

Unveiling the Role of Director-Specific Quality in Creating Firm Value

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Abstract

We provide a measure, which we term director-specific quality (DSQ), that captures a director's repeatable and transferable skill that they can use to improve value across different firms. We find that DSQ is correlated with difficult-to-quantify soft skills and easy-to-quantify hard skills. Moreover, DSQ is impactful, accounting for 10% of the variation in firm value. Consistent with DSQ capturing value-relevant traits, investors respond more (less) favorably when they are appointed (die), and directors with higher DSQ garner stronger voter support. Further, boards with higher DSQ demonstrate improved decision making related to cash management, CEO compensation, innovation, and mergers and acquisitions. Analyses utilizing director deaths confirm these effects. Exploiting the COVID-19 pandemic, we also find that firms with higher board-level DSQ performed better during this period. Overall, our study contributes to a nuanced understanding of directorial efficacy and provides a measure of DSQ that can be used in future studies.

Keywords: Board of Directors, Director Quality, Firm Value, Director Characteristics

JEL Classifications: G14, G30, G32, G34

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UNVEILING THE ROLE OF DIRECTOR-SPECIFIC QUALITY IN CREATING FIRM VALUE

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ABSTRACT

We provide a measure, which we term director-specific quality (DSQ), that captures a director's repeatable and transferable skill that they can use to improve value across different firms. We find that DSQ is correlated with difficult-to-quantify soft skills and easy-to-quantify hard skills. Moreover, DSQ is impactful, accounting for 10% of the variation in firm value. Consistent with DSQ capturing value-relevant traits, investors respond more (less) favorably when they are appointed (die), and directors with higher DSQ garner stronger voter support. Further, boards with higher DSQ demonstrate improved decision making related to cash management, CEO compensation, innovation, and mergers and acquisitions. Analyses utilizing director deaths confirm these effects. Exploiting the COVID-19 pandemic, we also find that firms with higher board-level DSQ performed better during this period. Overall, our study contributes to a nuanced understanding of directorial efficacy and provides a measure of DSQ that can be used in future studies.

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1 Introduction

Directors can add significant value to firms in many ways (e.g., [Nguyen and Nielsen, 2010](#); [Burt, Hrdlicka, and Harford, 2020](#)). For example, the alignment of their professional experiences with the immediate needs of firms, as well as how their skill sets complement those of other board members, are crucial factors in enhancing their ability to monitor and advise managers (e.g., [Fahlenbrach, Low, and Stulz, 2010](#); [Adams, Akyol, and Verwijmeren, 2018](#)). However, despite the extensive literature on the circumstances under which directors add value, important questions remain unanswered. In particular, it is unknown whether directors have repeatable and transferable skill that they can use to improve value across different firms, what traits this skill might reflect, and what the potential channels are through which repeated and transferable skill influences firm value.

In this study, we address these fundamental corporate governance questions by creating a measure that captures how much a director contributes to increasing firm value, regardless of the board they sit on. We call this measure director-specific quality (DSQ). We find that DSQ is correlated with both difficult-to-quantify soft skills (e.g., emotional intelligence and adaptability) and easy-to-quantify hard skills (e.g., graduating from an elite university and obtaining an advanced degree). Further, investors recognize that DSQ captures value-relevant attributes. Investors respond more positively when high DSQ directors are appointed and more negatively when they die, and directors with higher DSQ garner stronger voter support during elections. Finally, boards with higher average DSQ demonstrate improved decision making related to four important areas of corporate policy: cash management, CEO compensation, innovation, and mergers and acquisitions (M&A). Overall, our study shows that DSQ captures an important dimension of what makes directors effective across boards, providing a measure that future research can use.

To measure DSQ, we decompose firm value into variation attributable to four components based on the methodology in [Abowd, Kramarz, and Margolis \(1999\)](#) (AKM): (i) time-invariant firm-specific effects, (ii) time-varying firm, board, and director effects, (iii)

year effects, and (iv) time-invariant director-specific effects.¹ This last term represents the unique portable attributes of directors that capture repeatable skill, and estimated coefficients on these director-specific effects is our measure of DSQ. This decomposition allows us to assess DSQ separately by isolating the unique contribution of specific directors to firm value from contributions that are contingent upon board interactions, satisfying board-specific needs, or directors matching to firms based on average quality.

This decomposition parallels the well-known concept of the significance of individual researchers for a department’s research productivity. When departments hire faculty members, they consider both the researcher’s productivity and their potential contributions to the department. While departmental resources and access to colleagues can influence output, a substantial portion relies on the researcher’s intrinsic creative ability and motivation. A productive researcher tends to remain productive, albeit to varying degrees, irrespective of their department. Their creativity and drive can also positively affect other faculty members’ research output, further adding value. Our empirical approach would isolate the portion of the department’s total research output attributable to the individual researcher, thus identifying their unique contributions.

DSQ captures all value-relevant attributes specific to a director that she has acquired up to entering our sample. It encompasses a diverse set of attributes without requiring them to be well defined and incorporates the multi-dimensional nature of director skills in a single measure. It can reflect not only the usual observable traits (e.g., early life and work experiences and gender) but also difficult to quantify characteristics (e.g., critical thinking skills, grit, creativity, and willingness to challenge management). It is distinct from value-relevant attributes that change over time or that a director acquires during our sample period, and it is orthogonal to how a director’s performance is influenced by her interactions with other directors or the alignment of her skills with those of other directors.

¹The AKM (1999) method has been used in several contexts in the finance literature, including to study the role of firm- and manager-specific effects in executive compensation (Graham, Li, and Qiu, 2012; Coles and Li, 2020) and examine whether venture capitalists have repeatable investment skill (Ewens and Rhodes-Kropf, 2015). Given advancements in computing power, one could recover estimates of the different fixed effects using Ordinary Least Squares regressions instead of relying on the AKM algorithm. However, because we have over 64,000 unique firms and directors in our full sample, we follow prior work and use the AKM method.

In this sense, our measure of DSQ can be compared to the setting of trying to separate the performance of superstar managers, analysts, or athletes from the performance of their “teams.”²

We first estimate DSQ and quantify how much directors display repeatable and transferable skill that they can use to improve firm value across different firms. We focus on non-employee directors to better capture transferable director quality arising from their advising and monitoring roles and find that DSQ accounts for an economically significant fraction of the variation in firm value, as measured by Tobin’s Q. After accounting for several other relevant factors, DSQ explains 10% of the total variation in firm value.³ In comparison, firm-specific effects explain 52% of the total variation, while time-varying firm-, board, and director-level characteristics explain 17%.

We next attempt to peer inside the black box of what director traits DSQ might be capturing by exploring how DSQ relates to observable and mostly time-invariant traits that have been found to be correlated with firm value as well as to soft skills. For observable traits, we find that DSQ is most positively correlated with whether the director has previous management experience, graduated from an Ivy League university, has a graduate degree, and is female. For soft skills, which we infer from biographies using natural language processing, DSQ is most positively correlated with whether the director is considered innovative, emotionally intelligent, analytical, honest, adaptable, and a good communicator. In general, we find higher correlations between DSQ and soft skills compared to observable traits, which highlights the importance of these hard to quantify traits in creating shareholder value.

²While understanding what factors drive director performance in the context of how the board interacts and functions as a whole is also of interest and has received attention in the literature (e.g., [Adams et al., 2018](#); [Griffin, Li, and Xu, 2021](#)), it is not the focus of our study.

³The original AKM method decomposes worker compensation into firm- and worker-specific effects to isolate each worker’s human capital. While this approach has advantages, it is not appropriate for our purposes. Unlike employee compensation, director pay is determined more by firm policy than individual contributions and effort. Firms often set a uniform base level of compensation for all directors and add meeting fees, committee fees, and extra pay for serving as a committee chair. Thus, heterogeneity in director pay within a firm is mostly driven by committee roles rather than a director’s contribution to firm value (e.g., [Farrell, Friesen, and Hersch, 2008](#)).

To examine whether DSQ captures director-specific value-relevant attributes that investors recognize, we study (i) the market reaction to director appointments and deaths, and (ii) shareholder support during director elections.⁴ We find larger cumulative abnormal returns (CARs) to the announcement of high DSQ director appointments. Following a large literature that infers director value by exploiting more exogenous deaths (e.g., [Nguyen and Nielsen, 2010](#); [Falato, Kadyrzhanova, and Lel, 2014](#); [Huang and Hilary, 2018](#); [Schmid and Urban, 2023](#)), we also find that announcement CARs are more negative when high DSQ directors die. Further consistent with investors distinguishing which directors have repeatable skill, high DSQ directors receive a higher fraction of votes in favor of appointing them and are less likely to receive a vote signaling lower confidence.

We explore our final question by investigating potential channels that firms with higher board-level DSQ may demonstrate improved decision making. We focus on decisions where managers' interests can diverge from those of shareholders and where directors can advise and provide oversight. High-quality directors can facilitate better firm-level decisions by preventing managerial misuse of firm resources, designing compensation packages that better align CEO incentives with shareholders' interests, helping set and ultimately approving a firm's strategic direction, and providing advice on and approving potential acquisitions (e.g., [Bebchuk and Fried, 2003](#); [Coles, Daniel, and Naveen, 2014](#); [Balsmeier, Fleming, and Manso, 2017](#); [Field and Mkrtchyan, 2017](#); [Griffin et al., 2021](#)). Thus, through their advising and monitoring roles, directors can affect (i) how efficiently managers use cash, (ii) the design of CEO compensation packages, (iii) the quality and quantity of innovation, and (iv) the quality of M&A decisions.

Overall, our evidence suggests that firms with higher average DSQ make decisions associated with increasing shareholder value. We capture the quality of a firm's cash management policies with its marginal value of cash ([Faulkender and Wang, 2006](#)) and find that the marginal value of a dollar of cash is higher at firms with higher board-level

⁴Based on econometrics terminology, our DSQ measure captures both observable and unobservable director attributes. However, in our context, unobservable more broadly relates to information that is not available to the econometrician, is available but difficult to quantify, or is known but with extreme noise. Thus, unobservable in this context does not mean that the attributes are unknown to the firm or investors or that the attributes cannot be incorporated into share prices.

DSQ. CEOs at firms with higher board-level DSQ also receive more of their compensation in the form of stock and option awards and have more wealth that is sensitive to stock price fluctuations. Further, firms with higher board-level DSQ create more value from patenting activities, produce more total patents, and receive more citations per patent. Last, at firms with higher board-level DSQ, bidder M&A announcement CARs are significantly higher, especially for larger deals in which directors are more likely involved.

Throughout our analyses, we address a number of econometric concerns. First, while estimating DSQ over the full sample period increases the precision of how much directors demonstrate repeatable skill, this approach incorporates future information. To further alleviate the concern that using future information substantially biases our findings, we show our results hold when we estimate DSQ using rolling windows and only information up to year $t-1$. Second, as a different measure of firm value, we show our results are similar when estimating DSQ from abnormal stock returns instead.

Third, the AKM method relies on directors that work at more than one firm (i.e., movers) to identify DSQ for all directors. Thus, a potential concern is that limited mobility or differences between movers and stayers could bias our estimates of DSQ or affect the interpretation of our results (e.g., [Andrews, Gill, Schank, and Upward, 2008](#); [Bonhomme et al., 2023](#)). The first concern is not significant, as our sample has over five times the number of movers compared to studies estimating executive specific effects (e.g., [Graham et al., 2012](#)). Further, our results continue to hold when we conduct the analyses on the mover and stayer samples separately. Moreover, instead of using the AKM method, we show our results are robust to estimating DSQ using the mover dummy variables method that restricts the analysis to directors who sit on at least two different public boards ([Bertrand and Schoar, 2003](#)).

Fourth, we take a number of steps to assess the extent and reduce the effect of assortative matching where specific types of directors based on quality match to specific types of firms. We first attempt to alleviate this concern by including several firm-, board-, and director-level control variables in all of our analyses. As long as the mechanism driving director-firm matching is captured by these variables, the issue is mitigated. To this end,

controlling for firm fixed effects when we estimate DSQ is powerful, as it holds constant average firm quality and eliminates the channel of assortative matching to firms based on average quality. Similarly, when we examine outcomes, we always control for firm-specific quality estimated from the AKM method as well as a measure of Tobin’s Q net of the director- and firm-specific components to further account for any residual correlation between our measure of DSQ, firm value, and our outcomes of interest (e.g., [Coles and Li, 2020](#)). Our outcome results also hold in specifications with firm fixed effects.

To more directly examine how much our estimates of DSQ could be biased from assortative matching, we follow [Card, Heining, and Kline \(2013\)](#) and compare how much the explanatory power of our Tobin’s Q regression increases when we use combined director-firm fixed effects that capture matching instead of separate director and firm fixed effects. If match effects are important, then the fully saturated Tobin’s Q regression should significantly outperform the model with the fixed effects estimated separately. We find the R^2 of the saturated model increases by a negligible 1.3%. Further, by examining the correlation between DSQ and the estimated firm-specific effects that indicates the extent of assortative matching, we find a correlation of almost zero at -0.03. We also follow [Ewens and Rhodes-Kropf \(2015\)](#) and show that our results are robust when we estimate separate regressions by directors that moved to better and worse performing firms, suggesting that endogenous moves due to voluntary and involuntary separations and appointments do not have a material effect on our conclusions. Finally, we show that our results hold after excluding firms in the top and bottom quartiles of Tobin’s Q. If our results are driven by high DSQ directors matching to the best performing firms or low DSQ directors matching to the worst performing firms, limiting our analyses to firms in the middle quartiles of firm value should mitigate this concern.

In our final analyses, we attempt to establish a more causal link between DSQ and corporate policies and firm performance in two ways. First, similar to [Fracassi and Tate \(2012\)](#), we examine how firm outcomes change around director deaths based on the DSQ of the directors who die and by how much board-level DSQ changes after the directors die. The results are consistent with our previous findings and suggest a causal effect of

DSQ on outcomes. Second, we exploit the COVID-19 pandemic and examine whether firms with higher average DSQ perform better during a large negative economic shock. We estimate board-level DSQ using data through 2019 so that DSQ is measured out-of-sample. The idea is that, as of 2019, firms have optimized their board for normal operating conditions, and the pandemic shocked firms out of equilibrium. To the extent that high DSQ is also beneficial during abnormal business conditions, firms with higher pre-pandemic board-level DSQ should perform better during the pandemic. We find that while increases in COVID-19 cases are associated with negative stock returns, this effect is attenuated by higher board-level DSQ.

2 Related Literature

The significance of boards and directors has been the subject of extensive research. Previous studies recognize the role of the board of directors as stewards of shareholders' interests, as acknowledged by the [American Bar Association \(2009\)](#) and illustrated by numerous policies focused on board and director characteristics (see [Adams \(2017\)](#) and [Adams et al. \(2018\)](#) for examples). However, our understanding of the factors that contribute to individual board member effectiveness remains incomplete. In attempting to address this gap, prior work has generally focused on one particular director trait at a time, such as independence, CEO experience, education, financial expertise, connections, and gender.⁵ While some studies focus on general settings or overall effects, others examine specific settings to provide a more detailed analysis of when a particular director skill or trait matters. For example, studies have found that political connections are valuable when the connected party is in power ([Goldman, Rocholl, and So, 2009](#)), the

⁵Examples of traits previously studied include prior CEO and CFO experience ([Fahlenbrach et al., 2010](#); [Bedard, Hoitash, and Hoitash, 2014](#)), independence ([Fich, 2005](#)), educational attainment ([White, Woidtke, Black, and Schweitzer, 2014](#)), financial expertise ([DeFond, Hann, and Hu, 2005](#); [Güner, Malmendier, and Tate, 2008](#)), entrepreneurial experience ([Li and Srinivasan, 2011](#)), gender ([Carter, Simkins, and Simpson, 2003](#); [Adams and Ferreira, 2009](#); [Ahern and Dittmar, 2012](#); [Kuzmina and Melentyeva, 2021](#)), receiving recognition awards ([Malmendier and Tate, 2009](#)), network size ([Fracassi and Tate, 2012](#)), legal expertise ([Krishnan, Wen, and Zhao, 2011](#)), industry expertise ([Dass, Kini, Nanda, Onal, and Wang, 2014](#); [Faleye, Hoitash, and Hoitash, 2018](#)), and busyness ([Fich and Shivdasani, 2006](#); [Field, Lowry, and Mkrtchyan, 2013](#)).

value of director independence is contingent on the cost of acquiring information ([Duchin, Matsusaka, and Ozbas, 2010](#)), busy boards contribute positively to firm value for IPO firms ([Field et al., 2013](#)), and having a director from a foreign country is valuable when making cross-border M&A ([Masulis, Wang, and Xie, 2012](#)).

