, legal |
| Management | The director has management and communications skills/experience. | experience in leading, experience in managing, management |
| Manufacturing | The director has manufacturing experience. | industrial, manufactured, manufacturing |
| Marketing | The director has marketing and sales skills/experience or knowledgeable in marketing activities | marketing |

*...cont. from previous page*

| Variable | Description | Word List |
|---|---|---|
| Outside board | The director has outside board experience. | board experience, board of other, board practices of other, boards of companies, boards of other, boards of several other, boards of various, director of other, director of several other, member of the board of, numerous boards, on the boards of, other company boards, prior service as a director, several corporate boards, several other corporate boards, varied boards |
| Outside executive | The director is an executive of another company. | as the chairman of a, business career, chief executive officer of a, executive experience, experience as a chief, experience as an executive officer of, experience as a senior, former executive of a, officer of a public, officer of other, officer of several companies, officer of numerous companies, president of a, senior-level executive, senior executive, senior management positions, serving as the CEO of a |
| Risk management | The director has risk management experience. | risk |
| Scientific | The director has engineering, scientific, or R&D skills/experience. | research and development, scientific expertise |
| Strategic planning | The director is someone that has strategy skills or strategy planning experience | business planning, decision-making, problem-solving, strategic, strategies |
| Sustainability | The director has experience on environmental and sustainability issues. | environmental, safety, sustainability, sustainable |
| Technology | The director has technology skills/experience | technological, technology |

# C. Identifying causes of death

BoardEx provides the date a given director left a company as well as data on the date a director died. For those directors that died while still serving on the board, I manually search news sources, company reports and press releases as well as obituaries to identify the cause of death. I follow Nguyen and Nielsen (2010) to classify deaths as sudden if the stated cause of death is a heart attack, stroke or accident. In case the cause was undisclosed, I classify deaths as being sudden only if the source explicitly states the death to be "unexpected" or "suddenly" and there is no evidence of deteriorating health prior to their death. In total I identify 12,792 dates where a director left a company, where 376 of these cases occurred due to the death of a director. The sample of 55 deaths in table 10 is the result of sample restrictions imposed by the estimation of the fixed effect and availability of sufficient data on returns. I can identify the cause of death for 362 cases, where roughly 25% can be classified as sudden. Figure A1 presents further summary statistics on the sudden and non-sudden causes of death.

**Figure A1**
**Causes of Death**

Figure A1 plots displays the different causes of death as a share of the total number of deaths classified as non-sudden in blue on the left and as a share of deaths classified to be sudden on the right in red. The date of death is taken from BoardEx and cause of death was determined by manually searching through news reports and obituaries. Causes of death are classified as sudden and non-sudden following Nguyen and Nielsen (2010). In total 269 deaths are classified to be sudden and 93 deaths occurred due to foreseen reasons.