Picking Winners: Managerial Ability and Capital Allocation[1]

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Abstract

We examine how division managers' human capital affects internal capital allocation using a hand-collected data set of divisional managers at S&P 1,500 firms. Based on a novel measure of division-manager ability, we show that more able division managers receive substantially larger capital allocations. This effect is robust to controlling for the possibility of assortative matching and more pronounced for firms with better governance. We also find that the allocation of extra capital to higher-ability managers creates firm value. These findings suggest efficient fund transfers to high-productivity managers and provide support for a largely unexplored bright side of internal capital markets.

JEL classification: G31, G32, G34, J24

Keywords: Managerial Ability, Managerial Efficiency, Human Capital, Capital Budgeting, Investment, Internal Capital Markets.

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1. Introduction

A fundamental question in finance, accounting, and organizational economics is whether and to what extent firms allocate capital to the most productive investment projects within and across different lines of business. When developing and testing models of the efficiency of capital allocation decisions (see the literature reviews by Stein, 2003; Maksimovic and Philips, 2007, 2013; Gertner and Scharfstein, 2013), the existing literature typically assumes that investment productivities arise exogenously from the "outside" and can be taken as given, but largely ignores the role of divisional managers – in particular, their "human capital" or "managerial ability" – in the success of a business unit or division. Implicitly, these studies take the view that the expected net present value of a division's set of investment projects and, hence, capital allocation is unaffected by whether the division manager, who proposes, oversees, and manages that project, is skilled at identifying investment opportunities, managing resources, developing and implementing strategies and/or leading organizations.[1] This "neoclassical" view of capital allocation stands in contrast to evidence from surveys and field work on internal capital markets and capital budgeting, which suggest that corporations and government agencies give high priority to divisional managers' abilities when making capital allocation decisions (see, e.g., Bower, 1970, 2005; Ross, 1986; Graham, Harvey, and Puri, 2015; Hoang, Gatzer, and Ruckes, 2023).[2] This disparity suggests that our understanding of the functioning of internal capital markets and capital budgeting is possibly incomplete. If firms do indeed allocate financial resources based on the human capital of divisional management, empirical studies that employ a neoclassical framework of capital allocation could inadvertently conclude that

[1] In the neoclassical model of the firm, the role of managers across all levels of the corporate hierarchy is to "passively" select in the given set of feasible production plans those that achieve the objectives of firm owners (see, e.g., Hart, 1989; Bertrand and Schoar, 2003). In this rigid framework, managers are either implicitly assumed to be homogenous inputs in the production process or, alternatively, there is no role for managerial heterogeneity with respect to individual features, characteristics, skill levels, or preferences; both imply that there are no relative performance-enhancing benefits across managers.

[2] For instance, in recent field evidence, Graham, Harvey, and Puri (2015) find that a divisional manager's "*reputation in terms of delivering on previous projects*" is the second most important factor in the capital allocation process after the NPV criterion.

allocations are inefficient, although firms do in fact engage in value-enhancing winner-picking – by channeling financial resources towards relatively more able managers.

The novel contribution of this paper is to provide – to the best of our knowledge for the first time – empirical evidence on this question by explicitly introducing a human capital dimension ("managerial ability") into a large-sample study of capital allocation. Using a hand-collected data set of divisional managers at S&P 1,500 firms, our analysis brings to the fore the importance of managerial human capital at the level of divisional management in shaping corporate investment decisions. We also explore various economic mechanisms underlying the substantial variation in financial capital allocated to more and less able division managers as well as uncover several channels through which managerial ability affects investment efficiency and firm value. As we discuss in more detail below, our findings yield novel insights into the workings of internal capital markets and provide a more complete characterization of the efficiency with which firms allocate financial resources across divisions.

A possible reason why the role of division-manager ability for investment outcomes has been empirically largely unexplored is the dearth of data on division managers in standard databases and the absence of a convincing ability metric at the division level. We address this deficiency by adapting the managerial ability score ("MA-Score") developed by Demerjian et al. (2012) to construct an ability score for division managers based on a hand-collected and comprehensive data set of divisional managers at S&P 1,500 firms. The *MA-Score* of Demerjian et al. (2012) measures the efficiency of operations, especially with respect to the generation of revenues, and then controls for factors outside of top management's control to disentangle manager-specific from firm-specific efficiency drivers. Using segment-level financial accounting data, we develop a novel variant of the score to quantify the ability of divisional management: the *DMA-Score*. Specifically, we adapt the two-stage approach in Demerjian et al. (2012) in the following way: In the first stage, we use data envelopment analysis (DEA) to estimate the division's relative efficiency by measuring the amount and mix of resources used to generate segment revenue. The second stage then uses Tobit regressions to remove the effects of segment-, firm-, and industry-specific characteristics (such as size or market share) that may affect the division's relative efficiency but are unlikely to be a direct result of the quality of divisional management. After controlling for these effects, we attribute the unexplained portion of divisional efficiency to the division manager. This residual from the second-stage regression is our measure of division-manager ability, the *DMA-Score*. Intuitively, division managers with higher *DMA-Scores* generate more revenue for a given level of resources and, thus, have higher productivity than division managers with lower *DMA-Scores*. We believe our measure of division-manager ability is particularly well-suited to explain internal capital allocation, because it clearly and directly reflects the firm's key objective in allocating capital to divisions – getting it to the division where the manager is going to most effectively convert scarce firm resources into desirable output.

Figure 1 documents the strong positive relationship between division-manager ability and segment-level capital allocation, which is the main result of the paper.

A. Segment Investment **B.** Industry-Adjusted Segment Investment

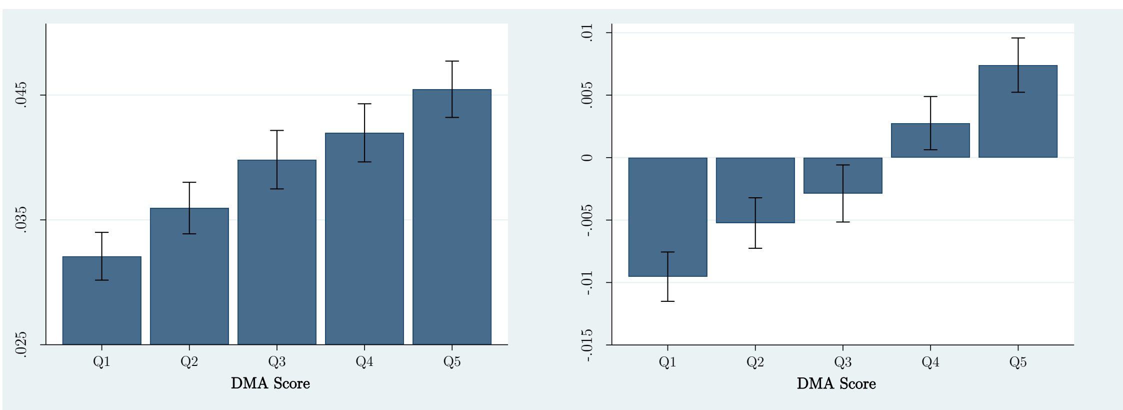

Figure 1: Division-Manager Ability and Capital Allocation. This figure plots measures of capital allocation for quintile groups of increasing division-manager ability. Panel A shows the average *raw* segment investment (segment capital expenditures scaled by segment book assets). Panel B shows the average *industry-adjusted* segment investment. *DMA-Score* is the measure of division-manager ability described in Section 3.4. For each bin, the graphs report 95% confidence intervals around the mean. Detailed variable definitions are provided in Appendix A.1.

Panel A shows the average segment investment (the ratio of capital expenditures scaled by book assets) for quintile groups of increasing division-manager ability as measured by the *DMA-Score*. Moving from the first to the fifth quintile of the *DMA-Score* monotonically increases capital allocation from 3.2% to 4.5%, which is an economically meaningful difference of 41% in relative terms. A similar pattern emerges for industry-adjusted segment investment (Panel B), our second measure of segment-level capital allocation. Overall, these stylized facts provide evidence consistent with the view that internal capital markets tend to move financial resources toward segments of relatively more able division managers. As we show in more detail in our main empirical sections, the association observed in Figure 1 cannot be explained by conventional determinants of capital allocation known from the literature.

In the baseline empirical analysis, we estimate segment-level regressions of capital allocation on division-manager ability (the *DMA-Score*) and a rich set of standard controls, including firm and segment characteristics (e.g., industry q, segment size, segment relative size, segment cash flow, cash flow of the firm's other segments, and sales growth). These regressions also control for a rich set of personal attributes of the division manager (e.g., age, gender, educational background) including proxies for the manager's formal influence within the firm (such as board membership, professional tenure, and senior leadership positions). The effect of division-manager ability is uniformly positive and statistically significant across different measures of capital allocation and across a variety of empirical specifications. The economic magnitude is also sizeable. For raw segment investment (the capital allocation measure that produces the most conservative estimates in our baseline analysis), a one-standard deviation increase in managerial ability is associated with a relative increase of 18.3% in segment investment for a division with median characteristics. In absolute terms, this difference translates into \$4.7 M in extra funds per year and \$31.1 M during the average tenure of a division manager in our sample.

One key challenge that we face in the empirical analysis is the possible influence of assortative (relative to random) matching between managers and firms/divisions on our results. For example, higher-ability managers may self-select into capital-rich firms (characterized by higher overall investments) or may be appointed to divisions with larger capital budgets. Then, unobserved variation at the level of the firm, division or manager might bias our estimates and create a spurious relation between division-manager ability and capital allocation. To mitigate this concern, we exploit the time-series variation in our ability measure to conduct a battery of robustness tests. Specifically, we find that our results are robust to the inclusion of (1) firm fixed effects, (2) division fixed effects, (3) manager fixed effects, (4) manager-division (pair) fixed effects[3], and (5) CEO fixed effects, suggesting that unobservable characteristics of this kind are unlikely to affect our conclusions. These findings also indicate that – despite budgets tending to be rigid (see, e.g., Ozbas and Scharfstein, 2010; Schneider and Spalt, 2016) – the data variation that identifies our baseline effect is both within and cross-sectional.

Another important caveat is that the existence of unobserved features at the level of a CEO-manager pair may affect the estimated impact of managerial ability on capital allocation. For example, commonality (e.g., Gaspar and Massa, 2011) and social connections (e.g., Duchin and Sosyura, 2013) between the CEO and the division manager, which may play a role in the resource allocation across divisions, could vary systematically with division-manager ability. Specifically, it is possible that higher-ability division managers have closer and more informal contact to the CEO, which may provide them with better opportunities to lobby for additional resources and induce an upward bias in the estimates of our baseline analysis. We rule out this possibility by showing that our empirical results are robust to the inclusion of CEO-manager (pair) fixed effects. This specification relies exclusively on the variation within-CEO-manager combinations and, thus, accounts for unobserved, time-invariant heterogeneity across CEO-manager combinations – including commonality, social connections, but also various forms of CEO favoritism (see, e.g., Xuan, 2009 and Glaser et al., 2013) that could be correlated with both managerial ability and capital allocation.

In our third set of analyses, we investigate the economic mechanisms behind our findings to provide richer insights and additional guidance for the interpretation of the observed patterns in our data. First, we explore the allocation of heterogeneously skilled managers to divisions in a firm's internal labor market in more detail and provide complementary evidence on its relevance beyond capital

[3] As we describe in detail, the manager-division (pair) fixed-effect estimator accounts for the possibility that division manager turnovers coincide with unobserved changes in corporate investment policies because it relies solely on time-series variation in managers' *DMA-Scores* during the tenure on a specific division.

allocation. Specifically, we focus on the appointment of division managers who were formerly responsible for a different division (job rotations) and examine how incoming managers' prior ability scores (estimated while being employed in the previous division) are related to the characteristics of the managers' new divisions. There is no evidence of a systematic assignment of high-ability managers to capital-rich divisions (i.e., divisions that historically received higher capital allocations already prior to the appointment), which explains why our main results are not affected by this channel. We also do not find evidence of a systematic relation between managerial ability and the appointment to segments with better investment opportunities. However, our findings reveal that high-ability managers are significantly more likely to be appointed to the larger divisions of the firm, which implies that they are responsible for managing larger capital stocks compared to their less able peers overseeing smaller divisions.

Second, we examine how our results vary with the quality of a firm's corporate governance. To the extent that larger capital allocations to segments of more able division managers create value for shareholders, the positive association between division-manager ability and capital allocation should be stronger in well-governed firms. Poorly-governed firms are likely to be characterized by top managers' opportunistic behavior and capital allocation for personal benefit, which is unlikely to be associated with efficient capital allocation towards the most able division managers. We formally test this conjecture by estimating regressions of segment investment on the interaction between division-manager ability and different measures of both internal and external governance. Consistent with our predictions, we find that investment by segments of well-governed firms is more sensitive to division managers' human capital productivity than investment by segments of poorly governed firms. This evidence suggests that the capital flow towards segments of more able managers likely reflects a value-enhancing and alternative form of winner-picking (Stein, 2003).

Third, we examine the sensitivity of our results to exogenous firm-wide cash windfalls that increase the firm's financial capacity to implement additional investment projects beyond the regular capital budgeting process (see, e.g., Blanchard, Lopez-de-Silanes, and Shleifer, 1994). An appealing feature of this analysis is that cash windfalls occur after the regular budget is determined and, therefore, provide a suitable setting to further address endogeneity concerns about unobserved factors specific to routine capital allocation such as, for example, mandatory investments required to sustain operations (e.g., maintenance, replacement investments or investments for regulatory compliance).[4] Consistent with the inferences drawn from our baseline analysis, we find that the effect of division-manager ability on capital allocation increases significantly in response to cash windfalls, suggesting that firms "efficiently" channel some of the additional cash toward segments of higher-ability division managers – although windfall allocations are known to be less formally structured, more ad hoc, and likely more agency-prone (see, e.g., Glaser et al., 2013).[5]

The analysis up to this point implicitly assumes that the capital flow towards segments of more able division managers reflects a value-adding and alternative form of winner-picking that benefits the firm as a whole. In the final set of analyses, we move our analysis from the *segment level* to the *firm level* to provide more definitive evidence on the question of whether *DMA*-sensitive resource allocation results in higher firm values. Inspired by the seminal work of Rajan, Servaes and Zingales (2000), we introduce a novel *firm-level* efficiency measure of the sensitivity of cross-segment investment to division-manager ability (i.e., the *DMA-Scores* of the firm's division managers). Then, we use standard excess value regressions (see, e.g., Rajan et al., 2000; Billett and Mauer, 2003; Ahn and Denis, 2004; Duchin and Sosyura, 2013; Schneider and Spalt, 2016) to estimate the value effect of *DMA*-sensitive investment. The results are strongly consistent with the notion that allocating more capital to higher-ability division managers is value-adding, which means that our earlier findings on the positive relationship between managerial ability and capital allocation can be interpreted as evidence of efficient investment.