More recent studies consider the multi-dimensional nature of director skills or traits with a particular focus on how a director’s characteristics fit with or diverge from those of other directors. The results suggest that boards focus on certain skill sets when nominating directors and that board fit appears to matter. However, the impact on firm value and whether any of these traits are transferable remains unclear. For example, [Kim and Starks \(2016\)](#) and [Adams et al. \(2018\)](#) utilize the 2009 amendment to Regulation S-K requiring public U.S. firms to describe their reasons for nominating directors to examine how director skill sets contribute to board skill sets and find that directors and boards are multi-dimensional. [Kim and Starks \(2016\)](#) also find that female directors contribute to skill diversity by providing new functional expertise. However, when examining commonality in director skill sets, [Adams et al. \(2018\)](#) find no evidence that increased diversity in board skills is associated with improved firm performance. [Giannetti and Zhao \(2019\)](#) also find that ancestral diversity increases performance volatility. In contrast, [Bernile, Bhagwat, and Yonker \(2018\)](#) find that diversity on boards is associated with better performance, while [An, Chen, Wu, and Zhang \(2021\)](#) and [Griffin et al. \(2021\)](#) show that innovation is greater at firms with more diverse boards.

Using a different approach to capture multi-dimensionality, [Erel, Stern, Tan, and Weisbach \(2021\)](#) employ machine learning algorithms to predict director performance using director-, board-, and firm-level data available to the nominating committee at the time of the nominating decision. They find predictably bad directors are more likely to be male, accumulate more directorships, and have larger networks than the directors the algorithm would recommend in their place, and these deviations in selection are stronger in firms with weaker governance. Together, these results suggest that weakly governed firms are more likely to appoint directors with traits more similar to the stereotypical director of large public U.S. firms when increasing board diversity might be beneficial.

The results in these studies imply that director skills are multi-dimensional, indicating that it is difficult to interpret valuation effects when a specific director trait is analyzed in isolation. We complement these studies that focus more on board dynamics (the team effect) by exploring whether there is a value-relevant component of multi-dimensional director traits that is transferable or separate from the team effect (the superstar effect).

Our paper also extends work that considers fixed effects and the AKM methodology in the board of directors setting. For example, [Cavaco, Crifo, Rebérioux, and Roudaut \(2017\)](#) show that the relation between director independence and accounting performance is negative after controlling for the importance of director characteristics in the nomination process with director fixed effects, and [Lu, Liu, and Liu \(2022\)](#) similarly find that director fixed effects are related to accounting performance in Chinese firms. Using director fixed effects to exploit relative firm prestige across a director’s directorships, [Masulis and Mobbs \(2014\)](#) show that directors have higher attendance rates at their more prestigious firms. [Richardson, Tuna, and Wysocki \(2003\)](#) find that director fixed effects explain variation in firms’ governance, financial, disclosure, and strategic policy choices. Similarly, [Bird, Boroichin, Knopf, and Ma \(2019\)](#) adopt the AKM methodology to document that individual directors have styles related to different corporate policies and that directors are more likely to leave their appointment or key committees when their policy style deviates from the board-level policy style. Distinct from these studies, we focus on both proposing and validating a measure of DSQ based on how much directors impact a market-based measure of firm value, which other researchers can use to pursue questions that were previously difficult to conduct and control for director quality (e.g., [Masulis, Wang, Xie, and Zhang, 2023](#)). Moreover, while these studies try to identify director styles or understand how controlling for director heterogeneity affects the relation between firm and director characteristics, we are interested in exploring possible traits that DSQ may reflect and the various ways that high DSQ directors affect firm value.

Our study is also related to research demonstrating the overall value of directors. For example, [Nguyen and Nielsen \(2010\)](#) find that firm value drops by 0.85% after the sudden death of an independent director. [Burt et al. \(2020\)](#) derive director value from

stock return comovement between firms that share a director, finding that 6.5% of the variation in stock prices is attributable to directors. We complement this work by showing that DSQ also explains about 10% of the variation in firm value. However, our primary contribution extends this and other previous work by specifically focusing on whether there is a component of director quality that is transferable across boards and significantly contributes to effectiveness. Thus, we aim to determine whether the isolated component of transferable DSQ contributes to firm value and how. The answer to this question holds important implications for firms and policy makers. If our findings indicate that there is no transferable component of DSQ, firms need to concentrate solely on searching for directors with skills that complement the existing board members’ skills to meet their current needs. However, if there is a transferable component of DSQ that contributes to effectiveness, firms can seek out directors with higher DSQ to enhance the effectiveness of their existing boards. This option becomes particularly valuable when certain skill sets are scarce in the market. Our study’s results indicate that transferable DSQ does indeed contribute separately to firm value. Overall, our study has implications for the ongoing discussion on whether directors matter, what makes an effective board, and how boards should be structured (e.g., [Boone, Field, Karpoff, and Raheja, 2007](#)).

3 Data and Empirical Methodology

3.1 Sample selection

Our sample starts with all non-employee directors in BoardEx between 2000 and 2020. BoardEx contains unique director and firm identifiers that allow us to track directors across firms and over time. It also contains information on director characteristics and board-related information. We obtain firm financial statement information from Compustat, stock return information from CRSP, and institutional ownership data from Thomson Reuters’ 13-F Holdings database. We obtain classified board information from [Guernsey, Guo, Liu, and Serfling \(2023\)](#) and [Guernsey, Sepe, and Serfling \(2022\)](#), who combine machine learning techniques, hand collection, and data from the IRRC Corporate Gover-

nance database to determine the classified board status for the universe of public firms. Poison pill data is from Refinitiv’s Securities Data Company (SDC) Platinum database. We also use the SDC database to obtain M&A information and the Voting Analytics database for information on director election vote outcomes. We manually merge Voting Analytics to BoardEx using CUSIPs and director name matches. After removing observations with missing data and estimating our AKM model described in the following section, our base sample has 436,383 firm-director-year observations, corresponding to 6,463 firms and 52,851 unique directors.

3.2 AKM methodology

To quantify an individual director’s contribution to firm value, we decompose firm value into several components using the connected group method from AKM (1999):

$$\text{Ln}(TQ_{ijt}) = \theta_i + \psi_j + \omega_t + X_{jt(t-1)}\beta + Z_{ijt}\gamma + \varepsilon_{ijt}. \quad (1)$$

where TQ_{ijt} is market value of assets scaled by book value of assets (Tobin’s Q) at director i ’s firm j in year t . We include director (θ_i), firm (ψ_j), and year fixed effects (ω_t), several time-varying firm and board characteristics ($X_{jt(t-1)}$), and time-varying director characteristics (Z_{ijt}). The estimated director fixed effects capture DSQ.

The goal of conditioning on time-varying controls is to isolate the director-specific effect from other factors that could be correlated with director quality and firm value as well as from specific time-varying needs of firms for specific director qualities. Firm-level controls include size, leverage, profitability, institutional ownership, R&D expenditures, stock return volatility, and beta. We measure point-in-time variables like size at the beginning of the fiscal year and flow variables like profitability over the contemporaneous fiscal year. We also control for whether the firm has a classified board and an explicit poison pill. Board-level controls include the proportion of independent directors, the proportion of female directors, indicator variables for whether the CEO is the chairman of the board and if the firm has a lead-independent director, and board size. Time-varying director-level controls include the total number of public boards the director has

served on, whether she sits on more than two other boards at the same time, board tenure, whether the director is independent, whether the director is at least 65 years old, whether the director has prior experience in the industry, and variables indicating committee memberships and leadership positions (chairman or lead director and member or chair of the audit, nominating, or compensation committees). The Appendix provides detailed definitions of the variables, and [Table 1](#) presents summary statistics for the variables used in the decomposition regression. We winsorize firm characteristics, i.e., financial statement and stock return variables, and director tenure at their 1st and 99th percentiles and express dollar values in 2017 dollars.

Ultimately, we want to separate director-specific effects from firm-specific effects, which requires within-firm variation in director appointments or a director to sit on at least two boards. Fortunately, there are abundant sources of variation in director appointments, even though our sample does not capture all the boards directors sit on (our sample is restricted to firms in the Russell 3000, but directors can sit on boards of other public and private firms). Director turnover is common (8.4% of directors leave a firm each year), creating within-firm variation in appointments. Many directors also sit on multiple boards throughout their careers (26.3% sit on more than one board) and sit on more than one board simultaneously (15.6% of directors sit on two or more boards in any year), creating time-series and cross-sectional variation within directors.⁶

The AKM approach uses connected groups to separately identify the director- and firm-specific effects. These connected groups are formed by arbitrarily selecting a director who sits on at least two different boards. For this director, the connected group comprises all firms that she has been a board member at, all the other directors that sit on the boards of these firms, and all other directors and firms that these “other directors” are connected to. This process is then repeated for the remaining directors until no unconnected directors are left. Then, within each connected group sample, the firm fixed

⁶These figures do not imply that 73.7% of directors never sit on other boards. Rather, they are specific to our sample and indicate that these directors only sit on one board in our sample. In fact, for these directors, 82.3% sit on at least one other public or private board at some point, while 61.7% sit on at least one other public or private board simultaneously.

effects are estimated by the least-squares dummy variables method after first demeaning all variables by director to remove the director-specific effects. Once the firm fixed effects are estimated, the director-specific effects within a connected group can be recovered through algebraic manipulation.⁷ More formally, and simplifying some of the notation based on the discussions in [Ewens and Rhodes-Kropf \(2015\)](#) and [Liu, Mao, and Tian \(2023\)](#), we can rewrite Eq. (1) as:

$$V_{ijt} = \theta_i + \sum_{l=1}^J F_{ilt} \psi_l + \omega_t + X_{jt} \beta + Z_{ijt} \gamma + \varepsilon_{ijt}, \quad (2)$$

where V_{ijt} is firm value, and F_{ilt} is a dummy variable equal to one for director i at firm l at time t , and zero otherwise.

The first step in the AKM method is demeaning all variables by director to remove the director-specific effects, such that the equation becomes:

$$V_{ijt} - \bar{V}_i = \sum_{l=1}^J (F_{ilt} - \bar{F}_{il}) \psi_l + (\omega_t - \bar{\omega}_t) + (X_{jt} - \bar{X}_i) \beta + (Z_{it} - \bar{Z}_i) \gamma + (\varepsilon_{ijt} - \bar{\varepsilon}_i), \quad (3)$$

where $\bar{Y}_i$ represents the mean of a variable for each director i across the entire sample. Notably, the director fixed effects have been removed through this demeaning process. Eq. (3) is then estimated using the least-squares dummy variables method. Finally, the parameter estimates from Eq. (3) are used to recover the director-specific effects as follows:

$$\hat{\theta}_i = \bar{V}_i - \sum_{l=1}^J \bar{F}_{il} \hat{\psi}_l - \bar{X}_i \hat{\beta} - \bar{Z}_i \hat{\gamma}. \quad (4)$$

There are two items worth pointing out from these equations. First, Eq. (3) makes it clear that firm fixed effects can only be identified using directors appointed to at least two boards during the sample period (i.e., $F_{ilt} \neq \bar{F}_{il}$). As Panel A of [Table A1](#) in the online Appendix shows, out of the 57,505 unique directors in the full sample before applying post-estimation filters (52,851 unique directors after the filters), 26.3% sit on at least two different boards during our sample period.⁸ As a comparison to related

⁷We implement the AKM (1999) estimation methodology using the Stata command `felsvdrvreg`.

⁸Panel B of [Table A1](#) shows the number of firms with directors that sit on more than one board and that can be connected to a group following the AKM method. In our sample, only 594 of the 7,057 firms cannot be connected to a group. For these firms, it is impossible to distinguish between the firm- and

studies, we have substantially more director movers than the 5% of managerial movers in [Graham et al. \(2012\)](#) and 16% of inventor movers in [Liu et al. \(2023\)](#). Our sample is more closely comparable to the 30% of venture capital partnership movers in [Ewens and Rhodes-Kropf \(2015\)](#). Thus, concerns about estimation bias arising from limited director mobility causing imprecision in the estimated director and firm fixed effects is less of an issue in our study compared to prior work (e.g., [Abowd, Kramarz, Lengermann, and Pérez-Duarte, 2004](#); [Andrews et al., 2008](#); [Bonhomme et al., 2023](#)).

Second, firms and directors can appear in only one group, and there is no overlap between groups. Because the excluded reference director and firm are different within each group, the estimated specific effects are not directly comparable across groups. While we address this concern by normalizing the specific effects by group ([Cornelissen, 2008](#)), our results are similar if we use only this first group that comprises 98.7% of the observations.

3.3 Estimating DSQ

[Table 2](#) presents results examining the determinants of firm value using the AKM estimation approach and the model presented in Eq. (1). While our Tobin’s Q regression is less standard in the sense that our models include both director and firm fixed effects, which makes comparing our results to prior work difficult, many of the variables are correlated with Tobin’s Q in a way that is consistent with prior research. For example, firm value is positively related to profitability, R&D investment, and institutional ownership, while it is negatively correlated with firm size and having a poison pill provision.

Panel A of [Table 3](#) decomposes variation in Tobin’s Q using the variance decomposition formula described in [Graham et al. \(2012\)](#) and [Coles and Li \(2020\)](#). The largest driver of Tobin’s Q is the firm-specific component, explaining 52.2% of the total variation. Time-varying firm-, board-, and director-level traits explain 17.5% of the total variation, while year fixed effects only account for 2.5% of the total variation. Relevant for our study is the non-trivial explanatory power of director-specific effects, accounting for 9.7% of the

director-specific effects, and we therefore exclude them from our analyses. While these firms account for 8.4% of all firms in our sample, they only account for 5.0% of all director-firm-year observations.

total variation in Tobin’s Q and 11.8% of all explainable variation. We use these estimated director-specific effects to capture value-relevant unique director attributes, which we can therefore interpret as a measure of transferable, including difficult to quantify, individual director-specific quality (i.e., DSQ).

In our tests, we use these estimated director-specific effects in two ways. For director-level tests, we define a continuous variable (DSQ) equal to the estimated director fixed effects. Panel B of Table 3 indicates that across all directors, DSQ has a standard deviation of 0.196. We also allow for a nonlinear relation between our outcomes and director-specific effects by grouping DSQ into quartiles ($DSQq1$ - $DSQq4$). For our firm-level analyses, we average DSQ estimates across all directors on a firm’s board to obtain a firm-level measure of DSQ ($AvgDSQ$). We also group $AvgDSQ$ into quartiles ($AvgDSQq1$ - $AvgDSQq4$). We define FSQ equal to the estimated firm fixed effects. Importantly, following an approach similar to Coles and Li (2020), we control for Tobin’s Q net of DSQ and FSQ ($ResidTQ$) in all our tests to account for any residual correlation between DSQ, firm value, and our outcomes of interest. The concern is that an outcome, such as innovation, is correlated with DSQ through components of Tobin’s Q other than the director-specific component. This concern arises from not having all possible determinants of Tobin’s Q as controls in Eq. (1) or not having these determinants as controls in subsequent analyses. Controlling for $ResidTQ$ helps alleviate this concern. While we believe controlling for $ResidTQ$ is econometrically appropriate to isolate the component of firm value attributable to transferable DSQ, the results are similar when we exclude this control from later regressions.⁹

From these estimates, we can also get a sense of the importance of director-firm sorting by examining the correlation between the estimated director- and firm-specific effects. This correlation is -0.078 and significant at the 1% level, implying negative assortative matching. Thus, directors with higher DSQ tend to gravitate towards firms with lower

⁹In the online Appendix (Tables A2-A6), we show that our main results are robust to estimating DSQ and FSQ using several different approaches and their effects on various subsamples, including estimating Eq. (1) after replacing Tobin’s Q as the dependent variable with a firm’s DGTW characteristic-adjusted buy-and-hold stock return over its fiscal year. We further show our results are similar in both mover and stayer subsamples, and thus, are not sensitive to any differences between movers and stayers. Our results also hold when we estimate DSQ using the mover dummy variables (MDV) method from Bertrand and Schoar (2003) that only uses directors with multiple board appointments.

average Tobin’s Q . This correlation shrinks to -0.026 after applying the bias correction from [Andrews et al. \(2008\)](#) and [Bonhomme et al. \(2023\)](#) that addresses the concern that this correlation is downward biased due to limited mobility causing the variance attributed to one of the fixed effects to be overinflated while the other is deflated. One interpretation of this result is that directors are most able to demonstrate their quality at firms that need their advice and monitoring, whereas any director can oversee an already high-quality firm. This negative assortative matching of director to firm quality is in contrast to much of the employee wage literature findings of positive assortative matching (e.g., [Engbom and Moser, 2022](#)) but consistent with the findings on inventor innovation productivity ([Bhaskarabhatla, Cabral, Hegde, and Peeters, 2021](#)).

