Corporate Diversification and Financial Policy

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Chapter 1 – Introduction

A good way to do econometrics is to look for good natural experiments and use statistical methods that can tidy up the confounding factors that nature has not controlled for us.

— Daniel McFadden

Do diversified organizational structures contribute to the creation of value or are they on average inefficient forms of organizations created and maintained by a breakdown of corporate governance? In the last few decades, this fundamental question has stirred considerable controversy and received a great deal of attention in corporate finance – without a clear answer emerging to date. Much of the early literature on this vigorously debated subject suggests that diversification promotes misallocation and resource waste. More recent studies, in contrast, put this view into doubt and caution against drawing premature conclusions. The overarching objective of this dissertation is to shed new light on the ambiguous evidence provided in prior work on the fundamental question posed above.

The corporate finance literature usually defines a diversified firm as one that operates dissimilar lines of business under the roof of a single parent company. In the United States, diversified firms represent a major form of organization of economic activity that accounts for more than half of the production of the economy (Maksimovic and Phillips, 2007).[1] Typical examples are conglomerates such as *General Electric, 3M Company, IBM*, or *The Walt Disney Company.* As a fundamental aspect of this form of organization, the corporate center (top management or, more generally, corporate headquarters) exercises financial control over the firm's business units (divisions or segments). From the perspective of a single division, there is no (direct) access to the external capital market (e.g.,

[1] In Germany, conglomerate firms represent a less dominating but still important form of organization. Examples for major industrial conglomerates are *Siemens*, *MAN*, *thyssenkrupp* or *Bayer*.

banks, the bond market, or the stock market). Instead, there is an "*internal capital market*" in which corporate headquarters acts as the sole provider of financial capital and the firm's business units are the recipients of capital allocations. A prime essential feature of internal capital markets is that control rights over the firm's assets reside with the supplier of capital (corporate headquarters), which is not the case, for example, with bank loan agreements. Corporate headquarters is thus in a position to reallocate financial resources within the firm and across divisions at any time. This is one of the key differences between the conglomerate structure and the alternative of running each business unit as a standalone firm with autonomous access to external capital markets (Gertner et al., 1994).

In corporate finance, one of the most fundamental questions about corporate diversification is whether and how this form of organization (and the associated creation of an internal capital market) affects financial outcomes.[2] Essentially, this strand of the literature aims to explain the specific costs and benefits of diversification and ultimately to determine whether integration of this sort creates or destroys value.[3] Intuitively, one might assume that firms would not become diversified unless there is some benefit from doing so. Following this argument, the remarkable presence of conglomerates in the economy may suggest that there is a "bright side" of diversification. However, most early (and to date influential) empirical studies produce opposite conclusions. In particular, they find evidence of a "dark side" of internal capital markets.

Academic interest in the dark-side view began to rise sharply with the seminal works of Lang and Stulz (1994) and Berger and Ofek (1995). Using data on US public firms, these authors find that diversified firms trade at a discount in the range of 13-15% relative to standalone firms in the same industries (henceforth called the "diversification discount"), which they interpret as evidence of value destruction by diversification. This result has provided an impetus for a large volume of empirical

[2] This question naturally arises from the more general problem raised by Coase (1937) of determining how firm boundaries should be set.

[3] For an overview, see Stein (2003) and Maksimovic and Phillips (2007), who survey the theoretical and empirical literature on internal capital markets.

work that has sought to find the source of the "diversification discount". The existing evidence on this issue is mixed. Several early and widely cited articles attribute the discount to distortionary forces on internal capital markets (see, e.g., Comment and Jarrell, 1995; Lamont, 1997; Shin and Stulz, 1998; Scharfstein, 1998; Lins and Servaes, 1999; Rajan et al., 2000). According to these studies, diversification destroys value, as information and agency problems inherent to the conglomerate form of organization lead diversified firms to overinvest in unprofitable industries and, thus, to promote misallocation of resources.[4] The evidence from these influential articles initially led to a broad consensus among financial researchers and the business press about the dark-side view mentioned above. Until the early 2000s, it was almost axiomatic to assume that diversification destroys value, as internal capital markets tend to engage in inefficient cross-subsidization.

In the years that followed, however, this popular explanation became increasingly controversial, with a series of follow-up studies sparking a debate about the existence of the "diversification discount" (see, e.g., Whited, 2001; Khanna and Tice, 2001; Graham et al., 2002; Campa and Kedia, 2002; Chevalier, 2004; Villalonga, 2004a and 2004b; Çolak and Whited, 2007; Hoang and Ruckes, 2015; Hund et al., 2010 and 2016; Benz and Hoang, 2021). The overarching conclusion of these studies is that the pioneering work on the discount and the alleged inefficiency of internal capital markets is tainted by self-selection and measurement error. Early empirical studies are prone to such econometric issues, as they largely ignore the endogenous nature of a firm's diversification decision. As a result, some follow-up studies find that much of the discount as calculated by Berger and Ofek (1995) can be explained by faulty comparisons embedded in the measurement itself. For example, Graham et al. (2002) show that diversification by acquisition creates a measured discount in the sense of Berger and Ofek because acquiring firms focus on targets that are already valued at a discount relative to their industry peers. Campa and Kedia (2002) and Villalonga (2004a and 2004b) find that the discount always drops and sometimes turns into a premium when they control for the endogenous diversification decision of the firm, which casts doubt on the view that diversification

[4] Most early studies on the diversification discount build on the methodology of Berger and Ofek (1995) and use regression-based comparisons between diversified firms and segment industry-matched portfolios of standalone firms.

per se destroys value. Similar issues arise with conclusions about the structural failure of internal capital markets drawn from traditional measures of investment efficiency, which rely on standalone firms' Tobin's q to proxy for (unobservable) segment investment opportunities (see Çolak and Whited, 2007).