Our paper makes several contributions to the literature. First, we contribute to the literature on the measurement of managerial talent/skills (Demerjian et al., 2012; Custódio et al., 2013, 2019;

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[4] Cash windfalls allow firms to pursue additional discretionary investment opportunities (e.g., capacity expansions, new businesses) on top of scheduled mandatory investments. For the distinction between mandatory and discretionary investment see, e.g., Ross (1986).

[5] These results are also robust to the inclusion of different measures of managerial power. Our analysis also replicates the evidence in Glaser et al. (2013) that more powerful managers exercise influence over windfall allocations.

Custódio and Metzger, 2014; Babenko et al., 2014; Falato et al., 2015; Kotter and Larkin, 2022) by providing a novel measure of division-manager ability: the *DMA-Score*. Conceptually, the score is a variant of the two-stage DEA-based managerial ability score of Demerjian et al. (2012) with similar features but measured directly at the division level. The *DMA-Score* overcomes several limitations of possible alternative measures to infer ability, which have been used mainly in the literature on CEOs but are difficult to transfer to the division level.[6] Similar to the original score, the *DMA-Score* is directly interpretable and isolates factors outside of the manager's control. The *DMA-Score* is also based on segment accounting information and is, thus, widely available for a large sample of managers and firms. In addition to answering questions about internal capital markets, we believe the *DMA-Score* will be also useful in other research settings, including internal labor markets and compensation contracting.

Second, our paper contributes to the literature on internal capital markets and capital budgeting. Prior archival studies almost exclusively model capital allocation as a function of industry-, firm- or segment-level characteristics, but fail to consider the crucial role of the individual corporate managers – divisional management – that propose, oversee, and manage investments in the firm's internal capital market (see the reviews of the literature by Stein, 2003; Maksimovic and Philips, 2007, 2013; Gertner and Scharfstein, 2013). We address this deficiency by explicitly considering the impact of divisional managers' valuable human capital, operationalized by an executive's ability to convert corporate resources into desirable output. Our results highlight that division-manager ability is a salient determinant of internal capital allocation and, thus, an important manager-level characteristic that shapes corporate investment policies.

[6] To infer managerial ability, the CEO literature generally relies on proxies such as firm size, past abnormal performance, compensation, tenure, media mentions, education, or manager fixed effects. Many of them either lack an equivalent for division managers or suffer from well-known limitations. For instance, media mentions, if at all available, are likely limited to C-suite executives. Abnormal accounting performance is noisy and affected by factors other than managerial ability. Manager fixed effects do not offer a standalone measure of ability that can be used to explicitly model and test directional hypotheses.

More broadly, our results also contribute to our understanding of the "efficiency" with which firms allocate capital across divisions. Theory suggests that firms should 'winner-pick' from competing investment projects by channeling capital toward the investment opportunities with the highest return (see Stein, 1997). To evaluate capital allocation efficiency, prior research almost exclusively uses a firm's adequate response to external market opportunities (measured by the Tobin's q of the industry in which a segment operates) as the benchmark against which capital allocation efficiency is assessed (see Busenbark et al., 2017). Yet, the empirical evidence, using this "neoclassical" efficiency framework as the reference system, is at best mixed.[7] This discrepancy is puzzling and unsatisfactory because it leaves open the possibility that one of the core attributes of the modern corporation and a major determinant of firm value – allocating resources to productive uses across divisions – might be fundamentally defective. At its core, our study inherently expands the prevailing benchmark system for evaluating the efficiency of capital allocation: Firms may achieve efficiency via a division-specific human capital channel, that is, by allocating funds to division managers with the highest human capital productivity.

The remainder of the paper is organized as follows. Section 2 discusses related literature. Section 3 describes the data and introduces the *DMA-Score* – our novel measure of division-manager ability. Sections 4 and 5 examine the effect of managerial ability on capital allocation and analyze economic channels. Section 6 studies investment efficiency and firm value. Section 7 concludes.

[7] Several earlier studies argue that internal capital markets are characterized by corporate socialism and misallocation of resources (see, e.g., Lamont, 1997; Shin and Stulz, 1998; Scharfstein, 1998; Rajan, Servaes and Zingales, 2000; Billett and Mauer, 2003; Ozbas and Scharfstein, 2010). A number of subsequent studies, in contrast, argue that this pioneering work presents a curtailed view and is tainted by measurement error (see, e.g., Whited, 2001; Khanna and Tice, 2001; Matsusaka 2001, Graham, Lemmon and Wolf, 2002; Maksimovic and Phillips, 2002; Chevalier, 2004; Guedj and Scharfstein, 2004; Çolak and Whited, 2007; Hoang and Ruckes, 2015; see also Erickson and Whited, 2000, 2002, 2006, and 2012 for the biases arising from measurement errors in q and their potential remedies). Therefore, more recent work focuses on analyzing investment efficiency in the cross-section or time-series (e.g., Cho, 2015; Sautner and Villalonga, 2010; Duchin and Sosyura, 2013; Shroff, Verdi, and Yu, 2014; Billett et al., 2015; Schneider and Spalt, 2016; Kuppuswamy and Villalonga, 2016; Guo and Zhong, 2023), instead of analyzing if the average firm exhibits efficient investment behavior.

2. Related Literature and Theoretical Framework

2.1. Related Literature

Our paper builds on several strands of the literature. First, the paper relates to the broader literature in finance, accounting, and management that examines the influence of individual managers on firm outcomes (see, e.g., Bertrand and Schoar, 2003; Fee and Hadlock, 2003; Milbourn, 2003; Bennedsen, Perez-Gonzalez, and Wolfenzon, 2006; Bamber, Jiang, and Wang, 2010; Dyreng, Hanlon, and Maydew, 2010; Ge, Matsumoto, and Zhang, 2011). These studies collectively challenge the neoclassical perspective that personal attributes, such as managerial ability, talent, reputation, and style have no bearing on corporate behavior. Among these characteristics, a CEO's managerial ability has recently received considerable attention. In particular, stimulated by the introduction of the managerial ability score developed in Demerjian et al. (2012), a large number of studies has documented a robust relationship between CEO-level managerial ability and a wide range of firm outcomes.[8] This body of work provides important insights into the economic relevance of managerial ability at the top executive level; however, none of them examines the role of managerial ability at the senior managerial level just below the CEO.

Second, our paper relates to the broader literature of investment, both across and within firms. Originally, this literature was primarily concerned with the fundamental question of whether external markets efficiently allocate capital across firms (see, e.g., Hubbard, 1998; Stein, 2003). A newer strand of the literature, building on insights from Alchian (1969) and Williamson (1975), focuses on how top management allocates capital to different business units and projects within the firm (see e.g., Stein, 2003; Gertner and Scharfstein, 2013). This line of research has made significant progress in identifying factors that affect top management's capital allocation in the cross-section, such as CEO career backgrounds, political connections, power, or communication incentives (Rajan et al.,

[8] These include corporate debt (Pan, Wang, and Weisbach, 2018; Bonsall, Holzman, and Miller, 2017; Cornaggia, Krishnan, and Wang, 2017), M&A performance (Li, Qiu, and Shen, 2018), earnings quality (Demerjian, Lev, Lewis, and McVay, 2013), earnings forecasts (Baik, Farber, and Lee, 2011), tax avoidance (Koester, Shevlin, and Wangerin, 2017), or earnings smoothing (Demerjian, Lewis-Western, and McVay, 2020).

2000; Xuan, 2009; Duchin and Sosyura, 2013; Glaser et al., 2013; Hoang and Ruckes, 2015; Duchin et al., 2021), managerial biases (Schneider and Spalt, 2016), or the information environment (Shroff et al., 2014; Billett et al., 2015; Cho, 2015; Guo and Zhong, 2023), as well as over time (e.g., Khanna and Tice, 2001; Matvos and Seru, 2014; Kuppuswamy and Villalonga, 2016; Giroud and Müller, 2015, 2019). Still, the variation in the within-firm distribution of investment across firms is remarkably poorly understood.

Third, our paper also extends recent empirical work in finance and accounting on the role of division managers in internal capital and internal labor markets. A small but growing literature examines implicit or explicit incentive mechanisms that affect division managers' career outcomes (e.g., Wulf, 2007; Cichello et al., 2009; Alok and Gopalan, 2018; Hadlock et al., 2022). Closer to our study, several papers examine how the relationship between the CEO and division managers affects capital allocation (e.g., Gaspar and Massa, 2011; Duchin and Sosyura, 2013; Glaser et al., 2013; Duchin et al., 2021). In contrast to these important works, the focus of our study is on the priority that firms give to investing in managerial human capital.

2.2. Theoretical Framework

To fix ideas, we sketch a standard model of corporate investment to illustrate the impact of division-manager ability on capital allocation in multisegment firms (e.g., Stein, 1997; Maksimovic and Phillips, 2002; Hoang and Ruckes, 2015; Giroud and Müller, 2019). Consider a firm with N operationally unrelated divisions, $i = 1, \dots, N$. In every period t, top management allocates financial resources $I_{i,t}$ across divisions to maximize the firm's profits, which equal the sum of divisional profits: $\max_{I_{1,t},\dots,I_{N,t}} \Pi_t = \sum_{i=1}^{N} \pi_i(I_{i,t}; q_{i,t}, a_{i,t})$. The manager of division i uses the division's capital allocation $I_{i,t}$ for investments (input) to generate a divisional profit (output). Divisional profit functions, $\pi_i(I_{i,t}; q_{i,t}, a_{i,t})$, display standard decreasing-returns-to-scale properties with respect to investment and depend positively on two parameters: the division's baseline productivity, $q_{i,t}$, and the division manager's ability, $a_{i,t}$. Specifically, a division manager's ability describes her capability to convert each unit of divisional resources (input) into profits (output). Thus, a higher ability level $a_{i,t}$ makes each additional unit of investment more profitable: $\frac{d^2\pi_i}{dI_{i,t}da_{i,t}} > 0$. The optimal capital allocation occurs period by period and varies with input parameters $q_{i,t}$ and $a_{i,t}$. Characterizing $q_{i,t}$ and $a_{i,t}$ as time-varying parameters captures temporary and/or persistent shocks to a division's economic environment that may affect both the division's baseline productivity (see, e.g., Rajan, Servaes, and Zingales, 2000; Brusco and Panunzi, 2005) and the divisions' human capital demand (see, e.g., Eisfeldt and Kuhnen, 2013).[9]

For brevity, suppose that the firm's financial constraint is not binding,[10] allowing the optimal investment level of a division to be determined independently from those of the other divisions. Concretely, a division's optimal investment level, $I^*_{i,t}$, is given by $\frac{d}{dI_{i,t}}\pi_i(I_{i,t}; q_{i,t}, a_{i,t}) = 0$. Then, performing comparative statics of the optimality condition reveals that optimal investment increases in a manager's ability (input-output productivity): $\frac{dI^*_{i,t}}{da_{i,t}} = -\frac{d^2\pi_i}{dI_{i,t}da_{i,t}} / \frac{d^2\pi_i}{dI^2_{i,t}} > 0$. Economically speaking, better managers use the firm's resources more effectively, which induces top management to grant them more resources relative to their less able peers.

[9] Even if manager-specific qualities are considered persistent, changes in the divisions' human capital demand may affect the manager's input-output-productivity over time.

[10] The predictions regarding the effect of division-manager ability on capital allocation remain the same if we model the firm's investment decision with a binding financial constraint.

3. Data and Variables

3.1. Sample selection

Our initial sample includes all multisegment firms in the S&P 1500 index in any year between 2000 and 2018. We restrict the analysis to this period because data in BoardEx, which is the main source of the division manager information, is incomplete before 2000.[11] For these firms, we retrieve firm-level information from Compustat North America Annual and merge these data with Compustat's Segment File. Following the literature, we exclude financial firms (SIC 6000-6999) and utilities (SIC 4900-4999); their financial policies are subject to specific regulation, and their accounting information can differ from those of firms in other sectors. For the same reasons, we remove firms if their segments operate in any of these industries. To be included in our sample, we also require non-missing and non-negative segment data on (1) capital expenditures, (2) assets, (3) net sales, (4) depreciation and nonmissing data on (5) operating profits. To ensure consistency between segment figures and firm totals, we require that the sum of segment sales must be within 5% of consolidated firm totals. For firms that meet this criterion, we allocate the unallocated portion of capital expenditures, assets, sales, depreciation, and operating income to the reported segments on an item-weighted basis. Finally, we exclude firms with missing data on divisional managers, as we discuss in more detail in Section 3.3. Our final sample consists of 346 firms, 1,192 divisions, and 5,328 segment-year observations for the period 2000-2018.[12] Table I summarizes the sample selection steps and provides the number of firms, divisions, and observations retained after each selection step.

Panels A and B of Table II report descriptive segment- and firm-level statistics for our final sample. On average, the firms in our sample operate 3.3 business segments in 2.3 different three-digit SIC code industries. The average (median) business segment owns book assets valued at $2,196 M ($911

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[11] In addition, segment data before and after 1997 are not directly comparable due to new segment reporting requirements under SFAS No. 131, see, e.g., Berger and Hann (2003), Cho (2015), Benz and Hoang (2021).

[12] Our sample is reduced by 2,717 segment-year observations due to the one-year lag requirement for our *DMA-Score* and control variables (see Section 4.1).

M), generates sales of \$2,360 M (\$904 M) and has a segment investment rate (as measured by the ratio of segment capital expenditures to segment assets) of 3.9% (2.9%).

3.2. Capital Allocation and Internal Capital Market Efficiency

To empirically investigate the relationship between managerial ability and capital allocation, we employ two approaches. The first approach estimates regressions of segment-level capital allocation on the *DMA-Score*, our main variable of interest, and a set of segment/firm characteristics. This approach is similar to that introduced by Shin and Stulz (1998) and captures the sensitivity of investment to managerial ability *at the segment level*. In our baseline analysis, we use two standard measures of capital allocation: (1) *segment investment* defined as the ratio of segment capital expenditures scaled by beginning-of-year segment book assets and (2) *industry-adjusted segment investment* defined as the difference between segment investment and the asset-weighted average industry investment (proxied by the capital expenditure-to-asset ratio of single-segment firms operating in the same three-digit SIC code industry).[13] We provide detailed descriptions of these variables in the Appendix.