We also note that our estimates of DSQ and FSQ are unlikely contaminated by a mechanical relation between the value-relevant events we study occurring when we measure Tobin’s Q . We measure Tobin’s Q using stock prices at the end of a firm’s fiscal year-end. Within the ± 5 days around a firm’s fiscal year-end, only 0.96% of firm-years have an M&A, director appointment, or director death announcement. This percentage remains low at only 2.89% when we consider a ± 14 day window around fiscal year-ends. Nevertheless, we have rerun all of our results after excluding firm-year observations in which these events occur close to the fiscal year-end, and the results are very similar.

For our primary measure, we estimate DSQ using the full sample. Because our goal is to estimate a measure of director quality that is unique to each director and does not change over time or across firms, utilizing the longer sample period and more director “moves” in the estimation produces more stable estimates of DSQ . However, this approach cannot address whether DSQ is persistent. To provide some insight into this question, we reestimate Eq. (1) over seven non-overlapping windows, collapse the data to one observation per director-period, and examine the persistence of DSQ . We find a strong positive relation between measures of DSQ in periods t and $t+1$, with an autocorrelation between the two measures of 0.26. Thus, the results indicate persistence in DSQ , validating that DSQ captures time-invariant quality.

Another concern with estimating DSQ using the full sample is that it uses future information that may be unknown to investors at time t . Therefore, we also include a specification in all of our main analyses in which we reestimate Eq. (1) using data only up to $t-1$ each year, excluding observations before 2005 so that we have at least five years of data to estimate the fixed effects. We treat these specifications as “out-of-sample” analyses, as only historical information is used to estimate DSQ and FSQ .

3.4 DSQ and director characteristics

To provide insight into whether DSQ captures qualities that are difficult to observe or the multi-dimensional nature of quality, we explore how DSQ relates to easily observable, quantifiable, and mostly time-invariant director characteristics examined in prior work as well as hard to observe soft skills inferred from director biographies.

We create 12 director traits based on BoardEx data, including education, gender, and managerial and financial experience, among others. Some of the traits we consider are completely time-invariant. Other traits, such as Ivy League school attendance, are time-invariant over our sample period, as these background traits were acquired many years before becoming a director. A few traits, such as entrepreneurial and financial experience, are time-varying to an extent. However, most directors do not experience changes in these traits during our sample period, as most of these types of experience were attained earlier in a director’s career. We note that while some of these characteristics like financial experience could directly capture the value of a particular early life or career experience, other characteristics like graduating from an Ivy League University may reflect an underlying quality of the director like intelligence.

We also create 11 measures that more directly capture soft skills that are hard to observe and quantify: adaptability, critical thinking, analytical, problem solving, innovative, effective communication, customer orientation, team building, honesty, emotional intelligence, and empathy. To create measures of these soft skills, we first use ChatGPT to obtain biographies of each director. We then employ a Transformer-based Natural Language Processing (NLP) technique on these biographies to create a score that indicates

how each biography relates to the 11 soft skills (see the Appendix for variable definitions and details of their construction).

Table 4 presents correlations between DSQ and these 23 characteristics. In this analysis, we restrict the sample to one observation for each of the 52,851 directors in our sample. However, we were only able to obtain biographical information to determine soft skills for 30,775 directors. A potential concern is that we are more likely to obtain biographies of high DSQ directors. While we find a positive correlation between *DSQ* and the likelihood that we obtain a biography, this correlation is marginal at a value of only 0.026. A one standard deviation higher value of *DSQ* increases the likelihood we obtain a biography by only 1.26 percentage points.

Overall, the results show that DSQ is correlated with many observable and quantifiable traits as well as harder to observe soft skills. The first columns present results for the full sample, and the last two columns restrict the sample to directors in the top and bottom deciles of DSQ. Focusing on the last two columns, of the observable traits, DSQ is most highly correlated with whether the director has previous management experience, graduated from an Ivy League university, has a graduate degree, and is female. These correlations range from 0.029 to 0.042. For the inferred soft skills, DSQ is most highly correlated with whether the director is considered innovative, emotionally intelligent, analytical, honest, adaptable, and a good communicator, with correlations ranging from 0.036 to 0.091.

In sum, these results imply that DSQ is not highly correlated with any single characteristic but instead has some correlation with several characteristics, including both easily quantifiable characteristics and more difficult to quantify proxies for soft skills. This suggests that DSQ captures the multi-dimensional nature of skills, including both easy- and difficult-to-quantify skills. The generally higher correlations between DSQ and soft skills compared to observable traits highlights the importance of these hard-to-quantify traits in creating shareholder value. Taken together, the results indicate that single measures of director quality commonly used are incomplete measures of repeatable DSQ. Not only

do they exclude measures of soft skills, but they are also unable to capture the multi-dimensional nature of DSQ.

3.5 Do investors recognize the value relevancy of DSQ?

To examine whether investors recognize the value relevancy of DSQ, we next study (i) the market reaction to director appointments and deaths, and (ii) shareholder support during director elections.

3.5.1 Director appointment and death CARs

Table 5 presents results examining the correlation between our estimates of DSQ and abnormal stock returns around the announcement of new director appointments, which reflect shareholders’ assessment of a director’s contribution to firm value (Shivdasani and Yermack, 1999). We obtain appointment announcement dates from the BoardEx Announcement file by filtering on descriptions that contain “join this board”, which has data between 2003 and 2020. Because BoardEx coverage of appointment announcements decreases substantially after 2012, we supplement this data with appointments announced in 8-K filings.¹⁰ We obtain a cleaner set of appointment announcements by removing observations accompanied by other major news events in the five-day window around the appointment. We obtain news events from Ravenpack News Analytics and exclude appointments with the following types of news events: dividends, earnings, conference calls and major-shareholder disclosures, mergers and acquisitions, and equity actions that involve buybacks, reorganizations, private placements, spin-offs, and stock-splits. We estimate five-day CARs around the announcement of director appointments, $CAR[-2,+2]$, using the market model based on CRSP value-weighted returns and parameters estimated over the $[-210,-11]$ trading days before the announcement. For this analysis and all subsequent analyses, our regressions include an extensive set of time-varying

¹⁰We obtain 8-K filings related to director appointments and match them to BoardEx in three steps. (i) We use WRDS SEC Analytics Suite to obtain all SEC links for 8-K filings of Item 5.02(d), which disclose the name and announcement date of a new director. (ii) We use textual analysis to parse director names and announcement dates. When an announcement date is missing, we use the report date of the filing as the announcement date. (iii) We match the director’s name and company to the BoardEx database.

firm-, board-, and director-level controls. The base specifications also include two-digit SIC industry and year fixed effects, and we cluster standard errors by firm.

Overall, the results show that appointing high *DSQ* directors is associated with higher announcement CARs. Column 1 shows a positive and statistically significant coefficient on *DSQ*. A one standard deviation higher *DSQ* is associated with 32.0 bps ($=1.631 \times 0.196$) higher CARs, which is economically significant when compared to the average and standard deviation of announcement CARs of 27.1 bps and 646 bps, respectively. This result holds in column 2 in our out-of-sample analysis. In column 3, there is a monotonic relation between announcement CARs and *DSQ* quartiles, and column 4 shows that this result is robust to controlling for firm fixed effects.

In our sample, 10.3% of firms announce more than one director appointment on the same day. In columns 1-4, we treat each appointment as separate observations. In column 5, we collapse the data to one observation per day for each firm by averaging *DSQ* across all directors appointed on the same day. As further robustness, column 6 excludes all observations when there are multiple appointments. In these robustness tests, we focus on the model specification from column 3 and continue to find a monotonic relation between *DSQ* quartiles and announcement CARs.

A concern with inferring director value from appointment announcements is that these appointments are not exogenous. The announcement CARs reflect investors' assessment of the director-specific contribution to value and the selection/matching of the director to the firm. Therefore, in column 7 of [Table 5](#), we examine the relation between *DSQ* and CARs around the announcement of director deaths. Because the BoardEx Announcements file appears to have stopped collecting announcements of deaths after 2012, we obtain the dates of director deaths from the BoardEx Profiles file that records a director's date of death. We verify that the director death dates match the announcement dates for the earlier years, and we make sure directors were sitting on the firm's board when they died. We continue to remove observations accompanied by other major news announcements. In addition to exploiting director deaths as more exogenous events, another benefit is that the *DSQ* of deceased directors is by construction estimated using only historical

information for that director. While these events are exogenous, one caveat is that CARs reflect the expected net effect of the impact from the loss of a director on the board’s average DSQ, which also depends on the replacement director’s DSQ. Thus, a negative relation between director death DSQ and CARs is consistent with the expectation that high (low) DSQ directors will be replaced with lower (higher) DSQ directors.

Consistent with our previous results, column 7 shows that CARs are more negative when high DSQ directors die. Compared to the first quartile of DSQ, CARs are 126 bps ($t\text{-stat} = 2.14$) lower when directors in the fourth quartile die. This effect is economically significant compared to the average and standard deviation of announcement CARs of -9.4 bps and 522 bps, respectively. Further, we find that when a high (low) DSQ director dies, firms tend to replace these directors with a lower (higher) DSQ director. Thus, these results suggest that DSQ captures directors’ contribution to firm value beyond selection/matching effects.

3.5.2 Director election outcomes

Table 6 presents results examining the relation between DSQ and election outcomes. We match election outcomes from Voting Analytics to BoardEx between 2004 and 2020, which is when the Voting Analytics database is more complete. We calculate the fraction of votes in support of a director ($\%Vote$) as the number of shares voted for a director scaled by the sum of votes for, against, and abstained. We also create two variables indicating low shareholder support ($\%Vote < 90$ and $\%Vote < 85$) that equal one if $\%Vote$ is less than 90% and 85%, respectively.

Overall, the results show that high DSQ directors have higher shareholder support. Column 1 shows a positive and statistically significant coefficient on DSQ . A one standard deviation higher DSQ is associated with 24.8 bps ($=1.266 \times 0.196$) more shareholder support. Even though voter support for directors is high with an average *for* vote percentage of 94.5%, this effect is still economically significant compared to the interquartile range

and standard deviation of *for* votes of 471 and 823 bps, respectively.¹¹ Moreover, based on the estimates from [Iliev et al. \(2015\)](#), this 24.8 bps higher shareholder support decreases director turnover by 5.3%. Column 2 continues to show a positive and statistically significant coefficient on *DSQ* when we measure *DSQ* using only information up to $t-1$. Column 3 further shows a monotonic relation between shareholder support and *DSQ* quartiles, and column 4 shows that this result holds after including firm fixed effects. Columns 5 and 6 further show that high *DSQ* directors are less likely to receive low shareholder approval. Compared to directors in the lowest quartile of *DSQ*, those in the top quartile are 150 bps less likely to receive less than 90% shareholder support, representing a 9.9% decline relative to the average rate of directors receiving low support of 15.1%. Similarly, directors in the top quartile of *DSQ* are 110 bps less likely to receive below 85% support.

4 Board-Level *DSQ* and Firm Outcomes

Our evidence indicates that *DSQ* captures unique value-relevant director attributes that are transferable across firms and recognized by shareholders. Next, we investigate channels through which high *DSQ* directors may contribute to firm value. We focus on four corporate policies where boards can play an important role in mitigating conflicts of interest between managers and shareholders: cash management, CEO equity-based compensation, innovation, and the quality of M&A deals. To interpret economic magnitudes, we use the standard deviation of the board-level variable *AvgDSQ* of 0.10.

4.1 *DSQ* and value of cash

Managers tend to build up cash reserves to take advantage of M&A, investment, and other growth opportunities when they arise. However, agency problems involving cash holdings are large, as liquid assets provide managers with the most discretion with how they can be used. Consequently, managers have incentives to use cash reserves, or

¹¹Studies find that while average support for directors is high, variation in director election outcomes still reflects the market’s assessment of director performance and has implications for career prospects ([Iliev, Lins, Miller, and Roth, 2015](#); [Aggarwal, Dahiya, and Prabhala, 2019](#)).

discretionary spending, to grow their firm beyond its optimal size or invest in projects that provide personal benefits at the expense of shareholders (e.g., [Jensen, 1986](#)). To evaluate whether directors are able to discipline managers and ensure that cash reserves are used to benefit shareholders, we focus on how board-level DSQ affects the firm’s marginal value of cash, which represents investors’ assessment of how much an additional dollar of cash holdings will increase shareholder value. Higher estimates indicate that investors believe that managers will use the cash to pursue investments that benefit shareholders, and prior work has shown that well-governed firms have higher marginal values of cash (e.g., [Dittmar and Mahrt-Smith, 2007](#); [Masulis, Wang, and Xie, 2009](#)).

[Table 7](#) examines the relation between board-level DSQ and the marginal value of cash following [Faulkender and Wang \(2006\)](#). The Appendix provides the formula for estimating the marginal value of cash. In this analysis, we are interested in the variable $\Delta C \times AvgDSQ$, where ΔC is the change in cash holdings from fiscal year $t-1$ to t scaled by lagged market value equity. Thus, the coefficient on $\Delta C \times AvgDSQ$ represents the incremental increase in the marginal value of cash if $AvgDSQ$ changes by one unit. All regressions include all the level and interaction terms, but we do not tabulate them for brevity. Following convention, we exclude financial and utilities firms for this analysis due to the unique nature of these industries with respect to cash holdings policies.

Overall, the results show that boards with higher average DSQ are better stewards of shareholder capital. Column 1 shows a positive and statistically significant coefficient on $\Delta C \times AvgDSQ$. A one standard deviation higher $AvgDSQ$ is associated with \$0.127 ($=1.267 \times 0.10$) higher marginal value of cash. Column 2 indicates that the results continue to hold using only historical information to estimate DSQ. Column 3 further shows a monotonic increase in the marginal value of cash across $AvgDSQ$ quartiles, and column 4 shows that controlling for firm fixed effects has little impact on this finding.

4.2 DSQ and equity-based compensation

An effective board of directors designs a compensation plan that incentivizes the CEO to maximize shareholder value ([Bebchuk and Fried, 2003](#)). The compensation scheme

that reduces the agency problem and aligns a CEO's incentives with shareholder interests involves providing the CEO with more equity-based compensation that ties the CEO's compensation more closely to firm performance. Consistent with this view, firms with stronger monitoring oversight and better governance structures award more pay-performance sensitive compensation to CEOs (Hartzell and Starks, 2003; Coles et al., 2014). Thus, if higher board-level DSQ reflects better governance, then high DSQ boards should award CEOs more performance-sensitive compensation.

In Table 8, we examine the relation between board-level DSQ and CEO equity-based compensation. For this analysis, we obtain data on CEO compensation from Execucomp. In columns 1-4, we focus on the *Delta* of CEO wealth, which measures how much a CEO's wealth changes in dollars for a 1% change in stock price. We calculate *Delta* based on the CEO's entire portfolio of stocks and options following Core and Guay (2002) and Coles, Daniel, and Naveen (2006). In columns 5-8, we measure equity-based compensation as the fraction of a CEO's total compensation in the form of option and stock awards (*%Equity*). In these analyses, we further control for CEO age and tenure.