The empirical literature on corporate diversification has proven to be fertile ground for an ongoing and contentious debate. However, the lack of conclusive evidence underscores the need for a deeper understanding of the economic mechanisms through which diversification is regarded to affect firm outcomes. From a theoretical point of view, corporate diversification offers firms both *investment* and *financing* advantages (Stein, 2003). However, theoretical work on this topic also points to the potential for agency problems within the firm, such as rent-seeking behavior at the division level, which may offset the potential benefits of diversification (e.g., Scharfstein and Stein, 2000; Rajan, Servaes, and Zingales, 2000; Stein, 2003; Wulf, 2009). While theory offers competing hypotheses regarding the specific costs and benefits of corporate diversification, empirical evaluation of these arguments has proven remarkably difficult. A major obstacle to progress in this area is the correct identification of the signs and magnitudes of the causal effects of diversification due to the challenge of finding good instruments or appropriate counterfactuals. This dissertation takes a step toward this goal by presenting new evidence of the constructive impact that corporate diversification and the associated creation of internal capital markets have on firm outcomes. These results provide new insights into the functioning of internal capital markets and contribute to a deeper understanding of the role that firm boundaries play in shaping corporate financial policies. Each chapter's motivation, main findings and contribution are outlined and summarized below.

Chapter 2 of the dissertation examines the surprisingly underexplored relationship between corporate diversification and debt financing, in particular capital structure. This chapter empirically investigates the hypothesis that distinct businesses (operating in different industries) under one corporate umbrella are able to raise more total resources from the outside market than could be raised by the individual businesses operating as standalone firms. The work on this question is inspired by the theoretical argument of Lewellen (1971) that coinsurance across imperfectly correlated businesses reduces the firm's risk of default, which improves access to credit and allows the firm to carry higher financial leverage. Although the coinsurance hypothesis represents one of the basic finance-related synergies associated with diversification in theory, relatively little attention has been devoted to this topic in the existing empirical literature. This dearth of research may result from the large impact of the early evidence on the "diversification discount" on subsequent work in the field. While the early literature on the dark side of internal capital markets sparked a flurry of empirical work on the investment efficiency/inefficiency of multisegment firms, it may have deterred researchers from exploring the financing benefits of diversification.[5] This is not only a major limitation of our understanding of how firm boundaries affect corporate financial policies but also the starting point for the empirical analysis of Chapter 2. In the baseline empirical analysis, the chapter examines financial leverage across diversified and standalone firms in the US during the 1981-2015 period. The results indicate that diversified firms are substantially more levered than standalone firms. This pattern holds robustly throughout the sample period and after controlling for standard determinants of leverage known from prior literature. Taken together, these findings suggest economically meaningful financing advantages of diversified firms.

The key question with this result, however, is whether it reflects a causal effect of diversification on financial leverage. Given the endogenous nature of a firm's decision to diversify, differences in leverage may simply arise from unobserved heterogeneity between diversified and standalone firms. Another issue that might arise is the possibility of reverse causality if firms mechanically increase their leverage to fund their diversifying investments. To answer this question, one would ideally conduct a controlled experiment that induces exogenous variation in the diversification status of randomly selected firms and then observe whether and how this treatment affects their leverage behavior. Of course, such an experiment is not possible to implement. Instead, Chapter 2 proposes a unique and novel empirical test for estimating the causal effect of diversification on capital

[5] One exception is Kuppuswamy and Villalonga (2016), who document that diversified firms became more leveraged than standalone firms during the 2007–2009 financial crisis. What remains unclear about their "out-of-equilibrium" finding is, however, whether and how this evidence extends to a more general setting without a severe credit shortage in the economy.

structure based on observational data that closely approximates the ideal of a randomized controlled trial. This is the main innovation of the chapter and a central contribution to the existing literature on the subject. The empirical strategy presented in Chapter 2 uses the introduction of new segment reporting standards (SFAS 131) in fiscal years following 1998 as a quasi-natural experiment. A major attraction of the SFAS 131 shock is that it provides a unique opportunity to study the effects of (revealed) diversification in the absence of potentially "contaminated" real changes in a firm's organizational status. This regulatory change forced (some) firms to reveal previously hidden information about their diversification strategies to outsiders, thus providing plausibly exogenous variation in a firm's (publicly observed) diversification status. Chapter 2 exploits this unique feature in a quasi-experimental research design that circumvents potential econometric problems related to the endogeneity of the firm's diversification decision. The treatment group consists of firms that disclosed a single segment prior to the introduction of SFAS 131 and appeared to operate as standalone firms. However, these self-proclaimed standalone firms in fact ran businesses in more than one industry and were forced to reveal their previously hidden diversification status upon the adoption of SFAS 131. Another salient feature of the SFAS 131 shock is that some firms were already compliant with the new standard before it went into effect. Thus, there is a group of firms that can be used to control for common temporal trends in leverage. In contrast, most regulatory shocks tend to affect the entire corporate population, which implies that there is usually no true control group.

Consistent with a causal effect of corporate diversification on a firm's capital structure, the chapter finds a sharp increase in leverage among the firms that newly reveal information about their diversification strategies upon the adoption of SFAS 131. In addition, the effect of diversification on leverage is strongest in firms with high cross-industry cash flow coinsurance and low within-firm agency problems. Overall, the evidence presented in Chapter 2 suggests economically large and persistent financing advantages of diversification and lends support for the benefit of coinsurance as a leverage determinant.

Chapter 3 of the dissertation focuses on the asset side of the balance sheet and examines the aforementioned open research question of whether internal capital markets bring financial resources to their best use within the firm. From a theoretical standpoint, the economic rationale for the existence of internal capital markets is that control rights reside with corporate headquarters, which acts as the sole provider of financial capital (Gertner et al., 1994; Stein, 1997). In contrast to a nonowner intermediary such as a bank, corporate headquarters has the authority to (re)allocate scarce resources to those segments where they can be most profitably employed. Consequently, theory predicts that conglomerate investment can create value to the extent that investment decisions in internal capital markets take advantage of such opportunities to "pick winners". On the other hand, theory also emphasizes that agency problems or information asymmetries can severely limit the investment efficiency of conglomerates relative to the external capital market.

It has been of longstanding interest to empirically evaluate whether internal capital markets actively shift funds toward "winners" and away from "losers". The early empirical literature on conglomerate investment efficiency has approached this question by studying a number of metrics designed to capture the sensitivity of capital allocation to (unobservable) segment investment opportunities (see, e.g., Lamont, 1997; Scharfstein, 1998; Shin and Stulz, 1998; Rajan et al., 2000; Billett and Mauer, 2003; Ozbas and Scharfstein, 2010).[6] Most of these studies use Tobin's q as a proxy for unobservable investment opportunities. However, since Tobin's q is not available at the segment level, *segment investment opportunities* are typically measured using Tobin's q for standalone firms in a segment's industry (called the "*industry q*").[7] Surprisingly, most early (and to date influential) studies find that internal capital markets are insufficiently responsive to differences in segment investment opportunities (with respect to *industry q*). Multisegment firms tend to overinvest (underinvest) in segments with poor (favorable) investment prospects, suggesting that they leave their potential to "pick winners" largely untapped. Consequently, researchers perceived this deviation from the

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[6] While there has been much concern about the measurement of segment investment opportunities (Whited, 2001; Maksimovic and Phillips, 2002; Çolak and Whited, 2007), the concept itself is widely accepted.