The second approach directly measures internal capital market efficiency (with respect to the *DMA-Score*) *at the firm level*. At its core (and as explained in more detail in Section 6), we construct a human capital-based variant of the *relative value added* (RVA) measure introduced by Rajan et al. (2000). Specifically, this firm-level measure of investment sensitivity to division managers' abilities is based on the correlation between investment and the *DMA-Scores* across divisions. The firm-level approach has the advantage of allowing us to directly estimate the value consequences of allocating extra funds to more highly skilled managers. The segment-level approach, in contrast, provides a larger sample size due to less restrictive conditions imposed on the data and allows us to control for a rich set of segment and manager characteristics, which we cannot implement in firm-level specifications.

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[13] The industry matching is based on the narrowest SIC grouping (beginning with three-digit SIC codes) that includes at least five segment observations per industry and year.

3.3. Division Managers

A major challenge for our analysis is that detailed information on division managers is not readily available from standard archival sources. We therefore use a combination of textual analysis and hand collection to, first, identify division managers and, then, assign them to corporate divisions – ultimately, to construct a data set that matches managers, divisions, and accounting data.[14] Division manager information is mainly drawn from BoardEx, Form 10-K reports, and DEF-14a proxy statements.

Broadly speaking, the manager-to-segment matching works in two steps: (Step 1) Division managers typically have the title of *division president*, *head of division*, *executive vice president*, *senior vice president*, or combinations thereof. We extract these titles from BoardEx. In most cases, BoardEx also provides job descriptions that include the segment's name (or a business description), which we process with text-matching scores to allocate managers to corporate segments. (Step 2) For validation of the algorithmic division-manager matches, we then retrieve executive information from the firms' annual Form 10-K reports and DEF-14a proxy statements gathered from EDGAR as well as other public sources (e.g., Bloomberg, Capital IQ, LinkedIn, D&B, firm websites, and press releases). With this information, we manually verify and clean the algorithmic matches by hand and one-by-one – in particular, we cross-check the exact start and end date of each manager's division presidency. Finally, we also supplement the textual analysis-based division-manager matches with additional hand-collected matches based on the public sources mentioned above.

Our final sample consists of 1,545 division managers (see Section A of the Internet Appendix for further details on the data collection process). Panel C of Table II shows summary statistics for our sample of division managers. A majority is male (95%), 80% hold a bachelor's degree, 52% hold a master's degree, 7% have a PhD. On average, division managers are 54.2 years old, have a tenure of 6.6 years, and earn a base salary of $441 K.

[14] Our data collection procedure follows the one proposed by Duchin and Sosyura (2013) and subsequently used in Duchin, Goldberg, and Sosyura (2017) and Duchin, Simutin, and Sosyura (2021). Other studies with related data collection procedures are, e.g., Fee and Hadlock (2004), McNeil, Niehaus, and Powers (2004), or Cichello, Fee, and Hadlock (2009).

3.4. Measure of Managerial Ability

To quantify the managerial ability of division managers, we follow the general structure of the *managerial ability score* (*MA-Score*) introduced by Demerjian et al. (2012). This measure of managerial ability provides an estimate of how efficiently top managers generate revenues from a firm's resources. The measure rests on the idea that high-quality (or more able) managers generate more output for a given level of resources than lower-quality (or less able) managers, for instance, by developing superior strategies or implementing more efficient operations.[15]

Using segment-level financial accounting data, we develop a novel variant of the score to quantify the ability of divisional management: the *DMA-Score*. Following Demerjian et al. (2012), the construction of the *DMA-Score* involves the following two stages. In the first stage, we use data envelopment analysis (DEA) to estimate the efficiency with which divisions convert the amount and mix of different resource inputs into outputs.[16] We retrieve inputs and outputs from segment-level financial accounting data. Specifically, we use segment revenues (*sales*) as the division's output and include a vector of two inputs that contribute to the generation of revenue. The first input, total segment assets (*ias*), represents long-term resources and encompasses all capitalized expenditures of the division that are recorded on the balance sheet. The second input is the segment's operating expenses (*opex*). This variable captures short-term resources and expenditures that are not afforded balance sheet recognition, but rather immediately expensed and recognized on the income statement. We construct this variable by subtracting operating profits (*ops*) and depreciation (*dps*) from segment sales (*sales*). We then estimate division-level efficiency scores separately by year over the period from 2000 to 2018 for the Compustat universe of reported business segments with non-missing input and output data.[17] The characteristics of the DEA-based divisional efficiency score resemble

[15] For more details on Demerjian et al.'s (2012) *MA-Score*, see Section B of the Internet Appendix.

[16] DEA is a nonparametric optimization technique that forms a Pareto-efficient frontier – the best performance that can be practically achieved – from the amount and mix of resources to generate revenue by "decision-making units" (here: a firm's divisions). The key innovation of DEA efficiency, relative to other measures (such as ROA or ROE), is that DEA allows for flexible, observation-level weights in the efficiency calculation rather than an explicit set of researcher-imposed weights (typically, equal to 1). This allows for observation-level variation in the optimal mix of inputs and outputs.

[17] An alternative estimation strategy is calculating DEA by industry while combining different time periods within the same calculation group. This method, however, has the potential disadvantage that information from future periods is used

those of the firm efficiency score calculated in Demerjian et al. (2012). The divisional score is bounded between zero and one and has a symmetric distribution with mean (median) of 0.473 (0.478) and minimal skew. We present the detailed summary statistics on the first-stage in Table IA.1 of the Internet Appendix.

The second stage then uses regressions to purge division efficiency (from the first stage) of segment-, firm-, and industry-specific features (such as size or market share) that may affect the division's efficiency but are unlikely to be a direct result of the quality of divisional management. Specifically, we regress *divisional efficiency scores* (from the first stage) on *segment size*, *segment market share*, *segment free cash flow*, and *business segment concentration* using annual Tobit regressions. These variables are direct segment-level analogues to that in the second stage in Demerjian et al. (2012) and capture factors that should aid or hinder a division from operating efficiently.[18] The first division-level covariate, *segment size* (the natural log of the segment's book assets), follows firm size from Demerjian et al. (2012). We expect larger segments to be more efficient than smaller segments due to economies of scale. The second covariate, *segment market share*, is segment sales scaled by total aggregated sales for all segments in the same industry. We expect a positive association between segment market share and efficiency, as a higher share means more market power. The third covariate is *segment free cash flow*, an indicator variable, which captures investment and operating flexibility at the division level, leading to higher efficiency. The fourth covariate is *business segment concentration*, measured as the Herfindahl-Hirschman index of segment sales across reported segments of the firm during the year. This variable measures diversification within the firm and controls for differences in efficiency between firms with varying levels of diversification and complexity (Stein, 1997; Hund et al., 2022). We provide more details on the construction of these

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to calculate current-period efficiency scores, which may introduce look-ahead bias (Demerjian, 2018). In our study, we obtain very similar results from year- and industry-calculated DEA efficiency.

[18] Two of the variables in Demerjian et al. (2012) – firm age and foreign currency transactions – have no segment-level equivalent and are therefore not included in our second stage.

variables in Appendix A1. We also include industry fixed effects (represented by three-digit SIC codes) to control for cross-industry variation in efficiency.[19]

The residual from this estimation is our measure of division-manager ability, the *DMA-Score*. Intuitively, division managers with higher *DMA-Scores* generate more revenue for a given level of resources and, thus, have higher productivity than division managers with lower *DMA-Scores*. Panel C of Table II provides descriptive statistics on the *DMA-Score* for the division managers in our segment-manager matched sample after performing the selection procedure described in Table I. The table reveals a substantial variation in the *DMA-Score* in our sample, with a mean (median) value of 0.021 (0.017) and an interquartile range (standard deviation) of 0.144 (0.113).[20, 21]

[19] We summarize the results from the second-stage regression in Table IA.2 of the Internet Appendix. The results confirm the predicted relations for all covariates.

[20] Similar to Demerjian et al.'s (2012) CEO's *MA-Scores*, the *cross-sectional* variation in division managers' *DMA-Scores* captures factors such as the limited supply of division managers at the top ability level and/or frictions in the external managerial labor market such as search or turnover costs (see the literature on labor and top executive markets, e.g., Baker, Gibbs, and Holmstrom, 1994; Taylor, 2010; Eisfeldt and Kuhnen, 2013; Cziraki and Jenter, 2022). The *time series* variation in the *MA-Scores* and *DMA-Scores* results from temporary or persistent shocks to divisions' human capital demands (see, e.g., Eisfeldt and Kuhnen, 2013) that affect a manager's input-output productivity (see also the theoretical framework in Section 2.2).

[21] In Table IA.3 of the Internet Appendix, we provide summary statistics on the *DMA-Score* for the full sample we use to calculate the score, the population of all Compustat segments (our "estimation sample"), and the manager-segment matched sample data based on the data collection procedure as described in Section 3.1 (our "analysis sample"). By design, the mean value of *DMA-Score* in the population of all Compustat segments is (close to) zero. The mean *DMA-Score* in the analysis sample is slightly higher than in the estimation sample but statistically indistinguishable from zero (untabulated).

4. Empirical Analysis

4.1. Baseline Results: The Effect of Managerial Ability on Capital Allocation

This section presents the formal regression analysis of the relation between managerial ability and capital allocation at the segment level. In the first set of analyses, we estimate different variants of the following equation:

$$SegInv_{i,t} = \alpha + \beta \times DMA\text{-}Score_{i,t\text{-}1} + X'_{i,t\text{-}1} \times \gamma + \eta_t + \epsilon_{i,t} \ . \qquad (1)$$

The dependent variable, $SegInv_{i,t}$, represents investment at the segment level. Here and throughout the paper, we employ the two alternative measures of segment investment described in Section 3.2: (1) *raw* segment investment and (2) *industry-adjusted* segment investment. The main variable of interest is the one-period lagged *DMA-Score* of the manager overseeing segment *i* in period *t*. *X* refers to (1) a set of standard determinants of capital allocation from the literature including industry q, segment size and firm size, the segment's relative size, segment sales growth, segment cash flow, and cash flow of the firm's other segments (see, e.g., Shin and Stulz, 1998; Rajan, Servaes and Zingales, 2000; Billett and Mauer, 2003; Ozbas and Scharfstein, 2010); and (2) a set of personal and professional attributes of the division manager including age, gender, educational background, professional tenure, board membership, and senior leadership position.[22] η_t is a set of year fixed effects, which absorb contemporaneous shocks to investment that all segments face, and $\epsilon_{i,t}$ is the error term. All regressions are with standard errors clustered at the firm level to account for the possibility that residuals may be correlated across segments of the same firm (Petersen, 2009).

Columns 1-3 of Table III report the results for our first measure of capital allocation, (raw) segment investment. We estimate specifications without controls (column 1), with controls for segment and firm characteristics (column 2), and the full set of controls including manager characteristics (column 3). These specifications include industry fixed effects to remove time-invariant common industry

[22] We provide detailed variable definitions of our control variables in Appendix A1.

factors. The association between managerial ability and capital allocation is uniformly positive, of similar magnitude, and statistically different from zero at the 1% level across all specifications, with estimated coefficients $\hat{\beta}$ that range from 4.7% to 5.0%. Moreover, the economic magnitude of these effects is uniformly large. In relative terms, a one-standard deviation increase in managerial ability is associated with a 0.14 standard-deviation increase in segment investment. In absolute terms, for a division with median characteristics, a one-standard-deviation increase in managerial ability results in an extra $4.7 M capital per year, which is an increase of 18% relative to the median absolute segment investment of $25.7 M.[23] This relation translates into aggregate extra capital allocations of $31.1 M during the average tenure of a division manager in our sample (6.6 years, see Table II).

The signs and statistical significance of the other covariates are consistent with the extant literature on segment investment: We find that segment investment is positively related to growth opportunities (proxied by industry q), segment cash flow, segment sales growth, and the segment's relative size compared to the other segments within the firm. Consistent with Shin and Stulz (1998) and the subsequent literature, we also find that a segment's capital investment is positively related to the cash flow of the firm's other segments, but significantly less than to its own cash flow. In addition, in line with recent evidence by Duchin et al. (2021) on the existence of a gender gap in capital budgets, we find that male division managers receive substantially larger capital allocations than do their female counterparts.

Next, we present results for the alternative baseline specification using *industry-adjusted segment investment* as the dependent variable (see, e.g., Lamont, 1997; Rajan et al., 2000) in columns 4-6 of Table III. Instead of controlling for industry fixed effects, we now adjust the dependent variable in columns 1-3, *segment investment*, by the asset-weighted average investment of single-segment firms operating in the same industry and year. A key difference between these two estimation strategies

[23] These estimates are based on column 3 of Table III (coefficient on *DMA-Score*: 0.047). The median segment in the sample has a segment investment rate of 0.029 and capital expenditures of $25.7 M. Thus, a one-standard-deviation increase in managerial ability (0.113, see Table II) is associated with a relative increase of segment investment of 18.3% (0.047 × 0.113 / 0.029), which translates into $4.7 M (18.3% × $25.7 M) additional capital per year.

is that industry-adjustments account for time-varying industry effects that might affect capital investment in an industry in a given year (such as time-varying shocks on technology, regulation, or demand). Moreover, the industry adjustment – as opposed to industry fixed effects – is based on out-of-sample information because the adjustment is calculated with data from single-segment firms. This adjustment method is fairly standard in the literature (see, e.g., Peyer and Shivdasani, 2001; Xuan, 2009; Duchin and Sosyura, 2013; Cho, 2015; Schneider and Spalt, 2016) and implicitly compares investment of segments to that of a benchmark of standalone companies.[24] The estimated coefficient on managerial ability is virtually unchanged (4.7-5.4%) and remains statistically different from zero at the 1% level.[25]

Even with these results, a possible concern is that using standard industry adjustments of the dependent variable (but unadjusted explanatory variables) can lead to distorted estimates (Gormley and Matsa, 2014).[26] Therefore, we also investigate the alternative estimation strategy of including industry-year fixed effects. Our baseline results are unaffected by that alternative design. The regression yields a similar (even slightly larger) coefficient on the *DMA-Score* (5.5%, column 8), which confirms the positive relation between managerial ability and capital allocation.