Overall, the results show that boards with higher average DSQ tie CEO compensation more closely to firm performance. Columns 1 and 5 show positive and statistically significant coefficients on *AvgDSQ*. A one standard deviation higher *AvgDSQ* is associated with 22.1% [$=\exp(1.997 \times 0.10) - 1$] higher delta and 2.81% ($=0.149 \times 0.10 / 0.530$) more equity-based compensation relative to the mean. Columns 2 and 6 show that these results hold in our out-of-sample analyses. Columns 3 and 7 show a monotonic relation between both measures of equity-based compensation and *AvgDSQ* across the quartiles. Columns 4 and 8 show that the results remain after controlling for firm fixed effects. In untabulated analyses, we separately calculate *AvgDSQ* for directors on the compensation committee and all other directors. While there is a statistically significant and monotonic effect of average DSQ on delta for both groups of directors, the fraction of pay from equity awards, which is determined by the current compensation committee, is only higher at firms with higher average compensation committee DSQ.

4.3 DSQ and innovation

Innovation is critical to a firm’s ability to compete and succeed in the long run. Directors can have a substantial impact on innovation through their monitoring function or contributing to a culture that is conducive to open dialogue, creativity, and long-term vision. Innovation, such as that resulting in patentable products or processes, often results from substantial investments in R&D. Due to the option-like payoff structure of R&D, namely highly uncertain outcomes characterized by enormous returns or complete failure, it is considered a risky form of investment. As such, risk-averse managers have incentives to underinvest in innovation than what risk-neutral shareholders would find optimal. By designing appropriate incentive schemes and offering a reasonable tolerance for failure, boards can foster an environment that promotes innovation (e.g., [Manso, 2011](#); [Balsmeier et al., 2017](#)). Directors can also shape a firm’s innovation strategy by setting the firm’s long-run strategic direction; helping identify, evaluate, and exploit R&D opportunities; providing better oversight of management’s R&D spending; facilitating knowledge diffusion; and being a conduit to outside markets (e.g., [Faleye et al., 2018](#); [An et al., 2021](#); [Chang and Wu, 2021](#); [Griffin et al., 2021](#)). To the extent that high DSQ directors are better advisors, monitors, or have value-relevant attributes that are conducive to innovation, firms with higher board-level DSQ should produce more and higher quality innovations.

[Table 9](#) examines the relation between board-level DSQ and innovation. Our analyses focus on innovation output, measured by patenting activity. In addition to patent and citation count measures of innovation used in prior studies, we use a measure of the private, economic value of patenting activity developed in [Kogan, Papanikolaou, Seru, and Stoffman \(2017\)](#). This measure combines patent and stock market data to estimate the value of patents. In general, this measure captures the value of patents using CARs around the announcement that a patent has been granted. We calculate the total value of patenting activity for a firm by summing up the market value of each patent granted dur-

ing a firm’s fiscal year and thus capture the quantity and quality of innovation output.¹² Following prior work (e.g., [Lerner, Sorensen, and Strömberg, 2011](#); [Bernstein, 2015](#)), we focus on potentially innovative firms that have at least one patent granted during our sample period. We also end our sample in 2017 to address concerns of a truncation bias in later years due to patents taking an average of about two years to be granted.

Overall, the results show that innovation output is highly correlated with board-level DSQ. In columns 1-4, the dependent variable is one plus the natural logarithm of the value of patents filed in a year. Column 1 shows a positive and statistically significant coefficient on *AvgDSQ*. A one standard deviation higher *AvgDSQ* is associated with 20.1% [$=\exp(1.829 \times 0.10) - 1$] more value in innovation. This result holds in our out-of-sample analysis in column 2. Column 3 shows a monotonic relation between the value of innovation and *AvgDSQ* across the quartiles, and column 4 shows that the results are robust to including firm fixed effects. Column 5 shows similar results when the dependent variable is the natural logarithm of one plus the number of patents. As an alternative measure of patent quality, column 6 focuses on the intensive margin of innovation and replaces the dependent variable with the number of citations per patent in a year, and the results show that boards with higher *AvgDSQ* produce more highly cited patents.

4.4 DSQ and M&A quality

Reputation, prestige, and compensation tied to firm size give managers ample incentives to use M&A as a tool to rapidly increase the size and scope of their firm, even if the deals destroy shareholder value in the process. Through their monitoring role, directors can act as gatekeepers that prevent managers from engaging in value-destroying M&A (e.g., [Masulis and Zhang, 2019](#)). High-quality directors can also improve M&A outcomes by helping managers identify potential targets that will contribute to the firm’s strategic mission, assess the risks and opportunities of specific deals, and provide guidance on post-M&A integration (e.g., [Cai and Sevilir, 2012](#); [Field and Mkrtchyan, 2017](#)). Like

¹²While announcement returns are calculated around the date when a patent is granted, the value of these patents is assigned to the patent’s filing date.

prior work, we use acquirer CARs around the announcement of an M&A deal to measure investors' assessment of the deal's quality.

Table 10 presents results examining the relation between board-level DSQ and acquirer CARs around M&A announcements. We obtain deal announcements of U.S. targets from the SDC database and apply standard filters to clean the data following Masulis, Wang, and Xie (2007). To be included in the sample, deals must satisfy the following criteria: (i) the acquirer owns less than 50% of the target before the deal and 100% of the target after the deal, (ii) the deal value is at least \$1 million, (iii) the deal amount scaled by the acquirer's market value of equity on the 11th trading day before the deal announcement is at least 1%, (iv) the deal form is "Merger", "Acq. of Assets", or "Acq. Maj. Int.", and (v) the deal is eventually completed. We calculate five-day CARs using the market model based on CRSP value-weighted returns and parameters estimated over the [-210,-11] trading days relative to the deal announcement. In these analyses, we also control for several deal-level controls.

Overall, the results indicate that boards with higher average DSQ make better M&A deals. Column 1 shows a positive and statistically significant coefficient on *AvgDSQ*. A one standard deviation higher *AvgDSQ* is associated with 22.1 bps ($=2.209 \times 0.10$) higher M&A CARs, which is economically significant when compared to the average and standard deviation of M&A CARs of 101 bps and 742 bps, respectively. In column 2, while the coefficient on *AvgDSQ* is still positive in our out-of-sample analysis, the estimate is not statistically significant. One possible reason for this weaker result is the smaller sample size combined with noisier estimates of *DSQ* when using only historical information. Column 3 further shows a monotonic relation between M&A CARs and *AvgDSQ* across quartiles, and adding firm fixed effects as controls in column 4 strengthens these findings. Columns 5 and 6 further restrict the deals to those where the deal value is at least 5% of the bidder's market value of equity. We impose this restriction to focus our analysis on more prominent deals in which board members are more likely to be involved. The results continue to show that boards with higher *AvgDSQ* have better M&A outcomes.

In sum, Tables 7-10 suggest that firms with higher board-level *DSQ* increase firm value by positively influencing major corporate decisions, including managing cash better, aligning CEO incentives more closely with performance, generating more and higher quality innovation, and making higher quality M&A deals.

4.5 Addressing assortative matching

Like all studies examining how directors affect firm outcomes and value, assortative matching where specific types of directors based on quality match to specific types of firms can be a potential concern. We take a number of steps to control for and assess the extent of assortative matching.

First, we try to limit issues arising from assortative matching by including a multitude of firm-, board, and director-level control variables in our regressions. As long as the mechanism driving director-firm matching is captured by these variables, the issue is mitigated. To this end, controlling for firm fixed effects when we estimate *DSQ* is powerful, as it holds constant average firm quality and eliminates the channel of assortative matching to firms based on average quality. Similarly, when we examine outcomes, we always include *FSQ* and *ResidTQ* in the regressions to account for average firm quality and time-varying residual firm quality that our control variables might not capture. We also show our outcome results hold in specifications with firm fixed effects.

Second, we follow Card et al. (2013) and compare how much the explanatory power of our Tobin's Q regression increases when we use combined director-firm fixed effects that capture matching instead of separate director and firm fixed effects. If match effects are important, then the fully saturated Tobin's Q regression should significantly outperform the model with the fixed effects estimated separately. We find the R^2 of the saturated model increases by a negligible 1.3%. We also show that the correlation between *DSQ* and *FSQ*, which measures whether specific types of directors tend to match to specific type of firms based on quality, is almost zero (-0.026).

Third, we follow Ewens and Rhodes-Kropf (2015) and separate directors that move to higher Tobin's Q firms where appointments are more likely voluntary and those that

move to lower Tobin’s Q firms where appointments are more likely a less desired position and a more exogenous move. Tables A7 and A8 show that our results continue to hold for both samples.¹³

Finally, we reestimate our results after excluding firms in the top and bottom quartiles of Tobin’s Q . If the concern is that our results are driven by high DSQ directors matching to the best performing firms or low DSQ directors matching to the worst performing firms, then limiting our analyses to firms in the middle quartiles of firm value should mitigate this concern. Table A9 shows that our results continue to hold on this subsample. Overall, all of the findings in this section suggest that biases arising from directors matching to specific types of firms is limited in our setting and cannot fully explain our results.

4.6 Addressing causality

While we have shown that DSQ is related to firm value by examining CARs around more exogenous director death announcements, we further examine whether DSQ has a causal effect on firm outcomes by examining how outcomes change around these arguably exogenous deaths. We also exploit the COVID-19 pandemic as an exogenous shock to study whether boards with higher average DSQ performed better during this period.

4.6.1 DiD analysis around director deaths

In Table 11, we first estimate the results in Tables 7-10 using the ± 3 years around director deaths, similar to Fracassi and Tate (2012).¹⁴ We create two treatment variables. DSQ is the director-specific effect of the director who died, and ΔDSQ captures how much the deceased director contributes to board-level DSQ (defined as the difference between $AvgDSQ$ with and without the director that died). We interact these variables with an indicator variable ($After$) that equals one if the firm’s fiscal period is after the date when the director died, and zero otherwise. For DSQ , we expect a negative coefficient

¹³The results are similar if we define directors that move up and down using market value of equity.

¹⁴Prior work uses instrumental variables based on geographic variation in the supply of directors to address this and other endogeneity concerns (e.g., Knyazeva, Knyazeva, and Masulis, 2013; Bernile et al., 2018), but these instruments produce a weak first-stage correlation in our setting because they tend to vary little over time and we orthogonalize DSQ to time-invariant firm-specific factors.

on the interaction term, as outcomes should worsen when high DSQ directors die and vice versa.¹⁵ For ΔDSQ , we expect a positive coefficient, as outcomes should improve when average board quality increases after low DSQ directors die and vice versa. In these tests, Panel A presents results without controls, and Panel B presents results with the same controls as in their respective tables. In all regressions, we include all the level and interaction terms but do not tabulate them for brevity. Given the stacked event approach in which events can overlap, we include separate cohort firm and year fixed effects for each director death year.

Overall, the results are consistent with our previous findings and suggest a causal effect of DSQ. After a high DSQ director dies or after the death of a director that causes board-level DSQ to decrease more, the marginal value of cash decreases, CEO compensation is tied less to performance, innovation declines, and M&A announcement CARs are lower.

4.6.2 DSQ during the COVID-19 pandemic

Our second test addresses endogeneity concerns by holding a board's composition and average DSQ fixed and examining how firms performed during the COVID-19 pandemic conditional on board-level DSQ prior to the shock. The idea is that in the year before the shock, firms have optimized their board composition for normal operating conditions. However, when COVID-19 became a pandemic, it shocked firms out of this equilibrium, allowing us to examine how pre-pandemic board-level DSQ affected the impact of COVID-19 on firm performance. To the extent that high DSQ directors can help manage turbulent times, firms with higher board-level DSQ should perform better during the pandemic.

Table 12 examines whether firms with higher *AvgDSQ* perform better during the pandemic by estimating regressions similar to Ding, Levine, Lin, and Xie (2021). We regress a firm's weekly stock return on the weekly growth rate in positive U.S. COVID-19 cases (*COVID*) interacted with *AvgDSQ* and other control variables, firm fixed effects, and sometimes week fixed effects. All regressions include all the level and interaction

¹⁵Recall that we find that when a high (low) DSQ director dies, firms tend to replace these directors with a lower (higher) DSQ director.

terms, but we do not tabulate them for brevity. We estimate director- and firm-specific quality using the AKM method using only data through 2019 (i.e., only pre-pandemic data). We cluster standard errors by firm, but the results are robust to clustering by firm and week. The sample period for this analysis starts the first week of March 2020 when the documented spread of COVID-19 cases begins in the U.S. and ends the first week of March 2021, which also corresponds to when The COVID Tracking Project stopped collecting data. We fix a firm’s level of *AvgDSQ* to its pre-pandemic value.

Column 1 estimates a baseline regression of weekly returns on only the growth rate in COVID-19 cases and firm fixed effects. Consistent with [Ding et al. \(2021\)](#), the results show stock returns are 1.84% lower during weeks when cases increase by one standard deviation ($=3.109 \times 0.593$). Further, the statistically significant coefficient of 1.415 on $COVID \times AvgDSQ$ in column 2 implies that the negative effect of an increase in cases on stock returns is offset by 5.7% [$=(1.415 \times 0.148)/3.700$] for a one standard deviation higher *AvgDSQ*. Column 3 shows a monotonic increase in the extent that DSQ offsets the negative effect of an increase in cases on returns across *AvgDSQ* quartiles. Compared to boards in the first quartile, the negative effect of increases in cases is offset by 4.2%, 7.2%, and 12.9% for firms with boards in the second, third, and fourth quartiles, respectively. Controlling for week fixed effects in column 4 has little impact on this finding. Column 5 shows that the results are also robust to allowing the effect of increases in cases on returns to vary with firm- and board-level characteristics. Last, column 6 shows that the results also hold after including industry $\times$ week fixed effects, which account for COVID-19 having differential effects on returns across industries. Overall, these results show that DSQ matters in an out-of-sample test during a large negative unexpected shock and provide additional support that high DSQ directors increase value.

5 Conclusion

Our study focuses on isolating a director’s repeatable and transferable skill, called director-specific quality (DSQ), and how it impacts firms. By separating DSQ from other

factors, we find that it plays a significant role in incrementally creating value, explaining around 10% of the variation in Tobin's Q. Our findings also reveal that investors react more positively (negatively) when high DSQ directors are appointed (die) and that high DSQ directors receive more shareholder support. By showing that directors possess unique value-relevant attributes that they bring to all the boards they sit on, our findings complement the growing literature on the importance of team dynamics among board members by showing that the team effect does not subsume the individual effect.

Further, through robustness checks and analyses exploiting director deaths, we confirm the strong relationship between DSQ and director effectiveness, performance, and various firm-level outcomes. Firms with boards featuring higher average DSQ demonstrate more efficient cash management, align CEO compensation more closely with stock returns, drive more and higher quality innovation, and engage in superior M&A. These results emphasize the value of directors possessing transferable skills that enhance decision making and create greater value for shareholders.

Our study holds implications for both firms and policymakers. By showcasing the distinct impact of DSQ on firm value, our research highlights the opportunity for firms to proactively recruit directors with higher DSQ, especially in cases where specific skill sets are in short supply. This valuable insight expands the framework for constructing effective boards, particularly when faced with constraints on director skill sets or traits. Moreover, our findings open up a promising avenue for further research in this area, presenting opportunities for deeper exploration and understanding of both the superstar and team dynamics of board effectiveness and composition. Our measure of DSQ can also be used by other researchers as a way to control for or further study individual or average board-level director quality for a large sample of firms.