[7] The use of *industry q* has been justified by the finding of Wernerfelt and Montgomery (1988) that industry effects account for much of the variation in Tobin's q.

predictions of the neoclassical model as evidence of inefficient cross-subsidization and concluded that conglomerate investment patterns are structurally flawed.

Chapter 3 is based on the notion that previous empirical research on the efficiency of conglomerate investment falls far short of telling the whole story. The reason is that existing investment efficiency measures implicitly emphasize the relevance of the general technological and business environment in the industry (as proxied by *industry q*) while ignoring the second important component needed to generate returns from investment: human capital (ability, talent, or reputation). It is well known that CEOs have a substantial impact on corporate performance (see, e.g., Bertrand and Schoar, 2003; Adams et al., 2005; Malmendier and Tate, 2005). The same should apply to the highest-ranking executives of the divisions (henceforth "division managers") within a conglomerate structure. Division managers play an important role in the operating efficiency of a firm and bear direct responsibility for lines of business (assets) of comparable size to standalone firms. Accordingly, in a world with heterogeneously skilled division managers within and across firms, investment opportunities cannot be satisfactorily approximated by *industry q*. Put colloquially, why should capital budgeting decisions focus solely on the "horse" (characteristics of the division) but ignore the "jockey" (the executive running the division)? Chapter 3 seeks to address this gap in prior research by investigating the largely unexplored empirical relation between division managers' ability and internal capital allocation. The chapter hypothesizes that internal capital markets tend to move financial resources toward divisions of relatively more able division managers. The theoretical argument is that top management's assessment of division managers' ability should allow for value-enhancing capital allocations across divisions.

Prior literature has largely ignored the role of division managers in internal capital allocation – specifically due to data limitations. Exceptions are Duchin and Sosyura (2013) and Gaspar and Massa (2011), who examine how social connections and commonalities between division managers and the CEO affect capital allocation.[8] A likely reason why this research has been done without explicit consideration of division managers' human capital is the absence of a convincing measure of division-manager ability.[9] To address this deficiency, Chapter 3 introduces a novel variant of the widely known managerial ability score ("MA-Score") developed by Demerjian et al. (2012). The MA-Score of Demerjian et al. is the most widely used measure of top management ability to date and has been used extensively in a variety of disciplines. Conceptually, the score measures the efficiency of operations, especially with respect to the generation of revenues, and then controls for factors outside the manager's control to isolate managerial contributions. Taking advantage of the recent advances in segment reporting, Chapter 3 introduces an elaborate variant of the Demerjian et al. (2012) managerial ability score at the level of division management: the "*DMA-Score*".

Using a large and unique data set of *text-matched* and *hand-collected* division managers of S&P 1500 multisegment firms in the 2000-2018 period, Chapter 3 provides striking evidence on the large impact of division managers' abilities on internal capital allocation. Conglomerate investment behavior strongly reflects what theorists have called "winner-picking": superior division managers receive substantially larger capital allocations than their less able peers. This result is robust to a wide variety of alternative specifications and survives a number of robustness checks, which among other things exclude potential concerns related to endogenous matching of managers to divisions or social connections to the CEO. In regard to the question of winner-picking in the budgeting process, headquarters appears to focus on human capital-based considerations rather than on general investment prospects of the division. This pattern is more pronounced in firms with stronger corporate governance structures and in firms with larger informational asymmetries between headquarters and divisions. In line with Hoang et al. (2021), these results suggest that multisegment firms take advantage of the flexibility in allocating financial resources by exploiting the heterogeneity

[8] Due to general data constraints, there is also not much literature on division managers in adjacent fields. Notable exceptions are Cichello et al. (2009), who study division manager turnover and promotions, and Alok and Gopalan (2018), who examine managerial compensation in multisegment firms.

[9] As will be explained in Chapter 3, frequently used ability measures suffer from a variety of methodological shortcomings.

in division-manager abilities to make better investment decisions. To provide more direct evidence on this interpretation, Chapter 3 further examines the valuation consequences associated with human capital-sensitive investment. The results corroborate the hypothesis that resource transfers from less to more able division managers lead to more efficient investment, thus indicating that managerial ability represents an important channel through which conglomerate investment may create value. Omission of this human capital component may lead to severely biased conclusions about the investment efficiency of conglomerate firms. In summary, these findings provide new evidence on the functioning of internal capital markets and highlight a largely unexplored bright side of diversification.

While the main focus of this dissertation is on examining the potential benefits associated with corporate diversification, Chapter 4 touches upon the ongoing debate on diversity and gender inclusion in organizations. Gender imbalances are enormous in the upper echelons of corporate America and around the world. While women now account for 44% of all *entry-level* managerial positions in the United States (BLS, 2021), their ranks gradually thin out at *higher levels* of the corporate hierarchy. Accordingly, the proportion of female senior executives, especially female CEOs in major US corporations, has remained extremely low over the past years.[10]

In the past few decades, much academic attention has been paid to analyzing the highly noticeable underrepresentation of women in top management and boardrooms. In the broad literature on the career advancement of women in business, a commonly used explanatory metaphor is the "glass ceiling" (Kanter, 1977; Morrison et al., 1987), an invisible barrier that prevents successful women from rising to the top.[11] As a result, apparently competent women aspiring to leadership positions tend to become "stuck" at lower levels of the firm's hierarchy. Taken literally, the glass ceiling metaphor implies an intensification of the disadvantages women face relative to men as they move up the corporate hierarchy that takes the form of a step function (Baxter and Wright, 2000). This

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[10] Women currently hold only 6.0% of CEO positions at S&P 500 firms (Catalyst, 2021).

[11] See Oakley (2000) for a review of the major barriers that retard women's progress in management.

view may suggest that gender barriers become most severe (and thus most relevant) at the top echelons of organizations. Therefore, most studies in the field focus on studying women's representation in boardrooms. However, little progress has been made so far in analyzing women's representation in the obviously largest group of a firm's top management, namely within the group of *division managers*. This is a significant limitation in our understanding of whether glass ceiling effects also apply to executive positions at the hierarchy level directly below the boardroom.