4.2. Unobservable Characteristics of Firms, Divisions, and CEOs

While we control for a large set of established determinants of internal capital allocation as well as personal and professional attributes of division managers in our baseline tests, unobservable or omitted factors correlated with our main variable of interest, the *DMA-Score*, might confound our

[24] Other studies (e.g., Lamont, 1994 and 1997) calculate the adjustment based on a control group of Compustat segments in the same SIC code industry. Using alternative measures of industry-adjustment does not affect our empirical results.

[25] In Column (7), we present results from another possible estimation strategy to account for time-varying industry effects. Instead of adjusting the dependent variable, the specification in column 7 of Table III includes (the asset-weighted average) industry investment as an additional control (as used in, e.g., Gertner, Powers, and Scharfstein, 2002). Statistical significance and economic magnitude of the estimates are similar to those in the baseline tests of columns (1) to (6).

[26] In our case, it is important to recognize that our main variable of interest, the *DMA-Score*, is already industry-adjusted by design, because it is calculated by year as the residual of segment-level DEA efficiency after removing a number of factors including industry fixed effects (see Section 3.4).

inferences. To mitigate concerns about this issue, we extend the baseline model to include four different groups of fixed effects: (1) firm, (2) division, (3) manager, and (4) CEO fixed effects.

Firm fixed effects remove unobserved, time-invariant firm heterogeneity, such as access to external financing, industry composition, or geographical footprint, and also account for a possible selection of managers into firms. For instance, it is possible that capital-rich firms (i.e., firms with abundant internal resources and higher overall investment) are more likely to attract better skilled managers. *Division fixed effects* remove a possible second source of endogenous matching, that of managers and divisions within the firm. This possible bias could arise from the appointment of managers based on unobserved factors (such as corporate culture or long-term investment policy) that are correlated with both managerial ability and capital allocation. Then, assortative matching of more able managers to divisions with higher capital allocations instead of extra capital allocations to more able managers may explain our baseline results. By exploiting the time-series variation in our ability measure, division fixed effects also absorb other sources of unobserved cross-divisional heterogeneity that remain constant throughout the sample period.[27] Similarly, *manager fixed effects* absorb unobserved persistent differences across managers outside the realm of managerial ability such as preferences or risk aversion that may be correlated with our main variable of interest. *CEO fixed effects* account for the possibility that differences across CEOs (such as attitudes or leadership styles) drive the results.[28]

Table IV presents the results for raw and industry-adjusted segment investment as dependent variables. In columns (1)-(8), we re-estimate the baseline model (see equation 1) with each of the above-mentioned groups of fixed effects. All specifications include year fixed effects and the time-varying controls from the prior regressions (see Table III). The estimated coefficients on the *DMA-Score* remain economically large and statistically different from zero (2.6% - 4.0%, columns 1-8).

[27] Division fixed effects absorb firm fixed effects because, by definition, divisions are hierarchically nested within firms. The analysis of both specifications allows for analyzing separately the two non-mutually exclusive sources of possible selection issues (manager-firm vs. manager-division).

[28] Prior research emphasizes the importance of CEO traits as a key determinant of corporate investment policies (see, e.g., Bertrand and Schoar, 2003; Bertrand, 2009; Malmendier and Tate, 2005 and 2015; Custódio, Ferreira, and Matos, 2013; Graham, Harvey, and Puri, 2015; Bennedsen, Pérez-González, and Wolfenzon, 2020; Guenzel and Malmendier, 2020).

These findings corroborate our baseline results and further mitigate the scope for alternative explanations related to unobservable or omitted factors driving our baseline results.[29]

Prior research also suggests that time-invariant characteristics at the level of a CEO-manager pair may affect capital allocations. For example, commonality (Gaspar and Massa, 2011) and social connections between the CEO and the division manager (Duchin and Sosyura, 2013) may play an important role in the resource allocation across divisions. Therefore, to capture commonality or social similarity between the CEO and division managers as well as any favoring/discriminatory attitudes the CEO might have regarding its division managers, we include CEO-manager (pair) fixed effects as a final alternative fixed effect specification (columns 9 and 10). The division manager ability score coefficients are positive, statistically significant at 5% or better, and remain economically large.

4.3. Managerial Appointments and Assortative Matching Between Managers and Divisions

As discussed in the previous section, assortative (relative to random) matching between managers and divisions as well as division manager appointments may explain the observed association between managerial ability and capital allocation. *Division fixed effects* (see Section 4.2) address this concern, in part, by absorbing unobserved cross-divisional heterogeneity that remains constant throughout the sample period allowing us to exploit the changes in human capital productivity within a division across time. The division fixed effect estimator may not, however, be sufficient to identify the effect of ability on capital allocation if division manager turnovers coincide with unobserved changes in corporate investment policies. As an example, appointments of high-ability managers could occur as part of a new business strategy, when divisions are contemporaneously earmarked for future extra investments. Therefore, we augment our empirical model with *manager-division* (pair) *fixed effects*. The manager-division fixed-effect estimator rules out this arguably most consequential selection concern because it exclusively relies on within-manager-division variation. In other words, the effect of ability on segment investment is estimated only within manager-division pairs; thus, the identification comes only from changes in managers' *DMA-Scores* during the tenure on a segment.

[29] In untabulated results, we obtain statistically and economically similar results when we jointly include division, manager, and CEO fixed effects.

Columns (11) and (12) report the results from the estimation with manager-division fixed effects for raw and industry-adjusted segment investment. The significance and magnitude of the estimates on managerial ability are qualitatively similar to those obtained from the other regressions using fixed effects. This evidence confirms our baseline results and further reduces the scope for alternative explanations driving our results.

Overall, the inclusion of different groups of fixed effects in the Sections 4.2 and 4.3 does not change the coefficient magnitudes in an economically or statistically meaningful way. Our findings also indicate that – despite budgets tending to be rigid – the data variation that identifies our baseline effect is both within and cross-sectional. In particular, we exploit a large degree of *DMA-Score* variation within the firm, within manager-division pairs, and within CEO-manager pairs and show that this variation meaningfully predicts segment investment differences across firms, managers, divisions, and over time.

5. Economic Mechanisms

In this section, we provide additional evidence on the underlying economic mechanisms that drive the positive relation between managerial ability and capital allocation in multisegment firms.

5.1. The Appointment Channel

With the fixed-effects specifications of the previous section, we rule out the possibility that assortative matching between managers and divisions drives our main results. In this section, we provide more direct insights into the economic mechanisms underlying the assignment of managers to divisions in a firm's internal labor market to give additional guidance for the interpretation of the observed results.

Specifically, we explore the allocation of heterogeneously skilled managers to divisions in more detail based on an alternative test and provide complementary evidence on its relevance beyond capital allocation. Our empirical approach is similar to that proposed by Duchin and Sosyura (2013) and focuses on newly appointed division managers who were formerly employed as division managers in a different division of their company (job rotations). This enables us to study the allocation of managerial talent within firms in more detail, albeit with a smaller sample compared to our previous tests. Essentially, we perform a regression analysis in which we investigate how the incoming division manager's prior ability score (measured over the time span as a division manager while being responsible for the prior division) is related to the characteristics of the manager's new division.

Empirical Design and Variables. In our sample, we identify 116 job rotations of division managers with available ability scores from their previous division-manager positions.[30] Following Duchin and Sosyura (2013), we restrict attention to the segments for which these managers took over

[30] We are able to classify a total of 1,018 appointments by using data on executive biographies from BoardEx. Approximately 53% of these appointments are internal promotions (n=543), 28% are internal rotations (n=281) and the remaining 18% are external hires (n=194). Of the 281 internal rotations, there are 116 (41%) for which we have data on the managers' ability scores from their previous divisions. The remaining internal rotations are other (lateral) appointments of managers who served as senior executive officers (e.g., senior vp or president) of a functional area or a region for which ability scores are not available.

responsibility after they had previously been responsible for another division. As dependent variables, we sequentially use: (i) our main capital allocation measures (*raw* and *industry-adjusted segment investment*) and (ii) segment characteristics beyond capital allocation that are potentially relevant to the determination of job allocation decisions (*segment cash flow*, *relative size*, *investment opportunities*, and two dummy variables indicating whether the segment is the *largest segment* within the firm and whether the segment is a *core segment* operating in the firm's main industry). The variable of interest is the manager's ability prior to the appointment, measured as the manager's average *DMA-Score* over the 5-year window preceding the appointment year (*Prior DMA-Score*).[31] In all specifications, we control for the same set of managerial characteristics as in the baseline regression, include year fixed effects, and cluster standard errors at the firm level. All variables are standardized to have zero mean and unit standard deviation to simplify interpretation of the coefficients. See Appendix A1 for detailed variable definitions.

Table V presents the results. In these specifications, we directly examine how the incoming managers' *Prior DMA-Score* relates to their new divisions' characteristics, measured in the year preceding the appointment. In columns (1) and (2), we estimate regressions of raw and industry-adjusted segment investment, respectively. A statistically significant and positive coefficient on our ability measure would indicate that more (less) able division managers are appointed to divisions that received larger (smaller) capital allocations already prior to the appointment. The estimated coefficients on managerial ability, however, are uniformly negative, close to zero (-0.004/-0.005) and statistically insignificant. Consistent with our previous findings, these null results add further support to the view that the allocation of managerial talent across divisions does not induce systematic differences in capital allocations to heterogeneously-skilled managers.

In columns 3-7, we run regressions in which we sequentially replace the dependent variable with the segment characteristics mentioned above (i.e., *segment cash flow*, *relative size*, *investment opportunities*, *largest segment*, and *core segment*) to explore the possibility of alternative forms of

[31] This design is similar to the approach used in Demerjian et al. (2012) who examine how the ability scores of 78 newly appointed CEOs (measured in their prior firm) relate to the performance of their new firm.

assortative matching between managers and divisions beyond capital allocation. For instance, it is possible that higher-quality managers are systematically appointed to segments with specific characteristics such as segments with higher cash flow or core segments of the firm. The results point to one salient segment characteristic: we document a positive and significant relation between managerial ability and the assignment to larger divisions of the firm. The corresponding regressions are reported in columns 3 (relative size) and 4 (largest segment), each with estimated coefficients on managerial ability that are statistically different from zero at the 1% level. Specifically, a one-standard-deviation increase in managerial ability is associated with a 5.4% higher relative segment size (column 3) and 14.0% higher likelihood of being appointed to the largest segment of the firm (column 4). Furthermore, we find no evidence that better-skilled managers are systematically assigned to divisions with better overall investment opportunities (column 5). Finally, there are insignificant correlations between division managers' abilities and assignment to segments that generate more cash flow (column 6) or that operate in the core business of the firm (column 7).

Overall, these findings suggest that human capital heterogeneity has substantial impact on the allocation of division managers in the firm's internal labor market. The key takeaway here is that more able managers are systematically appointed to larger divisions of the firm, which also implies that, all else equal, their capital budgets are larger in absolute terms compared to those of their peers running smaller divisions. On a relative scale, however, there is no evidence of a direct relationship between the appointment of heterogeneously skilled division managers and capital allocation, which further suggests that our main results are not affected by this channel.

5.2. The Governance Channel

In this section, we examine the impact of corporate governance on the relation between division-manager ability and capital allocation. To the extent that allocating more capital to more able division managers is value-enhancing, the link between division-manager ability and capital allocation should be stronger in well-governed firms than in poorly-governed firms. Poorly-governed firms are likely to be characterized by top managers' opportunistic behavior and capital allocation for personal benefit, which is unlikely to be associated with "efficient" capital allocation towards the most able division managers.

To formally investigate this hypothesis, we interact our main variable of interest, *DMA-Score*, with a standardized composite index (*GOV*) of three individual measures representing both *internal* and *external* governance:[32] (1) *Board Independence*, the fraction of outside directors on the board; (2) *CEO Equity-based Pay*, the fraction of shares held by the CEO; and (3) *Institutional Ownership*, the percentage of shares held by institutional investors. This index captures the three main constituents of governance: (1) Managerial incentives via executive compensation (see, e.g., Edmans, Gabaix, and Jenter, 2017), (2) Internal monitoring via board of directors (see, e.g., Adams, 2017), and (3) External monitoring via institutional investors (see, e.g., Edmans and Holderness, 2017). To construct the index, we standardize each governance measure to have mean zero and standard deviation one, and then take their averages. Finally, we standardize the index to facilitate interpretation.

Columns (1)-(4) of Table VI present the results. The dependent variable is one of the two measures of divisional capital investment: raw segment investment (columns 1 and 3) and industry-adjusted segment investment (columns 2 and 4). Our variable of interest is the interaction between division-manager ability (the one-period-lagged *DMA-Score*) and our index of corporate governance quality, *GOV*. Other independent variables are the *DMA-Score*, the index of corporate governance quality *GOV*, and the set of controls from our baseline analysis. Columns (1) and (2) of Table VI present the results of this specification. In columns (3) and (4), we also interact all control variables with the governance index to address the concern that the interaction between division-manager ability and the governance index spuriously absorbs other heterogeneities for different levels of governance.

Consistent with our hypothesis, we find that investment by segments of well-governed firms is more sensitive to division managers' ability than investment by segments of poorly governed firms. Across all specifications and measures of segment capital investment, the coefficients on the interaction term *DMA-Score* $\times$ *Governance Index* are uniformly positive and statistically significant at the 1%

[32] These measures are imperfectly correlated and capture different economic dimensions of corporate governance.

level. The magnitudes of these coefficients are also economically large (1.8-2.8%). For example, for the specification that produces the most conservative result, column (1), a one-standard-deviation increase in corporate governance quality, as measured by our composite index, increases the effect of division-manager ability on capital allocation by 1.8 percentage points (which is approximately 49% of a standard deviation in raw segment investment of 3.7%, see Table II).

We also consider each of the three corporate governance measures separately. Columns (5)-(10) of Table VI estimate the interaction between division-manager ability and governance for each of the abovementioned governance measures (instead of the composite index *GOV*).[33] The coefficients on the interaction are uniformly positive and statistically significant at the 10% level or better across all specifications and measures of segment capital investment. The magnitudes of the standardized coefficients are also economically large (1.2-2.5%) and similar to those of the regressions based on the composite index of governance.

This evidence suggests that when allocating capital, well-governed firms engage more strongly in winner-picking activities based on division managers' abilities. The findings also provide indirect evidence that DMA-sensitive segment investment reflects an optimal capital allocation policy (an empirical question that we explore, in more detail, in Section 6).