References

- Abowd, John M, Francis Kramarz, Paul Lengermann, and Sébastien Pérez-Duarte, 2004, Are good workers employed by good firms? A test of a simple assortative matching model for France and the United States, Cornell University, Working paper.
- Abowd, John M, Francis Kramarz, and David N Margolis, 1999, High wage workers and high wage firms, *Econometrica* 67, 251–333.
- Adams, Renée B, 2017, Boards, and the directors who sit on them, in *Handbook of the Economics of Corporate Governance*, volume 1, 291–382 (Elsevier).
- Adams, Renée B, Ali C Akyol, and Patrick Verwijmeren, 2018, Director skill sets, *Journal of Financial Economics* 130, 641–662.
- Adams, Renée B, and Daniel Ferreira, 2009, Women in the boardroom and their impact on governance and performance, *Journal of Financial Economics* 94, 291–309.
- Aggarwal, Reena, Sandeep Dahiya, and Nagpurnanand R Prabhala, 2019, The power of shareholder votes: Evidence from uncontested director elections, *Journal of Financial Economics* 133, 134–153.
- Ahern, Kenneth R, and Amy K Dittmar, 2012, The changing of the boards: The impact on firm valuation of mandated female board representation, *Quarterly Journal of Economics* 127, 137–197.
- American Bar Association, 2009, Report of the task force of the ABA section of business law corporate governance committee on delineation of governance roles and responsibilities, *The Business Lawyer* 65, 107–151.
- An, Heng, Carl R Chen, Qun Wu, and Ting Zhang, 2021, Corporate innovation: do diverse boards help?, *Journal of Financial and Quantitative Analysis* 56, 155–182.
- Andrews, Martyn J, Len Gill, Thorsten Schank, and Richard Upward, 2008, High wage workers and low wage firms: Negative assortative matching or limited mobility bias?, *Journal of the Royal Statistical Society* 171, 673–697.
- Balsmeier, Benjamin, Lee Fleming, and Gustavo Manso, 2017, Independent boards and innovation, *Journal of Financial Economics* 123, 536–557.
- Bebchuk, Lucian Arye, and Jesse M Fried, 2003, Executive compensation as an agency problem, *Journal of Economic Perspectives* 17, 71–92.
- Bedard, Jean C, Rani Hoitash, and Udi Hoitash, 2014, Chief financial officers as inside directors, *Contemporary Accounting Research* 31, 787–817.
- Bernile, Gennaro, Vineet Bhagwat, and Scott Yonker, 2018, Board diversity, firm risk, and corporate policies, *Journal of Financial Economics* 127, 588–612.
- Bernstein, Shai, 2015, Does going public affect innovation?, *Journal of Finance* 70, 1365–1403.
- Bertrand, Marianne, and Antoinette Schoar, 2003, Managing with style: The effect of managers on firm policies, *Quarterly Journal of Economics* 118, 1169–1208.

- Bhaskarabhatla, Ajay, Luis Cabral, Deepak Hegde, and Thomas Peeters, 2021, Are inventors or firms the engines of innovation?, *Management Science* 67, 3899–3920.
- Bird, Robert C, Paul Borochin, John Knopf, and Luchun Ma, 2019, Do boards have style? Evidence from director style divergence and board turnover, University of Connecticut, Working paper.
- Bonhomme, Stéphane, Kerstin Holzheu, Thibaut Lamadon, Elena Manresa, Magne Mogstad, and Bradley Setzler, 2023, How much should we trust estimates of firm effects and worker sorting?, *Journal of Labor Economics* 41, 291–322.
- Boone, Audra L, Laura Casares Field, Jonathan M Karpoff, and Charu G Raheja, 2007, The determinants of corporate board size and composition: An empirical analysis, *Journal of Financial Economics* 85, 66–101.
- Burt, Aaron, Christopher Hrdlicka, and Jarrad Harford, 2020, How much do directors influence firm value?, *Review of Financial Studies* 33, 1818–1847.
- Cai, Ye, and Merih Sevilir, 2012, Board connections and M&A transactions, *Journal of Financial Economics* 103, 327–349.
- Card, David, Jörg Heining, and Patrick Kline, 2013, Workplace heterogeneity and the rise of West German wage inequality, *Quarterly Journal of Economics* 128, 967–1015.
- Carter, David A, Betty J Simkins, and W Gary Simpson, 2003, Corporate governance, board diversity, and firm value, *Financial Review* 38, 33–53.
- Cavaco, Sandra, Patricia Crifo, Antoine Rebérioux, and Gwenael Roudaut, 2017, Independent directors: Less informed but better selected than affiliated board members?, *Journal of Corporate Finance* 43, 106–121.
- Chang, Ching-Hung, and Qingqing Wu, 2021, Board networks and corporate innovation, *Management Science* 67, 3618–3654.
- Coles, Jeffrey L, Naveen D Daniel, and Lalitha Naveen, 2006, Managerial incentives and risk-taking, *Journal of Financial Economics* 79, 431–468.
- Coles, Jeffrey L, Naveen D Daniel, and Lalitha Naveen, 2014, Co-opted boards, *Review of Financial Studies* 27, 1751–1796.
- Coles, Jeffrey L, and Zhichuan Li, 2020, Managerial attributes, incentives, and performance, *Review of Corporate Finance Studies* 9, 256–301.
- Core, John, and Wayne Guay, 2002, Estimating the value of employee stock option portfolios and their sensitivities to price and volatility, *Journal of Accounting Research* 40, 613–630.
- Cornelissen, Thomas, 2008, The Stata command `felsdvvreg` to fit a linear model with two high-dimensional fixed effects, *The Stata Journal* 8, 170–189.
- Dass, Nishant, Omesh Kini, Vikram Nanda, Bunyamin Onal, and Jun Wang, 2014, Board expertise: Do directors from related industries help bridge the information gap?, *Review of Financial Studies* 27, 1533–1592.

- DeFond, Mark L, Rebecca N Hann, and Xuesong Hu, 2005, Does the market value financial expertise on audit committees of boards of directors?, *Journal of Accounting Research* 43, 153–193.
- Ding, Wenzhi, Ross Levine, Chen Lin, and Wensi Xie, 2021, Corporate immunity to the COVID-19 pandemic, *Journal of Financial Economics* 141, 802–830.
- Dittmar, Amy, and Jan Mahrt-Smith, 2007, Corporate governance and the value of cash holdings, *Journal of Financial Economics* 83, 599–634.
- Duchin, Ran, John G Matsusaka, and Oguzhan Ozbas, 2010, When are outside directors effective?, *Journal of Financial Economics* 96, 195–214.
- Engbom, Niklas, and Christian Moser, 2022, Earnings inequality and the minimum wage: Evidence from brazil, *American Economic Review* 112, 3803–47.
- Erel, Isil, Léa H Stern, Chenhao Tan, and Michael S Weisbach, 2021, Selecting directors using machine learning, *Review of Financial Studies* 34, 3226–3264.
- Ewens, Michael, and Matthew Rhodes-Kropf, 2015, Is a VC partnership greater than the sum of its partners?, *Journal of Finance* 70, 1081–1113.
- Fahlenbrach, Rüdiger, Angie Low, and René M Stulz, 2010, Why do firms appoint CEOs as outside directors?, *Journal of Financial Economics* 97, 12–32.
- Falato, Antonio, Dalida Kadyrzhanova, and Ugur Lel, 2014, Distracted directors: Does board busyness hurt shareholder value?, *Journal of Financial Economics* 113, 404–426.
- Faleye, Olubunmi, Rani Hoitash, and Udi Hoitash, 2018, Industry expertise on corporate boards, *Review of Quantitative Finance and Accounting* 50, 441–479.
- Farrell, Kathleen A, Geoffrey C Friesen, and Philip L Hersch, 2008, How do firms adjust director compensation?, *Journal of Corporate Finance* 14, 153–162.
- Faulkender, Michael, and Rong Wang, 2006, Corporate financial policy and the value of cash, *Journal of Finance* 61, 1957–1990.
- Fich, Eliezer M, 2005, Are some outside directors better than others? evidence from director appointments by Fortune 1000 firms, *Journal of Business* 78, 1943–1972.
- Fich, Eliezer M, and Anil Shivdasani, 2006, Are busy boards effective monitors?, *Journal of Finance* 61, 689–724.
- Field, Laura, Michelle Lowry, and Anahit Mkrtchyan, 2013, Are busy boards detrimental?, *Journal of Financial Economics* 109, 63–82.
- Field, Laura Casares, and Anahit Mkrtchyan, 2017, The effect of director experience on acquisition performance, *Journal of Financial Economics* 123, 488–511.
- Fracassi, Cesare, and Geoffrey Tate, 2012, External networking and internal firm governance, *Journal of Finance* 67, 153–194.
- Giannetti, Mariassunta, and Mengxin Zhao, 2019, Board ancestral diversity and firm-performance volatility, *Journal of Financial and Quantitative Analysis* 54, 1117–1155.
- Goldman, Eitan, Jörg Rocholl, and Jongil So, 2009, Do politically connected boards affect firm value?, *Review of Financial Studies* 22, 2331–2360.

- Graham, John R, Si Li, and Jiaping Qiu, 2012, Managerial attributes and executive compensation, *Review of Financial Studies* 25, 144–186.
- Griffin, Dale, Kai Li, and Ting Xu, 2021, Board gender diversity and corporate innovation: International evidence, *Journal of Financial and Quantitative Analysis* 56, 123–154.
- Guernsey, Scott, Feng Guo, Tingting Liu, and Matthew Serfling, 2023, Thirty years of change: The evolution of classified boards, University of Tennessee, Working paper.
- Guernsey, Scott, Simone M Sepe, and Matthew Serfling, 2022, Blood in the water: The value of antitakeover provisions during market shocks, *Journal of Financial Economics* 143, 1070–1096.
- Güner, A Burak, Ulrike Malmendier, and Geoffrey Tate, 2008, Financial expertise of directors, *Journal of Financial Economics* 88, 323–354.
- Hartzell, Jay C, and Laura T Starks, 2003, Institutional investors and executive compensation, *Journal of Finance* 58, 2351–2374.
- Huang, Sterling, and Gilles Hilary, 2018, Zombie board: Board tenure and firm performance, *Journal of Accounting Research* 56, 1285–1329.
- Iliev, Peter, Karl V Lins, Darius P Miller, and Lukas Roth, 2015, Shareholder voting and corporate governance around the world, *Review of Financial Studies* 28, 2167–2202.
- Jensen, Michael C, 1986, Agency costs of free cash flow, corporate finance, and takeovers, *American Economic Review* 76, 323–329.
- Kim, Daehyun, and Laura T Starks, 2016, Gender diversity on corporate boards: Do women contribute unique skills?, *American Economic Review* 106, 267–271.
- Knyazeva, Anzhela, Diana Knyazeva, and Ronald W Masulis, 2013, The supply of corporate directors and board independence, *Review of Financial Studies* 26, 1561–1605.
- Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2017, Technological innovation, resource allocation, and growth, *Quarterly Journal of Economics* 132, 665–712.
- Krishnan, Jayanthi, Yuan Wen, and Wanli Zhao, 2011, Legal expertise on corporate audit committees and financial reporting quality, *The Accounting Review* 86, 2099–2130.
- Kuzmina, Olga, and Valentina Melentyeva, 2021, Gender diversity in corporate boards: Evidence from quota-implied discontinuities, Working paper, New Economic School and CEPR.
- Lerner, Josh, Morten Sorensen, and Per Strömberg, 2011, Private equity and long-run investment: The case of innovation, *Journal of Finance* 66, 445–477.
- Li, Feng, and Suraj Srinivasan, 2011, Corporate governance when founders are directors, *Journal of Financial Economics* 102, 454–469.
- Liu, Tong, Yifei Mao, and Xuan Tian, 2023, The role of human capital: Evidence from corporate innovation, *Journal of Empirical Finance* 74, 101435.
- Loughran, Tim, and Jay Ritter, 2004, Why has IPO underpricing changed over time?, *Financial Management* 33, 5–37.

- Lu, Di, Guanchun Liu, and Yuanyuan Liu, 2022, Who are better monitors? comparing styles of supervisory and independent directors, *International Review of Financial Analysis* 83, 102305.
- Malmendier, Ulrike, and Geoffrey Tate, 2009, Superstar CEOs, *Quarterly Journal of Economics* 124, 1593–1638.
- Manso, Gustavo, 2011, Motivating innovation, *Journal of Finance* 66, 1823–1860.
- Masulis, Ronald W, and Shawn Mobbs, 2014, Independent director incentives: Where do talented directors spend their limited time and energy?, *Journal of Financial Economics* 111, 406–429.
- Masulis, Ronald W, Cong Wang, and Fei Xie, 2007, Corporate governance and acquirer returns, *Journal of Finance* 62, 1851–1889.
- Masulis, Ronald W, Cong Wang, and Fei Xie, 2009, Agency problems at dual-class companies, *Journal of Finance* 64, 1697–1727.
- Masulis, Ronald W, Cong Wang, and Fei Xie, 2012, Globalizing the boardroom—The effects of foreign directors on corporate governance and firm performance, *Journal of Accounting and Economics* 53, 527–554.
- Masulis, Ronald W, Cong Wang, Fei Xie, and Shuran Zhang, 2023, Directors: older and wiser, or too old to govern?, *Journal of Financial and Quantitative Analysis*, Forthcoming.
- Masulis, Ronald W, and Emma Jincheng Zhang, 2019, How valuable are independent directors? Evidence from external distractions, *Journal of Financial Economics* 132, 226–256.
- Nguyen, Bang Dang, and Kasper Meisner Nielsen, 2010, The value of independent directors: Evidence from sudden deaths, *Journal of Financial Economics* 98, 550–567.
- Richardson, Scott A, A Tuna, and Peter D Wysocki, 2003, Accounting for taste: Board member preferences and corporate policy choices, London Business School, Working paper.
- Schmid, Thomas, and Daniel Urban, 2023, Female directors and firm value: New evidence from directors’ deaths, *Management Science* 69, 2449–2473.
- Shivdasani, Anil, and David Yermack, 1999, CEO involvement in the selection of new board members: An empirical analysis, *Journal of Finance* 54, 1829–1853.
- White, Joshua T, Tracie Woidtke, Harold A Black, and Robert L Schweitzer, 2014, Appointments of academic directors, *Journal of Corporate Finance* 28, 135–151.

Appendix. Variable Definitions

This table provides the definitions for the main variables used in this study. Variables not included here are defined in the corresponding table captions. Compustat and CRSP variables are in *italics* when appropriate.

Variable	Definition
<u>Director-Level Variables</u>	
ΔDSQ	The difference between <i>AvgDSQ</i> with and without a director that died.
#Seats	Total number of boards of publicly listed companies that a director has served on at the annual report date.
%Vote	Total number of “for” votes divided by the total number of votes cast (“for” + “against” + “abstain”).
Academics	Indicator variable equal to one if the director has taught at a university or holds a Ph.D. degree, and zero otherwise.
Age65	Indicator variable equal to one if a director is at least 65, and zero otherwise.
AuditChair	Indicator variable equal to one if a director is the audit committee chair, and zero otherwise.
AuditCom	Indicator variable equal to one if a director serves on the audit committee, and zero otherwise.
Busy	Indicator variable equal to one if a director sits on three or more boards during a year, and zero otherwise.
Chair-Lead	Indicator variable equal to one if a director is a lead independent director or chairman of the board, and zero otherwise.
CompChair	Indicator variable equal to one if a director is the compensation committee chair, and zero otherwise.
CompCom	Indicator variable equal to one if a director serves on the compensation committee, and zero otherwise.
DSQ	Director-specific quality estimated using the AKM method.
DSQq2-DSQq4	Indicator variables that equal one if director-specific quality (<i>DSQ</i>) is in the second through fourth quartiles, respectively, and zero otherwise.
Entrepreneur	Indicator variable equal to one if a director has founded a company or organization, and zero otherwise.
Financial Exp	Indicator variable equal to one if a director has worked as an accountant, banker, CFO, treasurer, loan officer, CFP, or in finance, and zero otherwise.
Grad Degree	Indicator variable equal to one if a director has a master’s degree other than an MBA, and zero otherwise.
IndExp	Indicator variable equal to one if a director has worked at another firm in the same two-digit SIC industry, and zero otherwise.
Indep	Indicator variable equal to one if a director is independent, and zero otherwise.
Ivy Univ	Indicator variable equal to one if a director graduated from an Ivy League school, and zero otherwise.
Legal Exp	Indicator variable equal to one if a director has a Juris Doctor degree or worked as a lawyer, judge, consultant, or attorney, and zero otherwise.
Management Exp	Indicator variable equal to one if a director has had the title of president, CEO, COO, manager, or supervisor, and zero otherwise.
MBA Degree	Indicator variable equal to one if a director has a master’s in business administration degree, and zero otherwise.
Military Exp	Indicator variable equal to one if a director has military experience, and zero otherwise.