The purpose of Chapter 4 is to extend prior literature by studying women's representation in division management based on a large panel data set of US firms in the 2000-2018 period.[12] Most notably, the chapter provides a striking illustration of the highly noticeable underrepresentation of women in division management. A majority of firms do not have a single woman among their division managers, and this imbalance has remained largely unchanged over the past two decades, suggesting that women face systematic obstacles in entering division management. The main implication that emerges from this analysis is that glass ceiling effects appear to be prevalent and also persistent at the hierarchy level directly below the boardroom.

Chapter 4 takes a first (exploratory) step toward analyzing these patterns by studying the differential characteristics of firms with and without female representation in division management. In particular, the chapter shows that firms led by female CEOs and firms with female directors on the board are significantly more inclined to appoint female division managers. In addition, gender-diverse firms are substantially larger, have lower tangible assets and appear to have stronger governance structures than firms with exclusively male-led divisions. Finally, the chapter shows that female representation in division management is positively associated with firm value, even after controlling for a host of factors that are conducive to better firm performance. Overall, these findings offer a point of departure toward developing a better understanding of women's integration in division management and its impact on firm outcomes.

[12] The division manager position is often a route to the boardroom as it is a top management position with direct responsibility for a business unit that engineers, manufactures and sells its own products.

Chapter 2 – Corporate Diversification and Debt Financing: Evidence from a Natural Experiment

2.1. Introduction

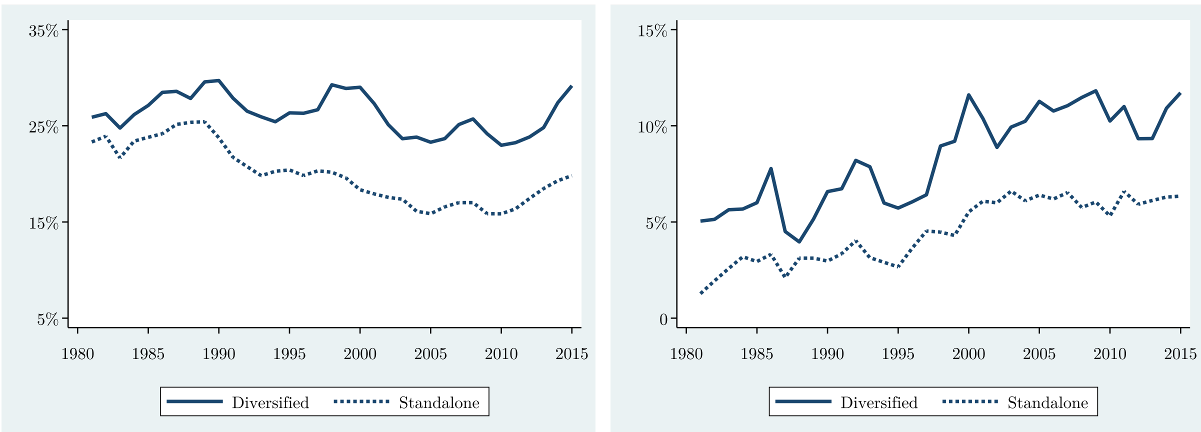
The motives for corporate diversification have been subject to considerable discussion in the finance, industrial organization, and strategic management literatures. Financial economists typically view diversified firms as portfolios of distinct operational units, the resources of which are under the control of corporate headquarters by virtue of ownership rights (Gertner et al., 1994). Theoretical arguments suggest that replacing an external capital market with such a powerful intermediary offers firms both *investment* and *financing* advantages (see Stein, 2003, for a comprehensive summary). First, the allocative flexibility associated with internal capital markets allows firms to shift funds in favor of divisions with low cash flow but strong investment opportunities (Stein, 1997). Second, diversified firms may exploit coinsurance across imperfectly correlated businesses to reduce their risk of default, which allows them to carry higher debt levels relative to comparable standalone firms (Stein, 1997; Lewellen, 1971). The vast majority of the empirical literature evaluating these arguments focuses on examining the efficiency of internal capital allocation relative to an external capital market benchmark (see, e.g., studies by Shin and Stulz, 1998; Rajan et al., 2000; Maksimovic and Phillips, 2002; Ozbas and Scharfstein, 2010; Matvos and Seru, 2014). However, surprisingly little research has been directed into the relationship between corporate diversification and financing, in particular capital structure. This is a major limitation in our understanding of how firm boundaries affect corporate financial policies.

In this chapter, we provide evidence on this question and empirically analyze how corporate diversification affects financial leverage. We find that diversified firms have, on average, higher leverage than comparable portfolios of standalone firms. Unconditionally, the average leverage of diversified firms is almost 31% higher than the leverage of standalone firms. From 1981 to 2015, diversified firms held, on average, 26.4% of their assets in (short- and long-term) debt, whereas standalone firms held 20.1% on average. Figure 2.1 compares the evolution of total book leverage (the ratio of total debt to book assets) for diversified and standalone firms from 1981 to 2015. The figure suggests persistent and economically meaningful differences in debt levels between diversified and standalone firms. As we will show in more detail below, this difference in leverage cannot be explained by leverage determinants known from prior literature (see, e.g., Graham and Leary, 2011; Lemmon et al., 2008; Welch, 2011).

Figure 2.1: Evolution of Leverage over Time

This figure plots the average book leverage ratio (y-axis) of diversified firms (solid lines) and standalone firms (dashed lines) for the period from 1981 to 2015. Firms are classified as "diversified" when they report two or more business segments in different four-digit SIC code industries and as "standalone" otherwise. In Panel A, leverage is defined as the ratio of total debt (the sum of short-term debt and long-term debt) to total book assets. Panel B shows industry-adjusted total book leverage, defined as the difference between a firm's actual leverage ratio and the firm's imputed leverage, which is the asset-weighted leverage of standalone firms in the same industry and year.