5.3. The Capital Budgeting Process, Cash Windfalls and Capital Allocation

In this section, we study unexpected exogenous firm-wide cash windfalls as a potential channel through which division-manager ability could affect capital allocation. Cash windfalls provide firms with greater financial capacity to undertake additional investments (see, e.g., Stein, 2003; Blanchard, Lopez-de-Silanes, and Shleifer, 1994), which – by their nature – tend to be discretionary (e.g., capacity expansions, new businesses) instead of mandatory (e.g., maintenance, replacement

[33] For brevity, columns (5) to (10) present regression results for specifications with all control variables interacted. We obtain economically and statistically similar results when estimating these specifications without these additional interactions.

investments or investments for regulatory compliance).[34] Given that mandatory investments are known to be relatively insensitive to criteria that typically determine capital allocation, the effect of division manager ability on capital allocation should be even stronger in periods of cash windfalls if windfalls are indeed channeled towards more able managers. Under a competing hypothesis, however, firms may use the liquidity windfalls for unprofitable purposes (instead of directing them towards the most productive managers), which may dampen the effect estimated in the baseline regression.[35] In either case, an appealing feature of this analysis is that cash windfalls occur after the regular budget is determined in a given period, which allows us to further address concerns about confounding factors specific to the budgeting process that could affect our baseline results.

Empirical Design and Variables. To explore the incremental effects of cash windfalls on our results, we interact our main variable of interest, *DMA-Score*, with a measure that captures positive unexpected shocks in a firm's cash flow based on time-series data. To construct our windfall measure, we adopt an approach from the literature (e.g., Irvine and Pontiff, 2009; Kale and Loon, 2011; Duchin et al., 2017) that uses time-series regressions to purge the firm's annual change in cash flow (i.e., the difference in current and preceding year's operating cash flow scaled by book assets) of serial correlation, persistence and business cycle variation. Specifically, we calculate unexpected cash flow shocks as the residual from regressing the firm's annual change in cash flow on the firm's annual cash flow changes over the past three years:

$$\begin{aligned} CF_{i,t} - CF_{i,t\text{-}1} = \alpha + \beta_1 \times (CF_{i,t\text{-}1} - CF_{i,t\text{-}2}) + \beta_2 \times (CF_{i,t\text{-}2} - CF_{i,t\text{-}3}) \\ + \beta_3 \times (CF_{i,t\text{-}3} - CF_{i,t\text{-}4}) + \gamma_i + \eta_t + \epsilon_{i,t}. \end{aligned} \tag{2}$$

The residuals $\epsilon_{i,t}$ from this regression represent vectors of unexpected shocks to a firm's cash flow. Because the focus of our analysis is on positive cash flow shocks, we define our windfall measure

[34] For the distinction between mandatory and discretionary investment see, e.g., Ross (1986). Mandatory investments are projects chacterized by very large NPVs and not implementing them would significantly harm the firm's/division's operations. Maintenance, replacement or regulatory compliance investments are typically approved without an elaborate decision process (see, e.g., Ross, 1986; Weston and Brigham, 1993; Hoang, Gatzer and Ruckes, 2022).

[35] For instance, Glaser et al. (2013) provide field evidence that cash windfalls can be a source of misallocation of capital.

(*Cash Windfall*) as the residual from equation (2) if the residual is *positive*, and zero otherwise. We then examine how cash windfalls affect the relation between managerial ability and capital allocation.

Table VII, columns (1) and (2), present the results of our main specifications. The dependent variable is either raw segment investment (column 1) or industry-adjusted segment investment (column 2). The variable of interest is the interaction between *DMA-Score* and *Cash Windfall*. Other independent variables are the *DMA-Score*, our windfall measure, and the set of controls from our baseline analysis. Consistent with our intuition, we find that capital allocation is more sensitive to division managers' abilities in periods with cash windfalls. The coefficients of the interaction term, *DMA-Score* × *Cash Windfall*, are positive, statistically significant at the 5% level and economically large in both specifications. Given the most conservative estimate of 0.580 (column 2), a one-standard-deviation increase in *Cash Windfall* (0.020, see Table II) increases the effect of managerial ability on capital allocation by 1.2 (calculated as 0.020 × 0.580) percentage points (or 28% in relative terms).

One concern with this result is that the interaction *DMA-Score* × *Cash Windfall* might spuriously reflect other heterogeneities between more and less able division managers during periods of firm-wide cash windfalls. For instance, Glaser et al. (2013), who study the internal capital market of a large European-headquartered conglomerate, find that powerful managers obtain significantly more investment approvals when a cash windfall occurs. To address this concern, we interact all covariates (including the manager and segment-level controls that capture managerial power such as age, tenure, board membership, relative segment size) with our windfall measure, which allows each manager- or division-level characteristic to have an effect on capital allocation that depends on the magnitude of the cash windfall. For both measures of segment capital investment, the results remain qualitatively similar to those reported in our main specifications (see Table VII, columns 3-4).

As an alternative approach, we calculate a managerial power index, which we include in the regressions, both separately and interacted with our windfall measure. Our index (*Power Index*), similar to the one in Glaser et al. (2013), is formed by averaging the following four variables, each normalized to fall between zero and one: (1) a dummy that equals one if the manager is a member of the board of directors; (2) the manager's professional tenure at the firm measured in years; (3)

the relative size of the manager's segment within the firm; and (4) a dummy that equals one if the manager's job title in BoardEx indicates a senior leadership role such as ”executive vice president”, ”group president”, or ”divison CEO”. Columns (5)-(6) of Table VII present the results. In both specifications, the interaction term, *Power Index* × *Cash Windfall*, enters with a positive and statistically significant coefficient, which replicates Glaser et al.'s result that more powerful managers obtain larger capital allocations when funds from cash windfalls are available. Nevertheless, the coefficients of interest, the interaction *DMA-Score* × *Cash Windfall*, remain economically and statistically significant, with even slightly larger magnitudes than those from the main model specification in columns (1) and (2).[36] This evidence dispels the notion that our results are driven by differences in managerial power.

6. Managerial Ability, Investment Efficiency and Firm Value

Our results in the previous sections document a positive and economically meaningful relationship between segment investment and division manager ability. These sections implicitly assume that the capital flow towards segments of more able managers likely reflects a *value-adding* and alternative form of winner-picking (Stein, 2003). Up to this point, however, we have provided no direct evidence for such a value-enhancing effect of human capital-sensitive resource allocations. In fact, higher capital allocations to more able managers could have no firm value effect or could be suboptimal in equilibrium.

To understand the value implications, in this section, we examine whether the extra capital allocated to more able division managers can be interpreted as evidence of efficient investment, i.e., whether it translates into higher firm values, and if so, if such an effect is economically relevant. To this end, we move our analysis from the *segment* level to the *firm* level. This allows us to directly estimate the relation between human capital-sensitive resource allocation and firm value with standard excess

[36] The correlation between *DMA-Score* and *Power Index* is statistically insignificant and close to zero (3.4%).

value regressions (see, e.g., Rajan, Servaes and Zingales, 2000; Billett and Mauer, 2003; Ahn and Denis, 2004; Duchin and Sosyura, 2013; Schneider and Spalt, 2016).

Measure of Excess Value. Following Berger and Ofek (1985), we define the excess value of a multisegment firm as the natural log of the ratio of the firm's *market value* to its *imputed value*. A firm's *market value* is computed as the sum of its book value of debt and its market value of equity. A firm's *imputed value* is the sum of the imputed standalone values of its segments. Each segment's imputed standalone value is given by the segment's book value of assets multiplied by the median market-to-book ratio of single-segment firms in the segment's three-digit SIC code industry.

Measure of Sensitivity of Cross-Segment Investment to DMA. To quantify firms' human capital-oriented resource allocation *at the firm-level*, we construct a novel measure (the main variable of interest in the following regressions) that captures the firm-level sensitivity of segment investment to its division managers' abilities. Our measure, labeled *DMA-Transfer*, is a variant of the concept of *relative value added (RVA)*, introduced by Rajan, Servaes and Zingales (2000), and measures the firm-level investment sensitivity to division managers' abilities based on the correlation between investment and the DMA scores across divisions. Specifically, we define *DMA-Transfer* as the asset-weighted covariance between cross-segment investment and division managers' abilities:[37]

$$DMA\text{-}Transfer = \sum_{i=1}^{n} w_i \times \left(DMA_i - \overline{DMA}\right) \times \left[\frac{I_i}{A_i} - \frac{I_i^{ss}}{A_i^{ss}} - \sum_{i=1}^{n} w_i \times \left(\frac{I_i}{A_i} - \frac{I_i^{ss}}{A_i^{ss}}\right)\right] \tag{5}$$

where $w_{i,t}$ is segment i's share of total firm assets at the beginning of period t, DMA_i is the one-period-lagged division-manager ability score described in Section 3.4, $\overline{DMA}$ is the asset-weighted average ability of the firm's division managers, I_i are the capital expenditures of segment i, A_i are the book assets of segment i at the beginning of the period, and I_i^{ss} and A_i^{ss} are the asset-weighted average capital expenditures and assets for single segment firms operating in the same three-digit SIC industry as segment i.

[37] For the covariance interpretation of Rajan, Servaes and Zingales (2000)'s RVA measure, see Çolak and Whited (2007).

The term in square brackets, $\left[\frac{I_i}{A_i} - \frac{I_i{}^{ss}}{A_i{}^{ss}} - \sum_{i=1}^{n} w_i \times \left(\frac{I_i}{A_i} - \frac{I_i{}^{ss}}{A_i{}^{ss}}\right)\right]$, proxies for the transfer of capital that segment *i* makes or receives. *DMA-Transfer* is positive if segments with high-ability division managers within the firm $\left(DMA_i - \overline{DMA} > 0\right)$ receive more transfers on an asset-weighted basis than low-ability managers $\left(DMA_i - \overline{DMA} < 0\right)$ do. Accordingly, the higher (lower) the value of *DMA-Transfer* is, the stronger the firm tilts its capital budget (and ultimately the distribution of its assets in place) towards relatively more (less) capable division managers.

Control Variables. In the excess value regressions, we control for a large set of common determinants of firm value, which we choose and define following Campa and Kedia (2002). In some specifications, we also add relative value added (RVA) as defined by Rajan, Servaes and Zingales (2000) to account for the possibility that our main variable of interest, *DMA-Transfer*, (partially) captures the sensitivity of investment to divisions' investment opportunities (as opposed to its division managers' abilities).

Results. Table VIII presents the results. In columns (1)-(5), we estimate different regressions of excess value on our main variable of interest, *DMA-Transfer*, with and without covariates as well as with and without firm fixed effects. All regressions cluster standard errors at the firm level.

In columns (1)-(2) of Table VIII, we run specifications with and without controls for our baseline sample. The results indicate a strong positive relation between *DMA-Transfer* and excess value. The coefficient on our variable of interest, *DMA-Transfer*, is uniformly positive (0.379-0.381) and statistically different from zero at the 5%-level. The magnitudes are also economically significant. A one standard-deviation increase in *DMA-Transfer* (0.085, see Table II) is associated with a 3.2% increase in excess value (calculated as 0.379 × 0.085 for column 1 and 0.381 × 0.085 for column 2), suggesting that capital flows towards more able managers increase firm value in a non-trivial way. For robustness, we also estimate a specification similar to that in column (2) but include RVA as an additional control (column 3). This regression yields an even slightly larger coefficient of interest (0.393), which is statistically significant at the 1% level and, thus, rules out the concern that capital flows towards divisions with better investment opportunities (i.e., higher q) are driving the positive relation between *DMA-Transfer* and firm value. To account for unobserved, time-invariant differences across firms, we also augment the multivariate specifications with firm fixed effects (columns 4 and 5). The positive coefficient is statistically significant at the 10%-level, which documents that the results also hold, with somewhat smaller magnitudes, *within* firms over time.[38]

To further assess the economic magnitude of the estimated effect, we evaluate our results against the benchmark of standalone firms, which we now include in the analysis. In columns (6)-(7) of Table VIII, we repeat the previous regressions but add a conglomerate dummy, which is equal to one for multisegment firms. Note that *DMA-Transfer* of standalone firms is zero by construction. In line with the existing literature on conglomerate valuation, we document that the multisegment firms in our sample are valued, on average, at a discount of about 8% to 11% relative to standalone firms.[39] The estimated coefficients on *DMA-Transfer* remain virtually unchanged in terms of size and significance compared to the ones in the previous specifications with and without firm fixed effects (columns 3 and 5). In economic terms, a one-standard-deviation increase in *DMA-Transfer* is associated with a 2.4 (column 7: 0.287×0.085) to 2.9 (column 6: 0.341×0.085) percentage-point increase in excess value, which translates into a reduction of the estimated discount by a nontrivial magnitude of about 22% (column 7) to 36% (column 6).

Overall, these results support the view that *DMA*-sensitive investment is beneficial to shareholder wealth, which suggests that the strong positive association between segment investment and division manager ability documented in our previous analysis can be interpreted as evidence of efficient investment.

[38] Note that, in untabulated analysis, we decompose the total variation in *DMA-Transfer* in our analysis sample and document that the majority of *DMA-Transfer* variation (62%) is across rather than within firms (38%).

[39] While the diversification discount is well-established in the literature on conglomerates, several important papers have shown that this empirical fact is not necessarily evidence of the inefficiency of diversification itself (see e.g., Campa and Kedia, 2002; Villalonga, 2004a and 2004b; Graham, Lemmon, and Wolf, 2002; Hyland and Diltz, 2002; Hoberg and Phillips, 2011; Whited; 2001; Çolak and Whited; 2007). Note that the focus of our analysis is the cross-sectional variation in excess values – as opposed to assessing the average discount or premium of a conglomerate.

7. Conclusion

Most prior studies model capital allocation as a function of industry-, firm- or segment-level characteristics, but do not acknowledge the role of divisional managers. This is surprising given that the return of a project likely depends not just on its project characteristics but also on the characteristics of the individual responsible for executing the project. In this paper, we explore how managerial skills of divisional managers affect capital allocation. Using a novel measure of division-manager ability and a hand-collected, matched dataset of divisional managers at S&P 1,500 firms, we find that firms allocate more capital to divisional managers with higher levels of ability. This relationship is robust to controlling for the possibility of assortative matching, is particularly strong in well-governed firms, and applies to both routine and windfall allocations. Notably, capital flows towards more able division managers also increase firm value. Overall, these findings provide new evidence on the functioning of internal capital markets and highlight a largely unexplored bright side of diversification.