NomChair	Indicator variable equal to one if a director is the nominating committee chair, and zero otherwise.
NomCom	Indicator variable equal to one if a director serves on the nominating committee, and zero otherwise.
Political Exp	Indicator variable equal to one if a director has experience as a senator or member of congress or has worked at the White House or in the House of Representatives, and zero otherwise.
Prof Quals	Total number of professional educational qualifications of a director.
ResidTQ	Natural logarithm of Tobin's Q minus director- and firm-specific quality $[\text{Ln}(TQ) - DSQ - FSQ]$. When this variable is at the board-level, we average <i>ResidTQ</i> across all directors at a firm during a year.
Soft Skills	We determine whether a director has 11 different soft skills in two steps. First, we use OpenAI's GPT 3.5 Turbo to generate detailed biographies for each director. For each director-firm pair, we construct prompts in the format of, <i>'Provide all the information you have about + director + at + firm. Please give all relevant information regarding his or her skills, experience, and abilities'</i> . Second, we employ a Natural Language Processing (NLP) technique known as zero-shot classification, which allows us to assign a score to each soft skill by measuring how closely the content of the biographies aligns with the description of that skill. We score how each biography relates to the following descriptions: adaptable, critical thinker, adaptable, problem solver, innovative, communication skill, customer oriented, team builder, honest, emotionally intelligent, and empathetic. We implement multi-class classification, which allows each skill to be scored independently.
Tenure	The number of years a director has served on a board.

Firm- and Board-Level Variables

#Cites	Number of citations to patents filed in a year that are eventually granted.
#Pats	Number of patents filed in a year that are eventually granted.
\$Pats	Market value of eventually granted patents filed in a year (Kogan et al., 2017).
%Equity	Fraction of a CEO's total compensation (<i>tdc1</i>) coming from stock and option awards (<i>rstkgmnt</i> , <i>stock_awards</i> , <i>option_awards_blk_value</i> , <i>option_awards</i>).
%Female	Percentage of female directors on a board.
%Indep	Percentage of independent directors on a board.
AvgDSQ	Average of director-specific quality (<i>DSQ</i>) across all directors at a firm during a year.
AvgDSQq2- AvgDSQq4	Indicator variables equal to one if the average director-specific quality is in the second through fourth quartiles, respectively, and zero otherwise.
Beta	Firm's sensitivity to market risk calculated using the value-weighted market model over the past three years and requiring at least 24 months of data.
BHAR	Firm's buy-and-hold return minus the buy-and-hold return on the CRSP value-weighted index over its fiscal year.
BrdSize	Total number of directors on a board.
CEO-Chair	Indicator variable equal to one if the CEO is also the chair of the board, and zero otherwise.
ClassBrd	Indicator variable equal to one if a firm has a classified board, and zero otherwise.
Delta	The dollar change in CEO stock and option wealth given a 1% change in stock price.
FSQ	Firm-specific effect estimated using the AKM method.
FSQq2-FSQq4	Indicator variables equal to one if the firm-specific effect is in the second through fourth quartiles, respectively, and zero otherwise.

IO	Percentage of a firm's shares outstanding owned by institutional investors.
LEV	Value of debt in current liabilities plus long-term debt scaled by book value of assets $[(dlc+dltt)/at]$.
Lead-Indep	Indicator variable equal to one if a firm has a lead independent director, and zero otherwise.
OROA	Operating income before depreciation scaled by book assets $(oibdp/at)$.
Pill	Indicator variable equal to one if a board has a poison pill, and zero otherwise.
R&D	R&D expenses scaled by sales $(xrd/sale)$. xrd is set to zero when missing.
Size	Book value of assets (at) (in millions and 2017 dollars).
TQ	Market value of assets scaled by book value of assets $[(at-ceq+prcc_f \times csho)/(at)]$.
VOL	Annualized standard deviation of monthly returns over a firm's fiscal year.

M&A Variables

AllCash	Indicator variable equal to one if a deal is all cash-financed, and zero otherwise.
BHAR	Bidder's buy-and-hold return over the [-210, -11] trading days before a deal announcement minus the buy-and-hold on the CRSP value-weighted index.
CAR[-2,+2]	Five-day bidder cumulative abnormal return centered around an M&A announcement date. Parameters are estimated using the market model and CRSP value-weighted index over the [-210,-11] trading days before a deal announcement.
DivAcq	Indicator variable equal to one if a bidder and target do not share a two-digit SIC code industry, and zero otherwise.
FCF	Operating income before depreciation $(oibdp)$ - interest expenses $(xint)$ - taxes (txt) - capital expenditures $(capx)$, all scaled by book value of total assets (at) .
Hitech	Indicator variable equal to one if a bidder and target are both from high tech industries defined by Loughran and Ritter (2004) , and zero otherwise.
MB	Market value of assets scaled by book value of assets $[(at-ceq+prcc_f \times csho)/(at)]$.
MLEV	Book value of debt scaled by market value of assets $[(dltt+dlc)/(at-ceq+prcc_f \times csho)]$.
MVE	Market value of equity on the 11th trading day before the deal announcement (in 2017 dollars).
Private	Indicator variable equal to one if a target is privately held, and zero otherwise.
RelSize	Deal value scaled by the bidder's market value of equity on the 11th trading day before the deal announcement.
StockDeal	Indicator variable equal to one if the deal is at least partially stocked-financed, and zero otherwise.
Subsidiary	Indicator variable equal to one if a target is a subsidiary, and zero otherwise.

Marginal Value of Cash Variables

The marginal value of cash is estimated following [Faulkender and Wang \(2006\)](#).

$$r_{jt} - R_{jt}^B = \gamma + \gamma_1 \frac{\Delta C_{jt}}{M_{jt-1}} + \gamma_2 \frac{\Delta E_{jt}}{M_{jt-1}} + \gamma_3 \frac{\Delta NA_{jt}}{M_{jt-1}} + \gamma_4 \frac{\Delta RD_{jt}}{M_{jt-1}} + \gamma_5 \frac{\Delta I_{jt}}{M_{jt-1}} + \gamma_6 \frac{\Delta D_{jt}}{M_{jt-1}} + \gamma_7 \frac{C_{jt-1}}{M_{jt-1}} + \gamma_8 L_{jt} \\ + \gamma_9 \frac{NF_{jt}}{M_{jt-1}} + \gamma_{10} \frac{\Delta C_{jt}}{M_{jt-1}} \times \frac{C_{jt-1}}{M_{jt-1}} + \gamma_{11} \frac{\Delta C_{jt}}{M_{jt-1}} \times L_{jt} + \gamma_{12} AvgDSQ_{jt} + \gamma_{13} \frac{\Delta C_{jt}}{M_{jt-1}} \times AvgDSQ_{jt} + \varepsilon_{jt},$$

ΔC	Change in cash holdings (che) scaled by lagged market value of equity $(prcc_f \times csho)$.
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ΔD	Change in common dividends (<i>div</i>) scaled by lagged market value of equity ($prcc_f \times csho$).
ΔE	Change in earnings before extraordinary items plus interest, deferred tax credits, and investment tax credits ($ib + xint + txdi + itci$) scaled by lagged market value of equity ($prcc_f \times csho$).
ΔI	Change in interest expense (<i>xint</i>) scaled by lagged market value of equity ($prcc_f \times csho$).
ΔNA	Change in total book assets minus cash holdings (<i>at-che</i>) scaled by lagged market value of equity ($prcc_f \times csho$).
ΔRD	Change in R&D expenditures (<i>xrd</i> , set to zero when missing) scaled by lagged market value of equity ($prcc_f \times csho$).
C_{t-1}	Lagged cash holdings (<i>che</i>) scaled by lagged market value of equity ($prcc_f \times csho$).
L	Book value of debt ($dlcc + dlt$) scaled by market value of assets ($dlc + dlts + prcc_f \times csho$).
NF	Total equity issuances minus repurchases plus debt issuances minus debt redemptions ($sstk - prstk + dlts - dltr$) scaled by lagged market value of equity ($prcc_f \times csho$).
$r - R^B$	A firm's stock return over its fiscal year minus the return on a size and book-to-market matched portfolio.

Table 1: Summary Statistics

This table reports summary statistics for the variables used in the decomposition of Tobin's Q regression in Table 2. This sample consists of 436,383 firm-director-year observations over the period 2000 to 2020 after excluding observations that are not part of the connected samples. All variables are defined in the Appendix.

	Mean	Std	P25	Median	P75
TQ	1.894	1.846	1.065	1.368	2.059
Ln(Size)	7.468	2.119	6.053	7.475	8.854
LEV	0.229	0.207	0.055	0.190	0.347
OROA	0.065	0.165	0.023	0.087	0.144
IO	0.589	0.296	0.357	0.646	0.839
R&D	0.210	1.086	0.000	0.000	0.032
VOL	0.116	0.075	0.064	0.095	0.143
Beta	1.194	0.843	0.613	1.072	1.608
Ln(#Seats)	1.660	0.865	1.099	1.609	2.303
Tenure	7.726	6.816	2.700	5.800	10.800
Busy	0.309	0.462	0.000	0.000	1.000
Indep	0.909	0.288	1.000	1.000	1.000
Age65	0.400	0.490	0.000	0.000	1.000
IndExp	0.225	0.418	0.000	0.000	0.000
Chair-Lead	0.059	0.237	0.000	0.000	0.000
AuditCom	0.535	0.499	0.000	1.000	1.000
CompCom	0.498	0.500	0.000	0.000	1.000
NomCom	0.488	0.500	0.000	0.000	1.000
AuditChair	0.137	0.344	0.000	0.000	0.000
CompChair	0.129	0.335	0.000	0.000	0.000
NomChair	0.120	0.325	0.000	0.000	0.000
%Indep	0.731	0.152	0.643	0.769	0.846
%Female	0.120	0.107	0.000	0.111	0.182
CEO-Chair	0.438	0.496	0.000	0.000	1.000
Lead-Indep	0.323	0.468	0.000	0.000	1.000
Ln(BrdSize)	2.274	0.317	2.079	2.303	2.485
Pill	0.201	0.401	0.000	0.000	0.000
ClassBrd	0.451	0.498	0.000	0.000	1.000

Table 2: Estimating Director-Specific Quality

This table reports results from estimating the following equation using the AKM method:

$$\text{Ln}(TQ_{ijt}) = \theta_i + \psi_j + \omega_t + X_{jt(t-1)}\beta + Z_{ijt}\gamma + \varepsilon_{ijt}.$$

$\text{Ln}(TQ)$ is the natural logarithm of a firm's market value of assets scaled by book value of assets. θ_i , ψ_j , and ω_t are director, firm, and year fixed effects, respectively. $X_{jt(t-1)}$ are time-varying firm and board characteristics, and Z_{ijt} are time-varying director characteristics. The estimated director fixed effects θ_i capture DSQ. All variables are defined in the Appendix. t -statistics are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Ln(TQ)	t -Statistic
<i>Time-varying director characteristics</i>		
Ln(#Seats)	0.006	1.00
Tenure	0.001***	3.06
Busy	-0.001	-0.51
Age65	-0.006**	-2.28
Indep	0.016***	4.02
Chair-Lead	-0.012***	-3.79
AuditCom	-0.003*	-1.68
CompCom	-0.002	-1.03
NomCom	-0.001	-0.47
AuditChair	-0.001	-0.61
CompChair	-0.003*	-1.68
NomChair	-0.004**	-2.12
IndExp	0.001	0.18
<i>Time-varying firm characteristics</i>		
Pill	-0.026***	-3.38
ClassBrd	0.002	0.34
Ln(Size)	-0.163***	-28.02
LEV	0.036*	1.80
OROA	0.663***	16.82
IO	0.060***	5.00
R&D	0.030***	6.13
VOL	0.063**	2.10
Beta	-0.002	-0.82
<i>Time-varying board characteristics</i>		
%Indep	-0.005	-0.24
%Female	0.021	0.69
CEO-Chair	0.021***	4.16
Lead-Indep	0.003	0.64
Ln(BrdSize)	0.053***	4.10
Director FE (θ_i)	✓	
Firm FE (ψ_j)	✓	
Year FE (ω_t)	✓	
Obs	459,479	
R ²	0.818	

Table 3: Contribution of DSQ and Summary Statistics

Panel A reports the decomposition of the variation in the natural logarithm of Tobin's Q from Table 2 into five components using the following variance decomposition formula:

$$R^2 = \frac{\text{cov}(\text{Ln } TQ_{ijt}, \text{Ln } \widehat{TQ}_{ijt})}{\text{var}(\text{Ln } TQ_{ijt})} = \frac{\text{cov}(\text{Ln } TQ_{ijt}, \hat{\theta}_i + \hat{\psi}_j + \hat{\omega}_t + X_{jt(t-1)}\hat{\beta} + Z_{ijt}\hat{\gamma})}{\text{var}(\text{Ln } TQ_{ijt})}$$

$$= \frac{\text{cov}(\text{Ln } TQ_{ijt}, \hat{\theta}_i)}{\text{var}(\text{Ln } TQ_{ijt})} + \frac{\text{cov}(\text{Ln } TQ_{ijt}, \hat{\psi}_j)}{\text{var}(\text{Ln } TQ_{ijt})} + \frac{\text{cov}(\text{Ln } TQ_{ijt}, \hat{\omega}_t)}{\text{var}(\text{Ln } TQ_{ijt})} + \frac{\text{cov}(\text{Ln } TQ_{ijt}, X_{jt(t-1)}\hat{\beta} + Z_{ijt}\hat{\gamma})}{\text{var}(\text{Ln } TQ_{ijt})}.$$

$\text{Ln}(TQ)$ is the natural logarithm of a firm's market value of assets scaled by book value of assets. θ_i , ψ_j , and ω_t are director, firm, and year fixed effects, respectively. $X_{jt(t-1)}$ are time-varying firm and board characteristics, and Z_{ijt} are time-varying director characteristics. The estimated director fixed effects θ_i capture DSQ. Panel B reports summary statistics for estimates of director-specific quality obtained from the Tobin's Q regression in Table 2. This sample consists of 52,851 director-level observations, excluding observations that are not part of the connected samples.

<i>Panel A: Contribution of director-specific quality</i>					
Component		R ² attributable to the component (in %)	% of R ² attributable to the component (in %)		
Director-specific effects		9.65	11.80		
Firm-specific effects		52.23	63.90		
Year effects		2.49	3.04		
Time-varying effects		17.45	21.34		
Residual		18.25	—		
<i>Panel B: Director-specific quality summary statistics</i>					
	<u>Mean</u>	<u>Std</u>	<u>P25</u>	<u>Median</u>	<u>P75</u>
DSQ	0.018	0.196	-0.061	0.023	0.099

Table 4: Univariate Correlations of Director-Specific Quality and Traits

This table presents result relating DSQ to director traits. There is only one observation per director. The first two columns present results from univariate correlations of *DSQ* with the listed director traits for the full set of directors, while the last two columns restrict the sample to directors in the top and bottom decile of *DSQ*. *DSQ* is the director-specific effect estimated using the AKM method. The full sample has 52,851 directors, and there are 30,775 directors with biographical information. All variables are defined in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	All Directors		Top & Bottom Decile of DSQ	
	Coefficient	p-Value	Coefficient	p-Value
<i>Easily observable and quantifiable director characteristics</i>				
MBA Degree	0.012***	0.007	0.022**	0.022
Grad Degree	0.014***	0.002	0.032***	0.001
Ivy Univ	0.016***	0.000	0.040***	0.000
Academics	0.012***	0.005	0.029***	0.003
Legal Exp	0.006	0.139	0.021**	0.030
Financial Exp	0.000	0.934	−0.004	0.686
Mangement Exp	0.020***	0.000	0.042***	0.000
Female	0.013***	0.003	0.029***	0.003
Entrepreneur	0.007	0.101	0.012	0.202
Military Exp	−0.001	0.849	−0.004	0.702
Political Exp	−0.001	0.848	−0.003	0.743
Ln(Prof Quals)	0.006	0.178	0.017*	0.078
<i>Hard to observe director soft skills</i>				
Adaptability	0.018***	0.002	0.036***	0.006
Critical Thinking	0.016***	0.006	0.030**	0.021
Analytical	0.020***	0.000	0.046***	0.000
Problem Solving	0.013**	0.019	0.031**	0.017
Innovative	0.036***	0.000	0.091***	0.000
Good Communicator	0.016***	0.004	0.036***	0.006
Customer Oriented	0.021***	0.000	0.055***	0.000
Team Building	0.014**	0.016	0.028**	0.031
Honesty	0.021***	0.000	0.041***	0.002
Emotional IQ	0.028***	0.000	0.063***	0.000
Empathy	0.012**	0.043	0.014	0.296