A Total Book Leverage **B** Industry-Adjusted Total Book Leverage



In the baseline empirical analysis, we estimate a set of regressions with different measures of (industry-adjusted) leverage as the dependent variable. Our results suggest statistically significant and economically large financing advantages of diversified firms relative to matching portfolios of comparable standalone firms. For total book leverage (the measure that produces the most conservative results), we find that diversified firms are associated with a 3.8 percentage-point higher industry-adjusted book leverage ratio, which is approximately 19% (24%) higher than the average (median) debt ratio in the standalone sample.[13] For the median diversified firm, this effect is associated with $67.6 M (converted into 2015 dollars) in additional debt financing. We estimate these magnitudes after controlling for standard determinants of leverage such as size, tangibility, profitability, R&D, dividend payments, and market-to-book ratio. The results also hold, with smaller magnitudes, when we estimate regressions with firm fixed effects exploiting within-firm variation across time in firms' organizational status.

An important concern of research in the area of corporate diversification is that a firm's organizational structure is endogenous, which makes causal tests of the effects of diversification challenging. Self-selection into diversification may bias empirical estimates (see, e.g., Maksimovic and Phillips, 2007; Prabhala and Li, 2007). Another potential (and related) concern is the possibility of reverse causality. Firms may increase leverage through debt issuances to fund diversifying investments (Denis and McKeon, 2012, 2016). To address these problems, we propose a novel empirical test for the effect of corporate diversification on capital structure. We interpret the mandatory adoption of SFAS 131[14] following fiscal years after 1997 as a quasi-exogenous shock to lenders' information about the level of a borrower's reported diversification. SFAS 131 forced (some) firms to reveal previously hidden information about their level of firm diversification to outsiders, allowing us to exploit plausibly exogenous variation in a firm's (publicly observed) diversification status. Under the prior standard, SFAS 14, firms frequently reported either no segment data, i.e., a single segment, despite operating in multiple distinct industries or even aggregated dissimilar lines of business into broad industry segments. The new standard forced firms to report segments consistent with their organizational structures (management approach).

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[13] This result continues to hold for the whole class of standard book and market measures of leverage introduced by prior literature (see Appendix 2.B).

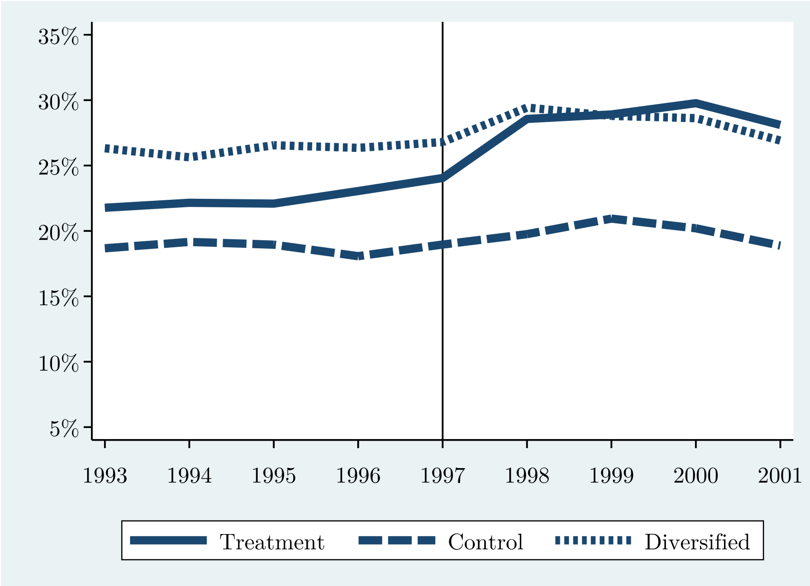
[14] SFAS 131 is FASB Statement No. 131, *Disclosures about Segments of an Enterprise and Related Information* (FASB, 1997) and superseded SFAS 14, *Financial Reporting for Segments of a Business Enterprise*. SFAS 131 became effective in January 1998 and required firms to report business segments consistent with their internal organization.

There is one major attraction of the SFAS 131 shock that we exploit in our identification strategy. Typically, regulatory shocks affect all firms in the economy, which implies that there is frequently no true control group. In our setting, some firms had already complied with SFAS 131 prior to its enactment, and we use a subset of these firms to control for common temporal trends. Our identification strategy builds on a difference-in-differences (DiD) design, which compares leverage outcomes before and after the implementation of SFAS 131 across two different groups of firms. The treatment group (labeled "*change firms*") contains firms that disclosed a single segment prior to the introduction of SFAS 131 and appeared as if they operated as standalone firms in a single (four-digit SIC code) industry. However, these self-proclaimed standalone firms in fact ran businesses in more than one industry and were forced to reveal their previously hidden diversification status upon the adoption of the new standard. We identify these firms with an algorithm proposed by Berger and Hann (2003), which allows us to interpret the transmission of new segment information as an exogenous shock on the main variable of interest: the firm's (observed) diversification status. We proxy the behavior of treated firms absent the shock with a control group of firms that were standalone pre- *and* post SFAS 131 (labeled "*no-change firms*"). These standalone firms had already complied with the new rule prior to its introduction and, as we show, behaved otherwise similarly before the shock compared to firms in the treatment group.

Figure 2.2 presents the novel result captured by our identification strategy. Consistent with a causal effect of corporate diversification on a firm's capital structure, we detect a sharp increase in leverage among the treatment group after the shock but no such change among the control group. The average treatment effect amounts to 3.9 percentage points and is statistically and economically large.

Figure 2.2: Leverage Dynamics of the SFAS 131 Shock

This figure reports the evolution of the average total book leverage ratio (y-axis) of treatment firms (solid line) and control firms (dashed line) for the period from 1993 to 2001. SFAS 131 was announced by the Financial Accounting Standards Board (FASB) in June 1997. The dotted line represents a benchmark group of diversified firms that already complied with the management approach under the prior standard SFAS 14.



We also provide more direct tests of the channel through which diversification is regarded to affect leverage. If there is a cash flow coinsurance effect, we should find not only a relative leverage increase for the *change firms* compared to *no-change firms* after the shock but also that firms with greater coinsurance (i.e., less cash flow correlation across divisions) react more sensitively to treatment. Therefore, we construct different continuous measures of cash flow coinsurance and bin the treatment group of *change firms* based on their hypothesized sensitivity to the SFAS 131 shock. Consistent with the coinsurance hypothesis, we find that treated firms with greater diversification in cash flows obtain higher levels of debt after the shock.

A core threat to the internal validity of our identification strategy is that the mandatory adoption of SFAS 131 might affect capital structure through channels other than *revealed diversification*. We conduct several robustness tests to rule out alternative channels and corroborate our results.