Appendix

Table A1. Variable Definitions

Variable	Definition
A. Segment Characteristics	
Segment investment	Annual capital expenditure of the segment (capxs) scaled by the segment's book assets at the beginning of the year (ias – capxs + dps).
Industry-adjusted segment investment	Segment investment adjusted for the asset-weighted average investment of single-segment firms operating in the same industry. The industry matching is based on the narrowest SIC grouping (beginning with three-digit SIC codes) that includes at least five single-segment firms per industry and year.
Industry q	The median Tobin's q across all single-segment firms operating in the segment's industry. The industry matching is based on the narrowest SIC grouping (beginning with three-digit SIC codes) that includes at least five single-segment firms per industry and year.
Segment cash flow	The segment's operating income before depreciation (ops + dps) scaled by the segment's book value of assets at the beginning of the year (ias – capxs + dps).
Other segments' cash Flow	The aggregated operating income before depreciation of the firm's other segments (ops + dps) scaled by the segments' aggregated book value of assets at the beginning of the year (ias – capxs + dps).
Segment size	The natural logarithm of the segment's book value of assets. Book values are computed as of the beginning of the year (ias – capxs + dps).
Segment relative size	Book value of segment assets (ias) divided by the sum of book asset across all segments of the firm.
Segment sales growth	The annual percentage change in segment sales (sales).
Segment operating expenses	Segment sales (sales) – segment profit (ops) – segment depreciation and amortization (dps).
Segment free cash flow	Indicator variable that equals one if the segment's free cash flow (ops + dps – capxs) is positive in a given period, and zero otherwise.

Segment market share	Segment sales (sales) scaled by the aggregated sales of segments and (single-industry) firms operating in the same FF-48 industry and year.
Business segment concentration	The Herfindahl-Hirschman index (HHI) of segment sales across reported segments of the firm during the year.
B. Firm Characteristics	
Number of segments	Number of business segments reported by the firm.
DMA-Transfer	The asset-weighted covariance between cross-segment investment and division managers' abilities: $$\sum_{i=1}^{n} w_i \times \left(DMA_i - \overline{DMA}\right) \times \left[\frac{I_i}{A_i} - \frac{I_i^{ss}}{A_i^{ss}} - \sum_{i=1}^{n} w_i \times \left(\frac{I_i}{A_i} - \frac{I_i^{ss}}{A_i^{ss}}\right)\right],$$ where $w_{i,t}$ is segment *i*'s share of total firm assets at the beginning of period t, DMA_i is the one-period-lagged division manager ability score described in Section 3.4, $\overline{DMA}$ is the asset-weighted average ability of the firm's division managers, I_i are the capital expenditures (capxs) of segment i, A_i are the book assets of segment i at the beginning of the period (ias – capxs + dps), and I_i^{ss} and A_i^{ss} are the asset-weighted average capital expenditures and assets for single segment firms operating in the three-digit SIC industry of segment i.
Excess value	The natural log of the ratio of the firm's actual value to its imputed value (Berger and Ofek, 1995). A firm's actual value is the sum of market value of equity plus book value of debt (csho × prcc_f + dltt + dlc). A firm's imputed value is the sum of the imputed values of its segments, where each segment's imputed value is the segment's book assets multiplied by the asset-weighted average of the market-to-book ratio for single-segment firms in the same industry. The industry matching is based on the narrowest SIC grouping (beginning with three-digit SIC codes) that includes at least five single-segment firms per industry and year.
Governance index	A composite index combining three measures of corporate governance: (i) board independence, the percentage of outside directors relative to board size, (ii) the percentage of shares held by institutional investors, and (iii) the fraction of equity-based pay in the CEO's total pay. The composite governance index is created by standardizing each measure (i.e., zero mean and standard deviation equal one) and then taking the standardized mean.
Cash windfall	The residual from a regression of the firm's annual change in cash flow on the firm's annual cash flow changes over the past three years (Duchin et al., 2017) multiplied by an indicator that equals one if the residual is positive, and zero otherwise.
Firm size	The natural logarithm of the firm's book value of assets (at).

CapEx	The ratio of firm capital expenditures (capx) to firm sales (sale).
Profitability	Earnings before interest and depreciation (ebit) scaled by firm sales (sale).
Leverage	The ratio of total debt (dlc + dltt) scaled by total book assets (at).
RVA (RSZ, 2000)	The relative value added measure as defined by Rajan, Servaes and Zingales (2000).
C. Division Manager Characteristics	
DMA-Score	The division-manager ability score as described in Section 3.4.
Male	Indicator variable that equals one if the manager is male, and zero otherwise.
Age	The division manager's age in years.
Tenure	The number of years the manager has spent on his or her current position.
Board member	Indicator variable that equals one if the divisional manager is a member in the board of directors, and zero otherwise.
Senior leadership position	Indicator variable that equals one if the divisional manager has the title "*executive vice president*", "*group president*", "*executive officer*" or "*division ceo*", and zero otherwise.
Power index	A combined index formed by averaging the following four variables, each normalized to fall between zero and one: (1) board member; (2) the manager's professional tenure at the firm measured in years; (3) relative segment size; and (4) senior leadership position.
Bachelor/Master	Indicator variable that equals one if the highest education level achieved by a division manager is a bachelor's degree or a master's degree, and zero otherwise.
PhD/MBA	Indicator variable that equals one if the highest education level achieved by the manager is a PhD degree or an MBA degree, and zero otherwise.
Ivy league degree	Indicator variable that equals one if the manager obtained a degree from an Ivy League institution, and zero otherwise.

Table I. Sample Selection

This table documents the sample selection procedure and provides the retained number of firms, divisions, and observations after each selection step. The sample consists of S&P 1500 firms that operate two or more business segments. The sample period ranges from 2000 to 2018. Division managers are identified based on text-matched and hand-collected data drawn from BoardEx, annual Form 10-K reports, and DEF-14a proxy statements.

	Number of Firms	Number of Firm-Years	Number of Segments	Number of Segment-Years
S&P 1500 firms with two or more segments (2000-2018)	1,509	16,526	9,200	55,523
Less:				
Financial firms and utilities (and firms with segments in these sectors)	309	3,874	2,273	14,993
Incomplete or anomalous financial data at firm or segment level	53	1,400	616	5,206
Firms with functional or geographic organizational structure; missing correspondence between Compustat segments and division manager information; unavailability of division manager information	740	7,779	4,818	27,279
Full sample	407	3,473	1,493	8,045
One-year lag requirement for DMA-Score and control variables	61	863	301	2,717
Final sample	346	2,610	1,192	5,328

Table II. Descriptive Statistics

This table reports descriptive statistics. The sample consists of S&P 1500 firms that operate two or more business segments. The sample period ranges from 2000 to 2018. The number of observations (Nobs) in Panel A represents firm-years, and the number of observations (Nobs) in Panel B and C represents segment-years. See Table A1 for detailed variable descriptions.

Variable	Mean	Median	Std. dev.	25th Perc.	75th Perc.	Nobs
A. Firm Characteristics						
Number of segments	3.263	3.000	1.144	2.000	4.000	2,610
Number of industries (SIC 3)	2.285	2.000	1.061	2.000	3.000	2,610
Assets ($ millions)	7,715	2,804	13,222	1,185	6,899	2,610
Sales ($ millions)	7,673	2,700	13,534	1,240	6,882	2,610
DMA-Transfer * 100	0.026	0.010	0.085	-0.013	0.060	1,951
Capital expenditure/assets	0.039	0.031	0.029	0.020	0.048	2,610
Profitability	0.101	0.098	0.085	0.057	0.141	2,610
Book leverage	0.240	0.243	0.130	0.153	0.324	2,610
Cash windfall	0.007	0.000	0.020	0.000	0.000	2,590
B. Segment Characteristics						
Segment investment	0.039	0.029	0.037	0.016	0.050	5,328
Ind.-adj. segment investment	-0.001	-0.005	0.036	-0.019	0.012	5,328
Assets ($ millions)	2,196	911	3,301	328	2,504	5,328
Sales ($ millions)	2,360	904	4,673	380	2,427	5,328
Industry q	1.478	1.404	0.381	1.211	1.657	5,328
Segment cash flow	0.112	0.126	1.976	0.078	0.185	5,328
Segement relative size	0.327	0.280	0.214	0.156	0.456	5,328
Segment sales growth	0.076	0.057	0.207	-0.019	0.142	5,328
C. Division Manager Characteristics						
DMA-Score	0.021	0.017	0.113	-0.052	0.092	5,328
Age	54.209	54.000	6.188	50.000	58.000	5,328
Male	0.951	1.000	0.216	1.000	1.000	5,328
Tenure (position)	6.625	6.000	4.011	4.000	8.000	5,328
Board member	0.016	0.000	0.127	0.000	0.000	5,328
Senior leadership position	0.365	0.000	0.482	0.000	1.000	5,328
Salary ($ thousands)	441	418	164	325	527	3,477
Salary + Bonus ($ thousands)	570	481	333	369	650	3,477
Bachelor	0.797	1.000	0.402	1.000	1.000	5,328
Master	0.516	1.000	0.500	0.000	1.000	5,328
MBA	0.333	0.000	0.471	0.000	1.000	5,328
PhD	0.067	0.000	0.249	0.000	0.000	5,328

Table III. Baseline Regression

This table presents the results of OLS regressions on the relation between division-manager ability and segment-level capital allocation. The sample period ranges from 2000 to 2018. The dependent variable is raw segment investment in columns (1)-(3), (7)-(8) and industry-adjusted segment investment in columns (4)-(6). The key variable of interest, *DMA-Score*, is the measure of division-manager ability described in Section 3.4. Explanatory variables are lagged one year, and continuous variables are winsorized at the 1% and 99% levels. Standard errors (in brackets) are clustered at the firm level. See Table A1 for detailed variable descriptions.

Dep. Var.:	Segment Investment			Ind.-Adj. Segment Investment			Segment Investment	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DMA-Score	0.050***	0.048***	0.047***	0.054***	0.047***	0.048***	0.042***	0.055***
	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)
Segment Controls								
Industry q		0.006**	0.006**		0.007***	0.008***	0.002	
		(0.003)	(0.003)		(0.002)	(0.002)	(0.002)	
Segment cash flow		0.028***	0.027***		0.033***	0.034***	0.039***	0.010
		(0.008)	(0.007)		(0.008)	(0.008)	(0.008)	(0.009)
Other segments' cash flow		0.021*	0.021**		0.006	0.006	0.014	0.003
		(0.011)	(0.010)		(0.011)	(0.011)	(0.011)	(0.011)
Segment size		-0.002***	-0.002***		-0.002**	-0.002*	-0.002*	-0.002**
		(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Segment relative size		0.008**	0.008**		0.010***	0.010**	0.012***	0.008
		(0.004)	(0.004)		(0.004)	(0.004)	(0.004)	(0.005)
Sales growth		0.008***	0.008***		0.005*	0.005*	0.006**	0.005
		(0.002)	(0.002)		(0.003)	(0.003)	(0.003)	(0.003)
Industry investment							0.532***	
							(0.078)	
Manager Controls								
Male			0.009***			0.006**	0.007***	0.009**
			(0.003)			(0.002)	(0.002)	(0.003)
Age			0.000			-0.000	0.000	0.000
			(0.000)			(0.000)	(0.000)	(0.000)
Tenure			0.000			-0.000	0.000	0.000
			(0.000)			(0.000)	(0.000)	(0.000)
Board member			0.001			-0.002	-0.002	0.004
			(0.003)			(0.005)	(0.004)	(0.004)
Senior leadership position			0.001			-0.001	0.000	0.001
			(0.002)			(0.002)	(0.002)	(0.002)
Bachelor/Master			0.002			-0.002	0.000	0.002
			(0.002)			(0.002)	(0.002)	(0.003)
PhD/MBA			0.001			-0.001	-0.000	0.002
			(0.002)			(0.002)	(0.002)	(0.003)
Ivy league degree			-0.000			-0.006*	-0.005*	-0.001
			(0.003)			(0.003)	(0.002)	(0.003)
Year FE	X	X	X	X	X	X	X	
Industry FE	X	X	X					
Industry-Year FE								X
Nobs	5,328	5,328	5,328	5,328	5,328	5,328	5,328	5,328
Adjusted R^2	0.36	0.38	0.38	0.03	0.05	0.05	0.21	0.47

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IV. Unobservable Characteristics and Matching of Divisional Managers to Firms and Divisions

This table presents the results of fixed-effects regressions on the relation between division-manager ability and segment-level capital allocation. The sample period ranges from 2000 to 2018. The dependent variable is raw segment investment (odd columns) or industry-adjusted segment investment (even columns). *DMA-Score* is the measure of division-manager ability described in Section 3.4. Control variables include the same characteristics of the division, firm, and manager used in Table III. Explanatory variables are lagged one year, and continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in brackets) are clustered at the firm level. See Table A1 for detailed variable descriptions.

Fixed Effect	Firm		Division		Manager		CEO		CEO × Manager		Manager × Division	
Dep. Var.:	Seg. Inv.	Ind.-Adj. Seg. Inv.	Seg. Inv.	Ind.-Adj. Seg. Inv.	Seg. Inv.	Ind.-Adj. Seg. Inv.	Seg. Inv.	Ind.-Adj. Seg. Inv.	Seg. Inv.	Ind.-Adj. Seg. Inv.	Seg. Inv.	Ind.-Adj. Seg. Inv.
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DMA-Score	0.040***	0.035***	0.026***	0.031***	0.032***	0.032**	0.040***	0.034***	0.029***	0.029**	0.033***	0.035***
	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.013)	(0.009)	(0.009)	(0.009)	(0.012)	(0.009)	(0.011)
Controls	X	X	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X	X	X
Industry FE	X		X		X		X		X		X	
Firm FE	X	X										
Division FE			X	X								
Manager FE					X	X						
CEO FE							X	X				
CEO × Manager FE									X	X		
Manager × Division FE											X	X
Nobs	5,328	5,328	5,328	5,328	5,328	5,328	5,328	5,328	5,328	5,328	5,328	5,328
Adjusted R^2	0.49	0.24	0.60	0.46	0.62	0.48	0.52	0.29	0.63	0.51	0.64	0.52

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table V. The Appointment Channel

This table presents the results of regressions examining how segment characteristics are associated with the appointment of division managers. The sample period ranges from 2000 to 2018. The sample includes segment-year observations in which newly appointed division managers took over responsibility after they had previously been responsible for another division (job rotations). The dependent variable is one of the characteristics of the manager's new division measured in the year preceding the appointment. The key variable of interest, *Prior DMA-Score*, is the newly appointed manager's average *DMA-Score* (the measure of division-manager ability described in Section 3.4) from the previous division measured over the 5-year window preceding the appointment year. Standard errors (in brackets) are clustered at the firm level. See Table A1 for detailed variable descriptions.