Table 5: Director-Specific Quality and Appointment and Death CARs

This table reports results from OLS regressions relating director appointment and death announcement CARs to DSQ over the period 2003 to 2020. When more than one director is appointed on the same day at a firm, the sample is collapsed to one observation per firm per day in column 5, and all these observations are excluded in column 6. The dependent variable $CAR[-2,+2]$ in columns 1-6 is the five-day cumulative abnormal return centered around the announcement of a director appointment. Column 7 examines the relation between director-specific quality and CARs centered around the announcement of a director death. DSQ are director-specific effects estimated using the AKM method. $DSQq2$ - $DSQq4$ are indicator variables that equal one if DSQ is in the second through fourth quartiles, and zero otherwise. FSQ controls include FSQ or $FSQq2$ - $FSQq4$. In column 2, DSQ and FSQ are estimated using the AKM method using data up to $t-1$. Other control variables include $ResidTQ$, $Ln(Size)$, $BHAR$, LEV , $OROA$, IO , $R\&D$, VOL , $Beta$, $\%Indep$, $\%Female$, $CEO-Chair$, $Lead-Indep$, $Ln(BrdSize)$, $Pill$, $ClassBrd$, $Ln(\#Seats)$, $Busy$, and $Age65$. Column 7 further controls for $Tenure$, $Indep$, $Chair-Lead$, $AuditCom$, $NomCom$, $CompCom$, $AuditChair$, $NomChair$, and $CompChair$. All variables are defined in the Appendix. t -statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	CAR[-2,+2] $\times$ 100						
	(1) Appt	(2) Appt	(3) Appt	(4) Appt	(5) Appt	(6) Appt	(7) Death
DSQ	1.631*** (4.27)	1.496** (2.07)					
DSQq2			0.308** (2.03)	0.201 (1.06)	0.331** (2.18)	0.315** (1.97)	-0.419 (-0.82)
DSQq3			0.549*** (3.66)	0.520*** (2.64)	0.490*** (3.24)	0.464*** (2.90)	-1.096** (-2.05)
DSQq4			0.796*** (4.88)	0.699*** (3.18)	0.754*** (4.77)	0.727*** (4.40)	-1.255** (-2.14)
FSQ Controls	✓	✓	✓		✓	✓	✓
Other Controls	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
SIC2 FE	✓	✓	✓		✓	✓	✓
Out-of-Sample		✓					
Firm FE				✓			
Obs	16,140	5,574	16,140	14,943	14,293	12,880	969
Adj R ²	0.036	0.034	0.037	0.141	0.034	0.034	0.040

Table 6: Director-Specific Quality and Election Outcomes

This table reports results from OLS regressions relating director election outcomes to DSQ over the period 2004 to 2020. The dependent variable $\%Vote$ in columns 1-4 is the fraction of “for” votes scaled by the the number of “for”, “against”, and “abstain” votes. The dependent variables $\%Vote < 90$ and $\%Vote < 85$ in columns 5 and 6 equal one if $\%Vote$ is less than 90% and 85%, respectively, and zero otherwise. DSQ are director-specific effects estimated using the AKM method. $DSQq2$ - $DSQq4$ are indicator variables that equal one if DSQ is in the second through fourth quartiles, and zero otherwise. FSQ controls include FSQ or $FSQq2$ - $FSQq4$. In column 2, DSQ and FSQ are estimated using the AKM method using data up to $t-1$. Other control variables include $ResidTQ$, $Ln(Size)$, $BHAR$, LEV , $OROA$, IO , $R\&D$, VOL , $Beta$, $\%Indep$, $\%Female$, $CEO-Chair$, $Lead-Indep$, $Ln(BrdSize)$, $Pill$, $ClassBrd$, $Ln(\#Seats)$, $Tenure$, $Busy$, $Indep$, $Age65$, $Chair-Lead$, $AuditCom$, $NomCom$, $CompCom$, $AuditChair$, $NomChair$, and $CompChair$. All variables are defined in the Appendix. t -statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	%Vote				%Vote<90	%Vote<85
	(1)	(2)	(3)	(4)	(5)	(6)
DSQ	1.266** (2.34)	1.158** (2.49)				
DSQq2			0.222* (1.77)	0.102 (1.27)	-0.002 (-0.45)	-0.004 (-1.07)
DSQq3			0.396*** (3.18)	0.239*** (2.68)	-0.010** (-2.09)	-0.011** (-2.57)
DSQq4			0.517*** (3.37)	0.418*** (3.79)	-0.015*** (-2.63)	-0.011** (-2.35)
FSQ Controls	✓	✓	✓		✓	✓
Other Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
SIC2 FE	✓	✓	✓		✓	✓
Out-of-Sample		✓				
Firm FE				✓		
Obs	157,691	146,128	157,691	157,619	157,691	157,691
Adj R ²	0.087	0.091	0.088	0.298	0.070	0.052

Table 7: Director-Specific Quality and Marginal Value of Cash

This table reports results from OLS regressions relating the marginal value of cash to board-level DSQ over the period 2001 to 2020. The dependent variable $r - R^B$ is a firm's stock return over its fiscal year minus the return on a size and book-to-market matched portfolio. DSQ are director-specific effects estimated using the AKM method. $AvgDSQ$ is the average DSQ across all directors during a year. $AvgDSQq2$ - $AvgDSQq4$ are indicator variables that equal one if $AvgDSQ$ is in the second through fourth quartiles, and zero otherwise. We control for the level terms of $AvgDSQ$ and $AvgDSQq2$ - $AvgDSQq4$ but do not report them for brevity. ΔC equals the change in cash scaled by lagged market value of equity. FSQ controls include the level terms and interactions of FSQ or $FSQq2$ - $FSQq4$ with ΔC . In column 2, DSQ and FSQ are estimated using the AKM method using data up to $t-1$. We also control for $ResidTQ$ and its interaction with ΔC . [Faulkender and Wang \(2006\)](#) control variables include ΔE , ΔNA , ΔRD , ΔI , ΔD , NF , $\Delta C \times L$, and $\Delta C \times C_{t-1}$. Other control variables include $\%Indep$, $\%Female$, $CEO-Chair$, $Lead-Indep$, $Ln(BrdSize)$, $Pill$, and $ClassBrd$. All variables are defined in the Appendix. t -statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	$r - R^B$			
	(1)	(2)	(3)	(4)
ΔC	1.329*** (19.09)	1.245*** (15.34)	0.947*** (9.13)	0.935*** (9.36)
$\Delta C \times AvgDSQ$	1.267*** (5.75)	1.003*** (4.58)		
$\Delta C \times AvgDSQq2$			0.132* (1.82)	0.149** (2.13)
$\Delta C \times AvgDSQq3$			0.203*** (2.78)	0.185*** (2.61)
$\Delta C \times AvgDSQq4$			0.341*** (4.00)	0.365*** (4.33)
DSQ & FSQ Controls	✓	✓	✓	✓
Other Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
SIC2 FE	✓	✓	✓	
Out-of-Sample		✓		
Firm FE				✓
Obs	39,903	32,266	39,903	39,470
Adj R ²	0.264	0.220	0.263	0.351

Table 8: Director-Specific Quality and Pay-Performance Sensitivity

This table reports results from OLS regressions relating CEO compensation to board-level DSQ over the period 2001 to 2020. The dependent variables in columns 1-4 and 5-8 are the natural logarithm of one plus the sensitivity of changes in CEO wealth to a 1% change in stock price ($\ln(\Delta)$) and the fraction of a CEO's total compensation coming from stock and option awards ($\%Equity$), respectively. DSQ are director-specific effects estimated using the AKM method. $AvgDSQ$ is the average DSQ across all directors during a year. $AvgDSQq2$ - $AvgDSQq4$ are indicator variables that equal one if $AvgDSQ$ is in the second through fourth quartiles, and zero otherwise. FSQ controls include FSQ or $FSQq2$ - $FSQq4$. In columns 2 and 6, DSQ and FSQ are estimated using the AKM method using data up to $t-1$. Other control variables include $ResidTQ$, the natural logarithm of CEO age and tenure, $\ln(Size)$, $BHAR$, LEV , $OROA$, IO , $R\&D$, VOL , $Beta$, $\%Indep$, $\%Female$, $CEO-Chair$, $Lead-Indep$, $\ln(BrdSize)$, $Pill$, and $ClassBrd$. All variables are defined in the Appendix. t -statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Ln(Delta)				%Equity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AvgDSQ	1.997*** (11.05)	1.549*** (10.20)			0.149*** (4.15)	0.175*** (5.35)		
AvgDSQq2			0.181*** (5.14)	0.189*** (6.53)			0.022*** (2.88)	0.012 (1.40)
AvgDSQq3			0.250*** (6.54)	0.299*** (8.69)			0.030*** (3.52)	0.024*** (2.69)
AvgDSQq4			0.420*** (9.83)	0.515*** (13.13)			0.033*** (3.84)	0.032*** (3.29)
FSQ Controls	✓	✓	✓		✓	✓	✓	
Other Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
SIC2 FE	✓	✓	✓		✓	✓	✓	
Out-of-Sample		✓				✓		
Firm FE				✓				✓
Obs	27,797	22,731	27,797	27,701	27,797	22,731	27,797	27,701
Adj R ²	0.559	0.550	0.546	0.751	0.156	0.138	0.157	0.311

Table 9: Director-Specific Quality and Innovation

This table reports results from OLS regressions relating innovation to board-level DSQ over the period 2000 to 2017. Columns 1-5 restrict the sample to firms that have at least one patent over the sample period and column 6 requires a firm to have a patent during the year. The dependent variable $\ln(1+\$Pats)$ in columns 1-4 is the natural logarithm of the market value of patents filed during a year from Kogan et al. (2017). The dependent variable $\ln(1+\#Pats)$ in column 5 is the natural logarithm of the number of patents filed during a year. The dependent variable $\#Cites/\#Pats$ in column 6 is the ratio of the total number of citations to patents filed in a year scaled by the number filed during the year. DSQ are director-specific effects estimated using the AKM method. $AvgDSQ$ is the average DSQ across all directors during a year. $AvgDSQq2$ - $AvgDSQq4$ are indicator variables that equal one if $AvgDSQ$ is in the second through fourth quartiles, and zero otherwise. FSQ controls include FSQ or $FSQq2$ - $FSQq4$. In column 2, DSQ and FSQ are estimated using the AKM method using data up to $t-1$. Other control variables include $ResidTQ$, $\ln(Size)$, $BHAR$, LEV , $OROA$, IO , $R\&D$, VOL , $Beta$, $\%Indep$, $\%Female$, $CEO-Chair$, $Lead-Indep$, $\ln(BrdSize)$, $Pill$, and $ClassBrd$. All variables are defined in the Appendix. t -statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Ln(1+\$Pats)				Ln(1+#Pats)	#Cites/#Pats
	(1)	(2)	(3)	(4)	(5)	(6)
AvgDSQ	1.829*** (8.09)	1.272*** (6.08)				
AvgDSQq2			0.149** (2.23)	0.178*** (3.89)	0.095** (1.99)	0.608 (1.56)
AvgDSQq3			0.159** (2.13)	0.261*** (4.58)	0.093* (1.77)	0.900** (2.12)
AvgDSQq4			0.330*** (4.46)	0.363*** (6.21)	0.153*** (2.94)	1.288*** (2.87)
FSQ Controls	✓	✓	✓		✓	✓
Other Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
SIC2 FE	✓	✓	✓		✓	✓
Out-of-Sample		✓				
Firm FE				✓		
Obs	23,199	17,073	23,199	23,175	23,199	14,336
Adj R ²	0.547	0.523	0.525	0.818	0.434	0.301

Table 10: Director-Specific Quality and M&A Announcement Returns

This table reports results from OLS regressions relating M&A announcement CARs to board-level DSQ over the period 2001 to 2020. In columns 5 and 6, the sample is restricted to deals where the deal value is at least 5% of the acquirer's market cap. The dependent variable $CAR[-2,+2]$ in columns 1-6 is the five-day bidder cumulative abnormal return centered around an M&A announcement. DSQ are director-specific effects estimated using the AKM method. $AvgDSQ$ is the average DSQ across all directors during a year. $AvgDSQq2$ - $AvgDSQq4$ are indicator variables that equal one if $AvgDSQ$ is in the second through fourth quartiles, and zero otherwise. FSQ controls include FSQ or $FSQq2$ - $FSQq4$. In column 2, DSQ and FSQ are estimated using the AKM method using data up to $t-1$. Other control variables include $ResidTQ$, $Ln(MVE)$, MB , FCF , $MLEV$, $BHAR$, $Hitech$, $RelSize$, $AllCash$, $StockDeal$, $DivAcq$, $Private$, $Subsidiary$, $\%Indep$, $\%Female$, $CEO-Chair$, $Lead-Indep$, $Ln(BrdSize)$, $Pill$, and $Class-Brd$. All variables are defined in the Appendix. t -statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	CAR[-2,+2]×100					
	(1)	(2)	(3)	(4)	(5)	(6)
AvgDSQ	2.209** (2.16)	0.156 (0.16)				
AvgDSQq2			0.409* (1.65)	0.873** (2.03)	0.384 (1.19)	0.983 (1.47)
AvgDSQq3			0.653** (2.52)	1.528*** (3.20)	0.642* (1.87)	1.434** (1.98)
AvgDSQq4			0.749*** (2.78)	1.844*** (3.45)	1.046*** (2.90)	2.327*** (2.83)
FSQ Controls	✓	✓	✓		✓	
Other Controls	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
SIC2 FE	✓	✓	✓		✓	
Out-of-Sample		✓				
Firm FE				✓		✓
Obs	8,543	6,635	8,543	7,367	5,525	4,243
Adj R ²	0.056	0.058	0.056	0.126	0.078	0.142

Table 11: Analysis Around Director Deaths

This table reports results from OLS regressions relating DSQ to the firm-level outcomes from Tables 7-10. The sample includes the +/- 3 years around a director death. The dependent variables and firm- and board-level control variables are the same as those in their respective tables. All regressions include all the level and interaction terms but are not tabulated for brevity. DSQ is the director-specific effect of the director who died. ΔDSQ captures how much the board-level average DSQ changes after the director dies. $After$ equals one if the firm's fiscal period is after the date when the director died, and zero otherwise. ΔC equals the change in cash scaled by lagged market value of equity. t -statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

<i>Panel A: Regressions do not include firm- and board-level controls</i>									
	$r - R^B$		Ln(Delta)		%Equity		Ln(1+\$Pats)		M&A CAR[-2,+2]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9) (10)
DSQ×After	-0.201** (-2.37)		-0.804*** (-2.81)		-0.211* (-1.94)		-0.486*** (-2.72)		-0.112** (-2.04)
$\Delta C \times DSQ \times After$	-1.894** (-2.30)								
$\Delta DSQ \times After$		2.511*** (3.37)		9.646*** (4.19)		2.123** (1.97)		3.103** (2.12)	0.737** (2.23)
$\Delta C \times \Delta DSQ \times After$		20.554** (2.42)							
Year×Death Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm×Death Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs	3,503	3,503	2,677	2,677	2,677	2,677	1,956	1,956	617
Adj R ²	0.060	0.066	0.780	0.781	0.335	0.335	0.877	0.877	0.172 0.169
<i>Panel B: Regressions include firm- and board-level controls</i>									
DSQ×After	-0.242*** (-3.07)		-0.900*** (-3.32)		-0.195* (-1.76)		-0.433** (-2.26)		-0.111** (-2.07)
$\Delta C \times DSQ \times After$	-1.969** (-2.54)								
$\Delta DSQ \times After$		2.586*** (3.56)		9.002*** (4.79)		1.975* (1.83)		2.857* (1.87)	0.827* (1.96)
$\Delta C \times \Delta DSQ \times After$		18.863*** (2.67)							
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year×Death Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm×Death Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Obs	3,503	3,503	2,651	2,651	2,651	2,651	1,954	1,954	617
Adj R ²	0.282	0.283	0.827	0.828	0.337	0.337	0.878	0.878	0.230 0.228

Table 12: Director-Specific Quality during the COVID-19 Pandemic

This table reports results from OLS regressions relating weekly stock returns to COVID-19 intensity and board-level DSQ from the first week of March 2020 through the first week of March 2021. The dependent variable *Return* in columns 1-6 is a firm's weekly stock return. *COVID* is the natural logarithm of one plus the number of positive COVID-19 cases in week t minus the natural logarithm of one plus the number of positive cases in week $t-1$. *DSQ* are director-specific effects estimated using the AKM method using data only through 2019. *AvgDSQ* is the average *DSQ* across all directors during 2019. *AvgDSQq2-AvgDSQq4* are indicator variables that equal one if *AvgDSQ* is in the second through fourth quartiles, and zero otherwise. We control for the level terms of *AvgDSQ* and *AvgDSQq2-AvgDSQq4* but do not report them for brevity. We control for the level terms and interactions of *FSQ* or *FSQq2-FSQq4* and *ResidTQ* with *COVID*. Other control variables interacted with *COVID* include *Ln(Size)*, *BHAR*, *LEV*, *OROA*, *IO*, *R&D*, *VOL*, *Beta*, *%Indep*, *%Female*, *CEO-Chair*, *Lead-Indep*, *Ln(BrdSize)*, *Pill*, and *ClassBrd*. All variables are defined in the Appendix. t -statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Return $\times 100$					
	(1)	(2)	(3)	(4)	(5)	(6)
COVID	-3.109*** (-68.89)	-3.700*** (-48.85)	-4.789*** (-30.58)			
COVID $\times$ AvgDSQ		1.415*** (4.80)				
COVID $\times$ AvgDSQq2			0.203 (1.54)	0.201 (1.52)	0.160 (1.19)	0.131 (1.05)
COVID $\times$ AvgDSQq3			0.343*** (2.76)	0.344*** (2.77)	0.255* (1.95)	0.251** (2.03)
COVID $\times$ AvgDSQq4			0.617*** (4.98)	0.612*** (4.94)	0.445*** (3.31)	0.396*** (3.14)
DSQ & FSQ Controls	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓
Out-of-Sample	✓	✓	✓	✓	✓	✓
Week FE				✓	✓	
COVID $\times$ Other Controls					✓	✓
SIC2 $\times$ Week FE						✓
Obs	148,316	148,316	148,316	148,316	148,316	148,200
Adj R ²	0.026	0.028	0.028	0.319	0.320	0.387

UNVEILING THE ROLE OF DIRECTOR-SPECIFIC QUALITY IN CREATING FIRM VALUE

ONLINE APPENDIX

Table A1: Director Board Seat Composition

This table reports the number of boards each director sits on over the period 2000 to 2020. Panel A breaks down the number of different boards each director sits on over the sample period, while Panel B shows the number of firms who have directors that sit on more than one board and can be connected to a group following the AKM method.