First, it is possible that our shock operates through increased information disaggregation, i.e., less opaqueness at the segment level (the transparency channel).[15] We construct a placebo test that enables us to distinguish the effect of increased segment reporting transparency on firms' capital structure after the shock from the effect of revealed diversification strategies. The placebo sample consists of firms that reveal an increased number of operating segments through the implementation of SFAS 131 while still operating in a single industry (i.e., focused multisegment firms). We find no evidence of an increase in leverage for firms in the placebo group upon the implementation of the new reporting standard relative to the control group.

Second, it is possible that the mandatory adoption of SFAS 131 forced firms to reveal more and higher-quality information beyond their diversification strategies, which might confound our results. A central issue related to the provision of additional information could arise if treated firms conceal their segments' industry affiliation and systematically report their high-leverage-industry segments during the pre-treatment era, while segments of low-leverage industries remain hidden under SFAS 14 (the industry composition channel). Then, SFAS 131 may reveal industry affiliation instead of diversification strategies, and specifications using (industry-adjusted) leverage as the dependent variable would mechanically overestimate the effect of revealed diversification. Therefore, we test whether the shock induced by SFAS 131 affects the asset-weighted median leverage ratio of the industries in which a firm operates (i.e., the firm's imputed leverage). Our results rule out this alternative explanation.

A third concern with our identification strategy is that firms may have incentives to conceal inefficient cross-segment transfers in favor of poorly performing business segments under the prior standard SFAS 14. To the extent that agency problems are negatively related to leverage, we expect our shock-based research design to underestimate the effect of diversification on capital structure if some of the firms in our sample pursue agency motives that the new standard reveals. We therefore

[15] Prior studies find that disaggregated segment data are important for financial statement users and that equity analysts consider segment reporting data as one of the most useful data for investment decisions (Epstein and Palepu, 1999; Berger and Hann, 2003; Cho, 2015).

construct a measure (introduced by Berger and Hann, 2007) that identifies inefficient cross-segment transfers for the final fiscal year before the adoption of SFAS 131. By constructing a hand-collected data set of restated SFAS 14 data, we identify a subset of firms with pronounced (but previously hidden) cross-segment subsidization in capital allocation suggesting agency problems at the segment level during the pre-treatment era. We then re-estimate our main difference-in-differences specification for both subsamples and find evidence that leverage increased around the shock only in the subsample of firms without revealed agency problems.

We conduct further robustness checks to assess the internal validity of the DiD estimator. In particular, we analyze pre-treatment leverage dynamics to assess the plausibility of the parallel trends assumption. There is no evidence that nonparallel trends could bias our estimates. We also demonstrate the functional form independence of our DiD estimator. The magnitude or even the sign of the DiD estimator may be sensitive to its functional form assumption when average outcomes for the control group and the treatment group are different at baseline. Our results continue to hold if we consider relative changes in debt levels instead of absolute changes in debt levels.

Finally, we also address the concern that firms systematically self-select into the treatment group ("*change firms*") and the control group ("*no-change firms*"). We match treatment and control firms based on different propensity scores prior to the introduction of SFAS 131 and perform a matched, conditional DiD analysis. We rely on theories of disclosure that guide our specification of the propensity score models. Our results continue to hold; statistical and economic significance remain unchanged.

The rest of Chapter 2 is organized as follows. Section 2.2 discusses related literature and empirical predictions. In Section 2.3, we describe the data sample and the main definitions of important variables. Section 2.4 presents the econometric model and the baseline results. Section 2.5 presents our identification strategy and the difference-in-differences results. In Section 2.6, we analyze economic channels and alternative explanations. Section 2.7 concludes.

2.2. Related Literature and Empirical Predictions

This chapter makes several contributions to the literature. First, the chapter empirically establishes corporate diversification as an important determinant of the firm's capital structure. Previous research provides inconclusive results. Early cross-sectional studies such as Berger and Ofek (1995) and Comment and Jarrell (1995) find either no association or weak associations between diversification and leverage. However, the evidence in these seminal studies is difficult to interpret, given their very limited sampling intervals. For instance, Berger and Ofek (1995) report that after adjusting for industry differences and controlling for size, profitability and growth opportunities, the debt ratio of multisegment firms is one percentage point higher than those of standalone firms during the 1986-1991 period. Comment and Jarrell (1995) examine the 1978-1989 period but provide only broad summary statistics and infer no association between corporate diversification and leverage. Although these influential studies are not mainly concerned with capital structure and its relationship with corporate diversification, subsequent research concluded that there is little evidence of an economically important effect of corporate diversification on leverage (see, e.g., Stein, 2003 or Maksimovic and Phillips, 2007). This general consensus may have discouraged researchers from turning their attention to the capital structure of diversified firms until recently. Kuppuswamy and Villalonga (2016) find that during the financial crisis, when capital became rationed, coinsurance induced diversified firms to become 8 percentage points more leveraged relative to comparable standalone firms. They employ a nuanced empirical strategy that provides the first evidence consistent with the "coinsurance" hypothesis of diversification. However, they are not able to exploit exogenous variation in the main variable of interest, and it remains unclear how/if their "out-of-equilibrium" findings extend to a more general setting without a severe shortage of credit. The potential importance of the coinsurance argument is also supported by recent survey evidence. Hoang et al. (2021) show that CFOs frequently claim that corporate diversification has a large positive impact on their firms' ability to raise external funds. In contrast to their work, we study firms' actions, not their CFOs' beliefs.

Second, the chapter contributes to the literature on corporate diversification. A large body of literature focuses on the value consequences of corporate diversification and its benefits and costs (e.g., Lang and Stulz, 1994; Berger and Ofek, 1995; Campa and Kedia, 2002; Graham et al., 2002; Villalonga, 2004a and 2004b). The majority of this literature examines how corporate diversification affects the asset side of the balance sheet, for instance, through channels such as capital (re)allocation (e.g., Rajan et al., 2000; Scharfstein and Stein, 2000; Ozbas and Scharfstein, 2010), labor/asset productivity (e.g., Schoar, 2002; Maksimovic and Phillips, 2002; Tate and Yang, 2015), corporate R&D (e.g., Seru, 2014), or cash holdings (e.g., Duchin, 2010; Bakke and Gu, 2017). This chapter provides evidence for another important potential benefit of diversification resulting from positive financial synergies of coinsurance on the right-hand side of the balance sheet.