Dep. Var.:	Seg. Inv. Lag 1	Ind.-Adj. Seg. Inv. Lag 1	Relative Size Lag 1	Largest Segment Lag 1	Industry Q Lag 1	Cash Flow Lag 1	Core Segment Lag 1
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prior DMA-Score	-0.004	-0.005	0.054***	0.140***	-0.051	0.017	0.022
	(0.003)	(0.004)	(0.017)	(0.050)	(0.071)	(0.011)	(0.059)
Male	-0.002	-0.000	0.124*	-0.028	-0.107	0.062	-0.283
	(0.011)	(0.012)	(0.073)	(0.276)	(0.213)	(0.037)	(0.208)
Age	-0.000	0.000	-0.003	-0.003	-0.000	-0.002	-0.009
	(0.001)	(0.001)	(0.004)	(0.010)	(0.007)	(0.003)	(0.010)
Bachelor/Master	-0.002	-0.001	-0.024	-0.019	-0.066	-0.036	-0.219
	(0.007)	(0.008)	(0.042)	(0.142)	(0.157)	(0.027)	(0.151)
PhD/MBA	0.003	0.004	-0.054	-0.166	0.008	-0.020	-0.258*
	(0.008)	(0.010)	(0.046)	(0.147)	(0.152)	(0.029)	(0.147)
Ivy league	-0.010	-0.007	0.019	0.077	-0.215*	-0.037	0.312
	(0.011)	(0.011)	(0.096)	(0.219)	(0.125)	(0.032)	(0.241)
Year FE	X	X	X	X	X	X	X
Nobs	116	116	116	116	116	116	116
Adj. R2	0.36	0.23	0.25	0.19	0.39	0.23	0.15

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table VI. The Governance Channel

This table presents regressions of segment-level capital allocation on the interaction between division-manager ability and corporate governance. The sample period ranges from 2000 to 2018. The dependent variable is raw segment investment (odd columns) or industry-adjusted segment investment (even columns). All governance measures are standardized to have zero mean and unit variance. *DMA-Score* is the measure of division-manager ability described in Section 3.4. Control variables include the same characteristics of the division, firm, and manager used in Table III. Explanatory variables are lagged one year and continuous variables are winsorized at the 1st and 99th percentiles. All regressions include year fixed effects. Standard errors (in brackets) are clustered at the firm level. See Table A1 for detailed variable descriptions.

Dep. Var.:	Seg. Inv.	Ind.-Adj. Seg. Inv.	Seg. Inv.	Ind.-Adj. Seg. Inv.	Seg. Inv.	Ind.-Adj. Seg. Inv.	Seg. Inv.	Ind.-Adj. Seg. Inv.	Seg. Inv.	Ind.-Adj. Seg. Inv.
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DMA-Score	0.048***	0.051***	0.048***	0.050***	0.048***	0.051***	0.047***	0.050***	0.049***	0.051***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
DMA-Score × Governance Index	0.018***	0.027***	0.020***	0.028***						
	(0.005)	(0.006)	(0.005)	(0.007)						
Governance Index	0.001	0.001	0.003	-0.004						
	(0.001)	(0.001)	(0.006)	(0.008)						
DMA-Score × Board independence					0.014**	0.017***				
					(0.006)	(0.007)				
Board Independence					0.008	0.008				
					(0.007)	(0.008)				
DMA-Score × CEO equity pay							0.012*	0.016**		
							(0.006)	(0.007)		
CEO equity pay							-0.002	-0.012*		
							(0.006)	(0.007)		
DMA-Score × Institutional ownership									0.015***	0.025***
									(0.005)	(0.006)
Institutional ownership									0.002	-0.003
									(0.007)	(0.007)
Controls	X	X	X	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X	X	X	X
Industry FE	X		X		X		X		X	
All Interacted			X	X	X	X	X	X	X	X
Nobs	4,764	4,764	4,764	4,764	4,764	4,764	4,764	4,764	4,764	4,764
Adj. R2	0.39	0.06	0.39	0.06	0.39	0.06	0.39	0.06	0.39	0.06

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table VII. The Capital Budgeting Process, Cash Windfalls and Capital Allocation

This table presents regressions of segment-level capital allocation on the interaction between division-manager ability and unexpected, firm-wide cash windfalls. The sample period ranges from 2000 to 2018. The dependent variable is raw segment investment (odd columns) or industry-adjusted segment investment (even columns). *Cash windfall* is the residual from regressing a firm's annual change in cash flow on the annual cash flow changes over the past three years (Duchin et al., 2017) multiplied by an indicator that equals one if the residual is positive, and zero otherwise. *DMA-Score* is the measure of division-manager ability described in Section 3.4. *Power index* is a combined index formed by averaging the following four variables, each normalized to fall between zero and one: (1) board membership; (2) the manager's professional tenure at the firm measured in years; (3) the relative size of the manager's segment within the firm; and (4) a dummy that equals one if the manager's job title in BoardEx indicates a senior leadership role. Control variables include the same characteristics of the division, firm, and manager used in Table III. Explanatory variables are lagged one year and continuous variables are winsorized at the 1st and 99th percentiles. All regressions include year fixed effects. Standard errors (in brackets) are clustered at the firm level. See Table A1 for detailed variable descriptions.

Dep. Var.:	Seg. Inv.	Ind.-Adj. Seg. Inv.	Seg. Inv.	Ind.-Adj. Seg. Inv.	Seg. Inv.	Ind.-Adj. Seg. Inv.
Model	(1)	(2)	(3)	(4)	(5)	(6)
DMA-Score × Cash windfall	0.814**	0.580**	0.623**	0.522*	0.864**	0.634**
	(0.372)	(0.266)	(0.289)	(0.289)	(0.398)	(0.286)
DMA-Score	0.042***	0.045***	0.043***	0.045***	0.040***	0.043***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
Cash windfall	0.053	0.065*	0.075	0.082	-0.079	-0.058
	(0.047)	(0.039)	(0.383)	(0.395)	(0.074)	(0.079)
Power index × Cash windfall					0.510***	0.478**
					(0.190)	(0.232)
Power index					0.030**	0.027
					(0.013)	(0.017)
Controls	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Industry FE	X		X		X	
All Interacted			X	X		
Nobs	5,292	5,292	5,292	5,292	5,292	5,292
Adj. R2	0.38	0.05	0.39	0.05	0.39	0.06

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table VIII. Managerial Ability, Investment Efficiency and Firm Value

This table presents estimates from OLS and fixed-effects regressions at the firm level. The sample period ranges from 2000 to 2018. In columns (1)-(5), the sample consists of S&P 1500 multisegment firms. Columns (6)-(7) present results for an extended sample that also includes single-segment firms. The dependent variable is *excess value*, which is the natural log of the ratio of a firm's actual value to its imputed value (Berger and Ofek, 1995). *DMA-Transfer* is the firm-level measure of DMA-sensitive investment described in Section 6. *Conglomerate* is an indicator that equals one if the firm operates two or more different segments in a given year, and zero otherwise. All regressions include year fixed effects. Standard errors (in brackets) are clustered at the firm level. See Table A1 for detailed variable descriptions.

Dep. Var.:	Excess Value						
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DMA-Transfer	0.381**	0.379**	0.393***	0.241*	0.232*	0.341**	0.287**
	(0.159)	(0.151)	(0.151)	(0.127)	(0.126)	(0.154)	(0.125)
Conglomerate						-0.080***	-0.111**
						(0.028)	(0.047)
Firm size		0.399**	0.396**	0.793***	0.788***	0.444***	0.255***
		(0.161)	(0.161)	(0.199)	(0.199)	(0.021)	(0.035)
CapEx		-0.191	-0.205	0.764	0.816	0.004	0.002
		(0.489)	(0.484)	(0.590)	(0.599)	(0.033)	(0.035)
Profitability		1.302***	1.305***	0.858**	0.861**	0.024***	0.018**
		(0.407)	(0.410)	(0.433)	(0.432)	(0.007)	(0.009)
Firm size (Lag 1)		-0.120	-0.119	-0.054	-0.053	-0.191***	-0.168***
		(0.083)	(0.082)	(0.067)	(0.067)	(0.019)	(0.017)
CapEx (Lag 1)		-0.032	-0.024	0.759	0.744	-0.039	-0.048
		(0.633)	(0.631)	(0.562)	(0.570)	(0.034)	(0.036)
Profitability (Lag 1)		0.330**	0.327**	0.087	0.085	-0.007	-0.004
		(0.134)	(0.134)	(0.118)	(0.119)	(0.008)	(0.008)
Firm size (Lag 2)		-0.156**	-0.156**	-0.174***	-0.175***	-0.202***	-0.134***
		(0.065)	(0.065)	(0.054)	(0.054)	(0.015)	(0.014)
CapEx (Lag 2)		0.568	0.575	-0.104	-0.105	-0.000	-0.044
		(0.421)	(0.420)	(0.391)	(0.394)	(0.028)	(0.032)
Profitability (Lag 2)		0.784***	0.784***	0.181	0.183	-0.030***	-0.011
		(0.172)	(0.171)	(0.158)	(0.160)	(0.009)	(0.010)
Book leverage		-0.493***	-0.497***	-0.473**	-0.468**	-0.359***	-0.290***
		(0.142)	(0.141)	(0.190)	(0.190)	(0.034)	(0.044)
Firm size^2		-0.011	-0.011	-0.044***	-0.043***	-0.001	-0.005*
		(0.008)	(0.008)	(0.012)	(0.012)	(0.001)	(0.003)
RVA (RSZ, 2000)			-0.065		0.059	-0.065	0.077
			(0.081)		(0.058)	(0.095)	(0.065)
Year FE	X	X	X	X	X	X	X
Firm FE				X	X		X
Nobs	1,951	1,951	1,951	1,951	1,951	24,485	24,485
Adj. R2	0.02	0.19	0.19	0.64	0.64	0.09	0.56

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Internet Appendix

Picking Winners: Managerial Ability and Capital Allocation

November 14, 2023

Not for Publication

A. Data Collection Process: Division Managers

A challenge for our analysis is that detailed information on division managers is not readily available from standard archival sources. As described in the main text, we use a combination of textual analysis and hand collection to, first, identify division managers and, then, assign them to corporate divisions – ultimately, to construct a data set that matches managers, divisions, and accounting data.[1] Division manager information is mainly drawn from BoardEx, Form 10-K reports, and DEF-14a proxy statements.

We complete manager-to-segment matching in two steps: In the first step, we gather information about senior managers below the CEO level at S&P 1,500 multisegment firms in the 2000-2018 period using the BoardEx senior management and disclosed earners (SMDE) profiles database. From the SMDE employment history file, we retrieve data on senior managers' professional appointments (including start and end dates of current and past positions), professional titles, and job descriptions. Division managers typically have the title of *division president*, *head of division*, *executive vice president*, *senior vice president*, *division CEO*, *group president*, or combinations thereof. We retrieve these titles directly from BoardEx. In most cases BoardEx also provides job descriptions that include the segment's name (or a business description), which we process with text-matching scores to allocate managers to corporate segments. Specifically, we calculate "similarity scores" by comparing segment names from Compustat with managers' job descriptions from BoardEx using several string-matching techniques based on phrases (bigrams or key words). Based on these scores, we identify the individual among all senior managers of a firm who is most closely associated with a particular segment.

In a second step, we verify and clean all algorithmic matches by hand and one-by-one using Form 10-K reports and DEF-14a proxy statements gathered from EDGAR. In particular, we manually

[1] Our data collection procedure follows the one proposed by Duchin and Sosyura (2013) and subsequently used in Duchin, Goldberg, and Sosyura (2017) and Duchin, Simutin, and Sosyura (2021). Other studies with related data collection procedures are, e.g., Fee and Hadlock (2004), McNeil, Niehaus, and Powers (2004), McNeil and Smythe (2009), Cichello, Fee, and Hadlock (2009), or Hadlock et al. (2023).

cross-check the exact start and end date of each manager's term as division president. For a manager to be assigned to a specific segment year, we require that the identified division manager has a time-in-position of at least two quarters prior to the end of the firm's fiscal year.[2] For the cases that cannot be processed with textual analysis (e.g., due to missing or incomplete job descriptions and titles in BoardEx), we use hand-collected (instead of textual analysis-based) manager-segment matches derived from annual reports, proxy statements, and other public sources (e.g., Bloomberg, Capital IQ, LinkedIn, D&B, firm websites, and press releases).

For a segment-year observation to be included in the final sample, we require a valid and unambiguous segment-manager match (i.e., there must be a one-to-one correspondence between segments and managers). If this condition is met, we designate the segment as "division" (since the firm's reported segment structure corresponds to its divisional structure) and the matched individual as "division manager". Firms that have no clear correspondence between managers, segments, and divisions (e.g., firms that aggregate multiple divisions into one reported segment or firms that use a functional organization where a single executive has responsibility for an entire functional area across all business units such as, for instance, operations, finance, or marketing) are excluded from the sample. Further, we exclude all firms for which information on division managers is not available from the data sources mentioned above.

This procedure leaves us with a final sample of 346 firms with 1,545 division managers and 5,328 segment-year observations, which compares favorably with the samples of prior studies on division managers.

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[2] This is particularly important in segment-years with a division manager turnover. For instance, if the firm's fiscal year ends at December 31, 2010 and a new division manager is appointed prior to (after) June 30, 2010, the manager's starting year in our data set is 2010 (2011).

B. Managerial Ability from Demerjian et al. (2012)

B.1 Two-Stage DEA to Measure Managerial Ability

To quantify the managerial ability of division managers, we follow the "two-stage DEA method" introduced in Demerjian, Lev, and McVay (2012). Their measure of managerial ability, the *MA-Score*, provides an estimate of how efficiently firms' top managers generate revenue from a firm's resources.