<i>Panel A: Number of Directors that Sit on Multiple Boards</i>			
More than one board	Number of different boards	Number of directors	Percentage
No	1	42,376	73.69
Yes	2	8,646	15.04
	3	3,315	5.76
	4	1,673	2.91
	5	757	1.32
	6	377	0.66
	7	180	0.31
	8	88	0.15
	9	37	0.06
	>9	24	0.10
	Total	57,505	100
<i>Panel B: Number of Firms with Directors who Sit on Multiple Boards Over the Sample Period</i>			
Number of “movers” per firm	Number of firms	Percentage	Cumulative percentage
0	594	8.42	8.42
1-5	3,420	48.46	56.88
6-10	1,904	26.98	83.86
11-20	960	13.6	97.46
21- 30	167	2.37	99.83
31- 50	12	0.17	100
Total	7,057	100	

Table A2: Robustness: Estimating DSQ from Stock Returns

This table reports results from OLS regressions relating DSQ to the director- and firm-level outcomes from Tables 5-10. The dependent variables in columns 1-7, samples, and control variables are the same as those in their respective tables. However, in this table, *DSQ* and *FSQ* are estimated from Eq. (1) except that the dependent variable is DGTW characteristic-adjusted stock returns over a firm's fiscal year instead of Tobin's Q. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Appt. CAR[- 2,2]×100	%Vote	$r - R^B$	Ln(Delta)	%Equity	Ln(1+\$Pats)	M&A CAR[- 2,2]×100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DSQq2	0.300* (1.80)	0.311*** (2.73)					
DSQq3	0.338** (2.03)	0.349*** (2.70)					
DSQq4	0.808*** (4.63)	0.428*** (2.93)					
ΔC			1.290*** (14.05)				
ΔC×AvgDSQq2			0.023 (0.31)				
ΔC×AvgDSQq3			0.001 (0.01)				
ΔC×AvgDSQq4			0.236*** (2.94)				
AvgDSQq2			-0.006 (-0.84)	0.432* (1.66)	0.250*** (6.94)	0.036*** (4.34)	0.164** (2.22)
AvgDSQq3			0.001 (0.15)	0.886*** (3.23)	0.447*** (11.84)	0.037*** (4.41)	0.265*** (3.14)
AvgDSQq4			0.042*** (5.73)	1.191*** (4.05)	0.586*** (13.85)	0.041*** (4.81)	0.227*** (2.68)
Controls	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
SIC2 FE	✓	✓	✓	✓	✓	✓	✓
Obs	12,759	149,254	35,163	25,830	25,830	20,508	7,293
Adj R ²	0.034	0.089	0.219	0.554	0.157	0.542	0.053

Table A3: Comparing Director Characteristics for Movers and Stayers

This table reports variable means for directors with more than one directorship (Movers) and those with only one directorship (Stayers). The sample consists of 15,129 mover and 37,722 stayer observations. All variables are defined in the Appendix. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, for a *t*-test of the difference in means between the two groups.

	Mean Mover	Mean Stayer	Difference
DSQ	0.023	0.016	0.008***
Ln(#Seats)	1.923	1.171	0.753***
Tenure	5.985	6.400	-0.415***
Busy	0.384	0.130	0.254***
Indep	0.901	0.822	0.079***
Age65	0.354	0.346	0.008*
IndExp	0.337	0.137	0.199***
Chair-Lead	0.063	0.054	0.009***
AuditCom	0.535	0.489	0.046***
CompCom	0.490	0.451	0.039***
NomCom	0.468	0.427	0.041***
AuditChair	0.139	0.100	0.038***
CompChair	0.126	0.100	0.026***
NomChair	0.113	0.091	0.022***

Table A4: Robustness: Use DSQ Estimates from Mover Sample

This table reports results from OLS regressions relating DSQ to the director- and firm-level outcomes from Tables 5-10. The dependent variables in columns 1-7, samples, and control variables are the same as those in their respective tables. However, in this table, we restrict the sample in columns 1 and 2 to directors with directorships at two or more firms, and in columns 3-7, we calculate *AvgDSQ* using directors with directorships at two or more firms. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Appt. CAR[- 2,2]×100	%Vote	$r - R^B$	Ln(Delta)	%Equity	Ln(1+\$Pats)	M&A CAR[- 2,2]×100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DSQq2	0.182 (0.93)	0.322** (2.56)					
DSQq3	0.380** (1.99)	0.495*** (3.85)					
DSQq4	0.719*** (3.33)	0.588*** (4.12)					
ΔC			0.996*** (9.32)				
ΔC×AvgDSQq2			0.030 (0.40)				
ΔC×AvgDSQq3			0.061 (0.80)				
ΔC×AvgDSQq4			0.249*** (3.06)				
AvgDSQq2			0.003 (0.43)	0.166 (0.64)	0.086** (2.31)	0.015* (1.95)	0.078 (1.08)
AvgDSQq3			0.006 (0.87)	0.638** (2.50)	0.190*** (5.00)	0.023*** (2.83)	0.185** (2.33)
AvgDSQq4			0.026*** (3.65)	0.653** (2.37)	0.353*** (8.34)	0.026*** (3.12)	0.268*** (3.52)
Controls	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
SIC2 FE	✓	✓	✓	✓	✓	✓	✓
Obs	9,266	98,182	37,675	26,999	26,999	22,229	7,987
Adj R ²	0.036	0.081	0.261	0.544	0.149	0.528	0.055

Table A5: Robustness: Use DSQ Estimates from Stayer Sample

This table reports results from OLS regressions relating DSQ to the director- and firm-level outcomes from Tables 5-10. The dependent variables in columns 1-7, samples, and control variables are the same as those in their respective tables. However, in this table, we restrict the sample in columns 1 and 2 to directors with directorships at only one firm, and in columns 3-7, we calculate *AvgDSQ* using directors with directorships at only one firm. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Appt. CAR[- 2,2]×100	%Vote	$r - R^B$	Ln(Delta)	%Equity	Ln(1+\$Pats)	M&A CAR[- 2,2]×100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DSQq2	0.393 (1.63)	-0.078 (-0.45)					
DSQq3	0.696*** (2.86)	0.136 (0.78)					
DSQq4	0.876*** (3.82)	0.251 (1.22)					
ΔC			0.987*** (9.28)				
$\Delta C \times \text{AvgDSQq2}$			0.240*** (3.21)				
$\Delta C \times \text{AvgDSQq3}$			0.203*** (2.58)				
$\Delta C \times \text{AvgDSQq4}$			0.315*** (3.58)				
AvgDSQq2			0.010 (1.43)	0.175 (0.68)	0.180*** (4.83)	0.026*** (3.14)	-0.057 (-0.75)
AvgDSQq3			0.006 (0.80)	0.324 (1.20)	0.234*** (5.61)	0.029*** (3.24)	-0.053 (-0.66)
AvgDSQq4			0.023*** (3.01)	0.508* (1.76)	0.421*** (9.80)	0.039*** (4.38)	0.337*** (4.32)
Controls	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
SIC2 FE	✓	✓	✓	✓	✓	✓	✓
Obs	6,872	74,681	36,562	25,286	25,286	20,762	7,721
Adj R ²	0.038	0.094	0.260	0.541	0.157	0.504	0.054

Table A6: Robustness: Mover Dummy Variables Approach

This table reports results from OLS regressions relating DSQ to the director- and firm-level outcomes from Tables 5-10. The dependent variables in columns 1-7, samples, and control variables are the same as those in their respective tables. However, in this table, *DSQ* and *FSQ* are estimated using the mover dummy approach that is restricted to only directors that have more than one board appointment. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Appt. CAR[- 2,2]×100	%Vote	$r - R^B$	Ln(Delta)	%Equity	Ln(1+\$Pats)	M&A CAR[- 2,2]×100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DSQq2	0.101 (0.53)	0.336*** (2.62)					
DSQq3	0.382** (2.08)	0.477*** (3.77)					
DSQq4	0.619*** (3.22)	0.555*** (4.06)					
ΔC			0.945*** (8.26)				
$\Delta C \times \text{AvgDSQq2}$			0.029 (0.39)				
$\Delta C \times \text{AvgDSQq3}$			0.095 (1.24)				
$\Delta C \times \text{AvgDSQq4}$			0.250*** (3.07)				
AvgDSQq2			0.006 (0.89)	0.294 (1.15)	0.082** (2.22)	0.013* (1.70)	0.094 (1.29)
AvgDSQq3			0.005 (0.77)	0.742*** (2.88)	0.185*** (4.95)	0.023*** (2.80)	0.171** (2.17)
AvgDSQq4			0.030*** (4.25)	0.682** (2.49)	0.324*** (7.72)	0.023*** (2.79)	0.263*** (3.47)
Controls	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
SIC2 FE	✓	✓	✓	✓	✓	✓	✓
Obs	9,268	90,623	37,675	26,999	26,999	22,229	8,065
Adj R ²	0.036	0.084	0.263	0.546	0.150	0.525	0.057

Table A7: Robustness: Estimate DSQ from Directors that Move Up

This table reports results from OLS regressions relating DSQ to the director- and firm-level outcomes from Tables 5-10. The dependent variables in columns 1-7, samples, and control variables are the same as those in their respective tables. However, in this table, *DSQ* and *FSQ* are estimated using directors with only one board appointment and directors that move to a firm with at least a 10% higher Tobin's Q ratio. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Appt. CAR[- 2,2]×100	%Vote	$r - R^B$	Ln(Delta)	%Equity	Ln(1+\$Pats)	M&A CAR[- 2,2]×100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DSQq2	0.462* (1.76)	0.606*** (3.15)					
DSQq3	0.732*** (3.02)	0.705*** (3.52)					
DSQq4	0.994*** (3.59)	0.825*** (3.60)					
ΔC			0.952*** (8.64)				
$\Delta C \times \text{AvgDSQq2}$			0.034 (0.41)				
$\Delta C \times \text{AvgDSQq3}$			0.182** (2.23)				
$\Delta C \times \text{AvgDSQq4}$			0.335*** (3.86)				
AvgDSQq2			-0.012* (-1.67)	0.369 (1.31)	0.174*** (4.25)	0.026*** (3.28)	0.314*** (3.77)
AvgDSQq3			-0.014* (-1.92)	0.420 (1.48)	0.314*** (7.02)	0.024*** (2.67)	0.411*** (4.52)
AvgDSQq4			-0.027*** (-3.29)	0.583* (1.77)	0.484*** (10.16)	0.055*** (5.82)	0.576*** (6.17)
Controls	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
SIC2 FE	✓	✓	✓	✓	✓	✓	✓
Obs	6,258	68,941	34,238	24,841	24,841	20,806	7,155
Adj R ²	0.034	0.092	0.262	0.542	0.151	0.537	0.056

Table A8: Robustness: Estimate DSQ from Directors that Move Down

This table reports results from OLS regressions relating DSQ to the director- and firm-level outcomes from Tables 5-10. The dependent variables in columns 1-7, samples, and control variables are the same as those in their respective tables. However, in this table, *DSQ* and *FSQ* are estimated using directors with only one board appointment and directors that move to a firm with at least a 10% lower Tobin's Q ratio. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Appt. CAR[- 2,2]×100	%Vote	$r - R^B$	Ln(Delta)	%Equity	Ln(1+\$Pats)	M&A CAR[- 2,2]×100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DSQq2	0.572*** (2.64)	0.272 (1.49)					
DSQq3	0.701*** (3.07)	0.568*** (3.15)					
DSQq4	0.840*** (3.56)	0.639*** (2.99)					
ΔC			0.843*** (7.78)				
$\Delta C \times \text{AvgDSQq2}$			0.176** (2.23)				
$\Delta C \times \text{AvgDSQq3}$			0.191** (2.42)				
$\Delta C \times \text{AvgDSQq4}$			0.467*** (5.53)				
AvgDSQq2			-0.028*** (-3.92)	0.174 (0.66)	0.238*** (6.18)	0.019** (2.10)	0.404*** (5.14)
AvgDSQq3			-0.038*** (-5.11)	0.332 (1.23)	0.352*** (8.44)	0.041*** (4.17)	0.452*** (5.17)
AvgDSQq4			-0.009 (-1.16)	0.711** (2.42)	0.617*** (12.95)	0.059*** (6.09)	0.697*** (7.74)
Controls	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
SIC2 FE	✓	✓	✓	✓	✓	✓	✓
Obs	7,794	85,733	35,055	25,536	25,536	21,120	7,467
Adj R ²	0.039	0.091	0.265	0.548	0.145	0.534	0.053

Table A9: Robustness: Drop High and Low Tobin's Q Firms

This table reports results from OLS regressions relating DSQ to the director- and firm-level outcomes from Tables 5-10. The dependent variables in columns 1-7, samples, and control variables are the same as those in their respective tables. However, in this table, we drop observations that fall into the top and bottom quartiles of *Tobin's Q*. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Appt. CAR[- 2,2]×100	%Vote	$r - R^B$	Ln(Delta)	%Equity	Ln(1+\$Pats)	M&A CAR[- 2,2]×100
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DSQq2	0.041 (0.19)	0.312** (2.15)					
DSQq3	0.349 (1.64)	0.463*** (3.20)					
DSQq4	0.652*** (2.90)	0.619*** (3.56)					
ΔC			1.168*** (4.25)				
$\Delta C \times \text{AvgDSQq2}$			0.161 (1.24)				
$\Delta C \times \text{AvgDSQq3}$			0.130 (1.02)				
$\Delta C \times \text{AvgDSQq4}$			0.322** (2.24)				
AvgDSQq2			0.005 (0.57)	0.137*** (3.40)	0.022** (2.39)	0.126 (1.57)	-0.044 (-0.13)
AvgDSQq3			0.006 (0.76)	0.227*** (5.14)	0.028*** (2.84)	0.141 (1.57)	0.329 (0.89)
AvgDSQq4			0.012 (1.40)	0.438*** (8.96)	0.030*** (2.78)	0.173* (1.89)	0.762** (1.97)
Controls	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
SIC2 FE	✓	✓	✓	✓	✓	✓	✓
Obs	8,104	80,529	20,045	13,925	13,925	11,911	4,310
Adj R ²	0.037	0.091	0.283	0.556	0.149	0.523	0.056

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