The literature on corporate diversification has also shown that firms self-select into their organizational forms. By using the introduction of SFAS 131 as an exogenous shock on the (observable) organizational status of the firm for identification, we mitigate some of the concerns that arise from this endogenous choice (for a review, see Maksimovic and Phillips, 2007 and 2013). In particular, unobserved firm characteristics that cause firms to diversify may also cause them to have more debt and thus higher leverage relative to firms that choose not to diversify. Alternatively, there might be reverse causality: firms with better access to debt markets may be more likely to diversify. Previous research on diversification (and its effect on different outcome variables, mainly firm value) addresses related endogeneity concerns with panel data designs with firm fixed effects, matching estimators, instrumental variables or Heckman two-step corrections (see, e.g., Campa and Kedia, 2002; Villalonga, 2004a and 2004b). However, identifying the "treatment effect" of diversification on capital structure is difficult with these designs due to the challenge of finding good instruments or appropriate counterfactuals. We address this issue with our shock-based empirical design. It exploits plausibly exogenous variation in the main variable of interest, the (publicly observed) organizational status of the firm, for some firms and forms a control group of firms without such a change as counterfactuals.

Third, our analysis also complements a related literature that examines the cost of capital of diversified firms (e.g., Aivazian et al., 2015; Franco et al., 2016; Hann et al., 2013). These studies find results consistent with the coinsurance effect of diversification. For instance, Aivazian et al. (2015) show that diversified firms pay lower loan rates than comparable focused firms; Franco et al. (2016) focus on bond offering yields in (primary) public debt markets and find a similar negative relationship between corporate diversification and the cost of debt.[16] Finally, Hann et al. (2013) show that diversified firms with less correlated segment cash flows have a lower cost of capital than comparable portfolios of standalone firms. However, the focus of their paper is on how coinsurance affects firms' systematic risk and cost of equity.

Finally, the chapter also relates to the literature on risk management and capital structure. Theoretical models suggest that risk management activities, such as hedging, enable firms to have higher debt levels due to lower cash flow variability resulting from a decrease in expected financial distress costs (Smith and Stulz, 1985). However, for financial risk management (hedging), the empirical validity of the argument has been questioned. There is scarce evidence of a positive relationship between derivative use and leverage, as predicted by theory (Dolde, 1995; Géczy et al., 1997). One potential explanation for these nonresults is that hedging with financial instruments is not a credible commitment. Firms have no incentive to hedge ex post after raising capital, which lenders may anticipate ex ante.[17] In contrast, corporate diversification is highly irreversible and therefore serves as a credible commitment of the organization to manage risk. Thus, the chapter also suggests that (irreversible) operational risk management − here, corporate diversification − may be a meaningful risk management instrument if firms aim to achieve higher debt capacity.

[16] Cost of debt ("price") and debt amount supplied ("quantity") are both endogenous and simultaneously/jointly determined by supply and demand. Cross-sectional studies of capital structure typically estimate reduced form equations with leverage as a function of demand and supply factors (see Faulkender and Petersen, 2006) or assume infinitely elastic capital supply.

[17] Creditors face an "asset substitution" problem ex post if incentives of managers and shareholders are aligned: shareholders have convex claims and benefit from increased risk, while debtholders, with their concave claims, are hurt.

2.3. Data, Variables, and Empirical Methods

2.3.1. Sample and Data

We construct our sample with data from Compustat North America Annual for the period from 1981 to 2015. From these files, we retrieve firm-level information such as leverage, book assets, operating profits, market-to-book ratios or dividend payments. We then merge these data with Compustat's Segment File, from which we obtain segment accounting information and the industry in which the firms' segments operate (represented by four-digit SIC codes). Because the Compustat Segment File may contain multiple, repeated segment data entries for a given reporting period if firms reorganize reportable segments and then restate prior segment-years for comparative purposes, we consider only the earliest source year for a given reporting period. Otherwise, reorganization of reported segments may contaminate our results. Following the literature, we exclude financial firms (SIC 6000-6999), utilities (SIC 4900-4999), and government agencies (SIC 9000-9999) because their capital structure is subject to specific regulation and their accounting information can also differ from those of firms in other sectors of the economy. For the same reasons, we remove industrial firms if their segments operate in any of these industries. We further eliminate firm- and segment-year observations with negative or missing book values of sales or assets and segment-year observations with missing or incomplete data on segment industries.

Multisegment firms frequently do not fully allocate total firm assets or sales to their reported business segments. To limit the effect of noise introduced by potential inconsistencies between segment figures and firm totals, we follow common conventions from the literature (e.g., see Berger and Ofek, 1995; Billet and Mauer, 2003). We require that the sum of segment sales (assets) be within 1% (25%) of consolidated firm totals. For firms that meet these criteria, we allocate the unallocated portion of sales (assets) to the reported segments on a sales-weighted (asset-weighted) basis. Finally, to reduce the effect of outliers, we truncate all variables at the 1^{st} and 99^{th} percentiles and require leverage ratios to lie in the closed unit interval. This selection procedure leaves us with a sample of 93,892 firm-year observations from 11,568 firms, for an average of 2,683 observations per year.

2.3.2. Empirical Strategy and Measures

Measure of Leverage. To empirically investigate the relationship between corporate diversification and capital structure, we run regressions of *industry-adjusted leverage* as the dependent variable on diversification, our main variable of interest, and a set of firm characteristics. We follow the prior literature (Berger and Ofek, 1995; Kuppuswamy and Villalonga, 2016) and define industry-adjusted leverage as the difference between a firm's actual leverage and its imputed leverage: For a diversified firm, the imputed leverage is the asset-weighted median leverage of standalone firms operating in the same industry and represents the leverage of an industry-matched, asset-weighted portfolio of a comparable standalone firm. For a standalone firm, the imputed leverage is the leverage of the median firm in its industry. Generally, industry adjustment removes common industry factors that are known to imply significant variation in leverage ratios across industries (e.g., MacKay and Phillips, 2005; Lemmon et al., 2008; Frank and Goyal, 2009). In the context of Chapter 2, industry adjustment has the additional advantage of eliminating systematic leverage differences between diversified and standalone firms if firms choose to diversify into high-leverage industries.[18] Industry matching is based on the narrowest SIC grouping (beginning with four-digit SIC codes) that includes at least ten standalone firms per industry and year. Detailed variable definitions are provided in Appendix 2.A.