The first stage of the model uses DEA to calculate relative efficiency. The variable returns-to-scale (VRS)[1] input-oriented DEA model solves the following optimization problem:

$$\max_{u,v} \theta_k = \frac{\sum_{r=1}^{s} u_r y_{rk} - u*}{\sum_{i=1}^{m} v_i x_{ik}} \text{ , for k = 1,...,} n$$

subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rk} - u*}{\sum_{i=1}^{m} v_i x_{ik}} \leq 1 \qquad (1)$$

$$u_1, \dots, u_s \geq 0 \qquad (2)$$

$$v_1, \dots, v_m \geq 0 \qquad (3)$$

The optimization program calculates relative efficiency for a group of n observations, termed *decision-making units* (*DMUs*). The objective function involves maximizing the weighted outputs (numerator) scaled by the weighted inputs (denominator). The vector y is the quantity or dollar value of outputs; there are s total outputs. Similarly, there are m inputs in the vector x. The vectors u and v are the weighting vectors calculated by the DEA optimization program. The ultimate

[1] The earliest DEA models (e.g., Charnes, Cooper, and Rhodes, 1978) assume constant returns to scale (CRS), where input changes result in proportional output changes. This rigid assumption is relaxed in the VRS model, allowing increasing, constant, or decreasing returns to scale. We opt for the more general VRS model (see Banker, Charnes, and Cooper, 1984) because it allows for more accurate and flexible measurement of θ_k if DMUs vary in size and θ_k may be affected by their scale of operations. The results of our paper are unaffected if we use CRS instead of VRS.

objective of the program is to find for each DMU k the vectors u and v that maximize θ_k, the DMU's efficiency relative to other DMUs in the group.

Specifically, the calculation of *DMU-specific* pairs of weighting vectors u and v works as follows. The program begins by applying weighting vectors to the output and input values of DMU 1 and calculates the ratio of weighted output to weighted inputs (the objective function θ, which captures efficiency). The program then applies these weights to DMU 2 through DMU n. For DMU 1, the program selects the set of weights that provides the highest efficiency for DMU 1 relative to all other DMUs in the group (whether this is the highest among all the DMUs or not). The program then proceeds to DMU 2, using DMU 1 and DMU 3 through DMU n to calculate weights; the program iterates through each DMU until each has weights assigned.

The first constraint serves as scalar, assigning any efficient observation a value of one. This means the value θ varies between zero (least efficient DMUs) and one (most efficient DMUs, on the efficient frontier). The second and third constraints require weights on each output and input to be non-negative; at least one input and one output must be strictly positive. The term u^* is an unconstrained scale factor, which balances out the effects of variable returns to scale (see Banker, Charnes, and Cooper, 1984). The inclusion of this term makes the VRS model more flexible than the CRS model, yielding more DMUs on the frontier.

The second stage uses regression analysis to extract measurable, DMU-level factors – contextual variables – to arrive at a measure capturing the portion of efficiency not described by contextual factors. In the Demerjian et al. (2012) model, the second stage is used to purge firm-level factors from firm efficiency to determine the portion of efficiency attributable to the firm's manager. The model is:

$$Firm\ Efficiency_i = \mathrm{f}(\alpha + \mathrm{B} \times Contextual\ Variables_i + fixed\ effects + \varepsilon)$$

Demerjian et al. (2012) use Tobit regression as *Firm Efficiency* is bounded between zero and one. Recent research suggests that OLS regression is also acceptable (Banker and Park, 2021). The residual from this equation – the actual value minus the predicted value – is the measure of managerial ability. The underlying assumption is that any portion of firm efficiency not explained by the contextual variables and fixed effects represents the manager's contribution.

B.2 Two-Stage DEA: Variable Definitions in Demerjian et al. (2012)

Demerjian et al. (2012) propose a firm-year measure of managerial ability using two-stage DEA. In the first (DEA) stage, they model a single output, revenue, for the firm. The inputs comprise a broad set of measurable capital inputs. The first is property, plant, and equipment, which captures the firm's investment in fixed assets. The second is operating leases, which captures assets held and used by the firm but not afforded balance sheet recognition. They calculate the operating lease input as the discounted value of future operating lease payments. The third input is research and development (R&D). Because R&D is immediately expensed, they capitalize the five most recent R&D expenses using the formula from Lev and Sougiannis (1996). The fourth and fifth inputs are goodwill and other intangible assets (e.g., patents). The sixth input is the cost of goods sold from the income statement. The authors opted to use this flow variable to capture firm expenditures in inventory because balance sheet-reported inventory is likely to be volatile (e.g., due to just-in-time inventory policies). The final input, selling, general, and administrative costs, capture a variety of expenditures that provide value to the firm but are not recorded on the balance sheet, such as advertising and marketing.

Demerjian et al. (2012) group firms by Fama and French (1997) 48 industry to run DEA, using a panel of observations from 1980 to 2009.[1] The authors exclude regulated firms and firms in financial industries, as these have fundamentally different revenue-generating properties than competitive commercial and industrial firms. The DEA implementation is an input-oriented variable-returns-to-scale (VRS) model.

In their second stage, Demerjian et al. (2012) identify a set of contextual variables that they predict will either positively or negatively affect firm efficiency. They predict that larger firms will be more efficient due to economics of scale and scope, so include total assets as their first contextual variable. Market share is included to capture the competitive position of the firm within its industry or product market, with higher values aiding efficiency. They also include an indicator for firms with

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[1] The authors update and post the data regularly. More recent iterations of the data have been calculated by year rather than by industry (see peterdemerjian.weebly.com/uploads/1/3/2/5/132532695/ma_score_description_2020.txt).

positive free cash flows, which they expect to be positively associated with firm efficiency. They also include firm age, assuming that newer, younger firms are likely to be less efficient. The final two contextual variables capture firm complexity, which are projected to be negatively associated with firm efficiency. The first is the business segment concentration, which measures the diversity of operations in the firm. The second is an indicator for whether the firm has foreign currency transactions as a proxy for global operations. Then, Demerjian et al. (2012) regress *Firm Efficiency* on these contextual variables and industry fixed effects (based on Fama and French (1997) 48 industry) in yearly Tobit regressions and aggregate regression coefficients across annual regressions following Fama and MacBeth (1973).

C. Division Efficiency and Division Manager Ability – Estimation Results

In this section, we present summary statistics and estimation results for the full sample we use to calculate the DMA-Score, the population of all Compustat segments (our "estimation sample"), and the manager-segment matched sample data based on the data collection procedure as described in Section 3.1 (our "analysis sample"). In Panel A of Table IA.1, we present summary statistics on the division efficiency measured in the first stage using data envelopment analysis (DEA). Similar to the firm efficiency measure in Demerjian et al. (2012), division efficiency is characterized by a symmetric distribution with a mean (median) of 0.473 (0.478). In Panel B of Table IA.1, we present descriptive results on division efficiency by industry, based on the Fama-French 30 (FF30) industry classification.[1] The data shows the variation in industry size, ranging from as few as 50 segment-year observations (smoking) to as many as 10,338 (personal and business services). There is also variation in the distributions of division efficiency across industries. The lowest mean (median) value is 0.388 (0.367) for communication, while the highest mean (median) value is 0.654 (0.676) for retail. Like the full distribution, the industry distributions are relatively free from skew, with means and medians very close to each other. Additionally, even with some cross-industry variation, the bulk of the variation in division efficiency is within industry.

In Table IA.2, we present estimation results from the second-stage estimation (described in Section 3.4) used to calculate the *DMA-Score*. We run six specifications in total. The first four include each of our contextual variables sequentially, with industry fixed effects (based on three-digit SIC code classifications). In each of these columns (which report average coefficients aggregated from the yearly regressions), the coefficient on the contextual variable is significant in the predicted direction. In the fifth column, we include the contextual variables concurrently but exclude industry fixed effects. Here, each of the four contextual variables remains significant. In the final column, we include industry fixed effects. In this specification, *Segment Size* loses significance. We use the residual from the sixth specification to calculate our measure of division-manager ability: the *DMA-Score*.

[1] As described in the main paper, we use 3-digit SIC codes in the second-stage Tobit regression. For the sake of clarity, Table IA.I presents summary statistics using the Fama-French 30 (FF30) industry classification.

Table IA.1 First-Stage Estimation: Division Efficiency

This table presents summary statistics on division efficiency calculated using data envelopment analysis (DEA) based on the vectors described in Section 3.4. The sample contains the population of all Compustat segments with nonmissing data on DEA variables ("estimation sample"). Division efficiency scores are calculated separately by year over the period 2000 to 2018. DEA variables include segment sales (output), segment assets (input 1) and segment operating expenses (input 2). Panel A presents statistics for the full sample. Panel B is sorted by industry, based on the Fama-French 30 (FF30) industry classification (Fama and French, 1997).

	Nobs	Mean	Std. dev.	25%	Median	75%
A. Division Efficiency Measure (Full Sample)						
Variable						
Division efficiency	75,049	0.473	0.199	0.338	0.478	0.609
B. Division Efficiency By Industry						
Industry						
Food products	2,098	0.579	0.185	0.454	0.585	0.708
Beer and liquor	244	0.438	0.197	0.294	0.409	0.555
Tobacco products	50	0.530	0.271	0.301	0.522	0.759
Recreation	1,755	0.440	0.167	0.332	0.439	0.545
Printing and publishing	1,101	0.478	0.152	0.383	0.483	0.574
Consumer goods	1,454	0.535	0.165	0.424	0.539	0.642
Apparel	1,132	0.538	0.151	0.440	0.558	0.641
Healthcare	8,742	0.352	0.214	0.175	0.348	0.506
Chemicals	2,866	0.496	0.155	0.405	0.502	0.594
Textiles	442	0.488	0.147	0.398	0.493	0.589
Construction	3,493	0.512	0.168	0.405	0.520	0.627
Steel works	1,603	0.518	0.154	0.424	0.521	0.613
Fabricated products	4,474	0.476	0.152	0.379	0.482	0.576
Electrical equipment	1,391	0.442	0.169	0.333	0.464	0.560
Automobiles and trucks	1,499	0.551	0.153	0.455	0.564	0.657
Aircraft, ships, and railroad	973	0.530	0.166	0.413	0.520	0.641
Metal mining	729	0.417	0.188	0.295	0.410	0.526
Coal	219	0.433	0.163	0.322	0.458	0.531
Petroleum and natural gas	2,831	0.440	0.222	0.275	0.412	0.571
Communication	2,080	0.388	0.190	0.253	0.367	0.505
Personal and business services	10,338	0.428	0.198	0.287	0.420	0.567
Business equipment	9,915	0.425	0.172	0.308	0.419	0.538
Business supplies	1,582	0.544	0.142	0.462	0.556	0.636
Transportation	2,193	0.509	0.211	0.339	0.511	0.673
Wholesale	3,752	0.609	0.194	0.488	0.631	0.740
Retail	4,466	0.654	0.169	0.567	0.676	0.772
Restaraunts, hotels, motels	1,400	0.530	0.169	0.427	0.542	0.642
Other	2,227	0.467	0.152	0.371	0.474	0.566

Table IA.2 DMA-Score: Second-Stage Estimation

This table presents the results from second-stage Tobit regressions of division efficiency. Regressions are estimated by year for the population of all Compustat segments with nonmissing data on division efficiency and explanatory variables ("estimation sample") over the period from 1999 to 2018. Division efficiency is measured using DEA based on the vectors described in Section 3.4. For illustrative purposes, we present the average of the year-specific coefficients and report Fama and MacBeth (1973) standard errors of these coefficients (in parentheses). Columns (1)-(4) summarize the results from univariate Tobit regressions; columns (5) and (6) summarize the results from multivariate Tobit regressions with and without industry fixed effects, respectively. The residual obtained from the estimation of column (6) is the *DMA-Score*, described in Section 3.4. See Table A1 for detailed variable descriptions.

Dependent Variable	Division Efficiency							
	Predicted Sign	Average Coefficient (Fama-MacBeth SE)						Proportion Significant (%)
Model		(1)	(2)	(3)	(4)	(5)	(6)	(6)
Segment size	+	0.021***				0.010***	0.002	65.0
		(0.003)				(0.003)	(0.003)	
Segment market share	+		2.213***			1.113***	1.856***	100.0
			(0.125)			(0.082)	(0.086)	
Segment free cash flow	+			0.141***		0.150***	0.125***	100.0
				(0.006)		(0.007)	(0.005)	
Business segment concentration	−				-0.099***	-0.043***	-0.044***	85.0
					(0.005)	(0.003)	(0.004)	
Industry FE		X	X	X	X		X	
# Estimations (by year)		20	20	20	20	20	20	
Nobs		75,049	75,049	75,049	75,049	75,049	75,049	

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table IA.3 Summary Statistics: DMA-Score and Two-Stage DEA Variables

This table reports summary statistics on the *DMA-Score* and two-stage DEA variables. The sample period is 2000-2018. Panel A reports summary statistics on the *DMA-Score* and division efficiency for the population of all Compustat segments ("estimation sample"), and the manager-segment matched sample data based on the data collection procedure as described in Section 3.1 ("analysis sample"). *DMA-Score* is the division-manager ability score described in Section 3.4. Panels B and C report summary statistics for the estimation sample on first-stage DEA variables (Panel B) and explanatory variables included in the second-stage Tobit regression (Panel C). The first-stage DEA variables include segment sales (output), segment assets (input 1) and segment operating expenses (input 2). Second-stage regression variables include segment size, segment free cash flow, segment market share, and business segment concentration. See Table A1 for detailed variable descriptions.

Variable	Mean	Std. dev.	Min	25%	Median	75%	Max	Nobs
A. DMA-Score and Division Efficiency (Estimation Sample and Analysis Sample)								
DMA-Score (estimation sample)	-0.002	0.137	-0.317	-0.088	-0.004	0.078	0.383	75,049
DMA-Score (analysis sample)	0.021	0.113	-0.317	-0.052	0.017	0.092	0.383	5,328
Division efficiency (estimation sample)	0.473	0.199	0.002	0.338	0.478	0.609	1.000	75,049
Division efficiency (analysis sample)	0.554	0.152	0.014	0.456	0.553	0.653	1.000	5,328
B. First-Stage DEA Variables (Estimation Sample)								
Segment sales ($ millions)	1,146	2,743	1.00	48	221	863	18,673	75,049
Segment assets ($ millions)	1,264	3,125	1.01	55	232	919	21,484	75,049
Segment operating expenses ($ millions)	968	2,294	0.04	48	193	734	15,438	75,049
C. Second-Stage Estimation (Estimation Sample)								
Segment size	5.422	1.974	0.889	4.011	5.442	6.816	10.137	75,049
Segment free cash flow	0.710	0.454	0.000	0.000	1.000	1.000	1.000	75,049
Segment market share (%)	0.868	2.825	0.000	0.023	0.113	0.542	100.000	75,049
Business segment concentration	0.721	0.293	0.100	0.439	0.807	1.000	1.000	75,049