In our leverage regressions, we focus on total (short-term plus long-term) book leverage as the main outcome variable. Total book leverage (TBL) is defined as the ratio of total debt to total book assets. This measure produces the most conservative estimates relative to alternative (book- and market-based) measures of leverage.[19] Appendix 2.D replicates the main regressions and reports results using

[18] A second approach to remove unobserved industry heterogeneity instead of using industry adjustments is to regress leverage on firm characteristics and to add a firm's imputed leverage as an additional control. In Appendix 2.D and some of the specifications below, we show that the results in such an alternative specification are virtually unchanged. A potential third approach, industry-year fixed effects, following Gormley and Matsa (2014), is infeasible to implement in studies of corporate diversification.

[19] There is no unified consensus or a universally "best" leverage measure in the literature (see also Frank and Goyal, 2009; Welch, 2011). Most capital structure studies scale debt by book values of assets instead of market values (see Parsons and Titman, 2008) because managers appear to be concerned primarily with book leverage (Graham and Harvey, 2001).

alternative leverage ratios introduced by prior literature: total gross market leverage, long-term book and market leverage, or net (of cash) book and market leverage.

Measure of Diversification. Our main variable of interest, diversification, is an indicator variable that measures the organizational status of a firm based on the industry classification of its divisions. The binary measure equals one if a firm operates in two or more different four-digit SIC code industries and zero otherwise.

Control Variables. In our multivariate regressions and the difference-in-differences analysis, we control for common determinants of capital structure, which we choose and define following the prior literature (Rajan and Zingales, 1995; Lemmon et al., 2008; Frank and Goyal, 2009): size (natural logarithm of total book assets), profitability (operating income before depreciation scaled by total assets), tangibility (net property, plant and equipment scaled by total assets), investment opportunities (proxied by the market-to-book ratio), product specialization (R&D expenses scaled by total sales), and a firm's dividend payer status. In some specifications, we also add cash flow volatility/firm risk as an additional covariate, which we measure as the standard deviation of the ratio of operating income before depreciation to assets based on a past rolling window of ten years with a required minimum of five valid observations (see Appendix 2.A for detailed variable definitions).[20]

2.4. Empirical Analysis

2.4.1. Descriptive Statistics and Differences-in-Means

We begin our analysis by presenting descriptive statistics for the sample and univariate results on the relation between diversification and leverage. Table 2.1 reports tests of differences in means (t-tests) and medians (Fisher's exact tests) between diversified and standalone firms. The full sample contains a total of 93,892 firm-years, including 18,051 (19%) observations from diversified firms. The

[20] The drawback of including firm-level volatility is that it decreases the sample size substantially. Many companies do not have sufficient available valid observations.

table shows that, on average, diversified firms are significantly more levered than standalone firms across all standard measures of leverage. The magnitudes are also economically important. For instance, the total book leverage ratio of the average (median) diversified firm is 6.3 (9.5) percentage points higher than that of the average (median) standalone firm. In relative terms, these numbers correspond to a 31% (61%) higher leverage of diversified firms than those of standalone firms. These leverage differences also persist when we industry-adjust our measures of leverage. The average (median) industry-adjusted total book leverage ratio (IAL) of diversified firms is 3.6 (6.7) percentage points higher than the corresponding value of the average standalone firm. This difference further increases in size for the remaining industry-adjusted standard measures of leverage.

The table also reveals that diversified and standalone firms differ across other firm-specific characteristics. Diversified firms operate 2.9 business segments in 2.6 different four-digit SIC code industries on average. They are significantly larger, hold more tangible assets, are more profitable, are more likely to pay dividends and have lower market-to-book ratios and lower R&D expenses relative to standalone firms. Cash flow volatility is significantly lower for diversified firms. As these firm characteristics were identified by prior literature as determinants of capital structure (see, e.g., Rajan and Zingales, 1995; Lemmon et al., 2008; Frank and Goyal, 2009), we will control for them in our multivariate regression.

Before conducting the formal regression analysis, it is also interesting to examine the time series behavior of industry-adjusted leverage. Appendices 2.B and 2.C plot the evolution of the different measures of industry-adjusted leverage for focused and diversified firms over time. Visual inspection of the panels reveals that throughout the sample period, diversified firms are persistently more levered across all leverage measures.

Table 2.1: Descriptive Statistics

This table reports descriptive statistics for our sample of diversified and standalone firms. The sample period ranges from 1981 to 2015. *Diversified* is a dummy that equals one if the firm operates segments in at least two different four-digit SIC code industries and zero otherwise. *Total book (market) leverage* is total debt scaled by the book (market) value of assets. *Net book (market) leverage* is total debt minus cash and short-term investments scaled by the book (market) value of assets. *Long-term book (market) leverage* is long-term debt scaled by the book (market) value of assets. Industry-adjusted leverage is the difference between a firm's leverage and its imputed leverage (the asset-weighted median leverage of standalone firms operating in the same industry and year). See all further variable definitions in Appendix 2.A.

	Total		(1) Diversified		(2) Standalone		(1)–(2)	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Firm characteristics								
Diversified	0.192	0.000	1.000	1.000	0.000	0.000	1.000***	1.000***
Firm size	4.853	4.663	5.932	5.898	4.596	4.423	1.336***	1.475***
Profitability	0.079	0.116	0.126	0.133	0.067	0.110	0.059***	0.023***
Tangibility	0.278	0.219	0.313	0.280	0.270	0.200	0.043***	0.079***
Market-to-book	1.670	1.179	1.186	0.981	1.785	1.252	−0.599***	−0.271***
R&D	0.110	0.000	0.017	0.000	0.132	0.000	−0.115***	0.000
Dividend payer	0.303	0.000	0.559	1.000	0.243	0.000	0.316***	1.000***
Cash flow volatility	0.093	0.028	0.033	0.018	0.110	0.032	−0.077***	−0.014***
No. of segments	1.420	1.000	2.864	3.000	1.076	1.000	1.787***	2.000***
Leverage measures								
Total book leverage	0.213	0.182	0.264	0.251	0.201	0.156	0.063***	0.095***
Net book leverage	0.167	0.094	0.224	0.211	0.153	0.041	0.071***	0.170***
Long-term book leverage	0.161	0.111	0.212	0.194	0.149	0.082	0.063***	0.112***
Total market leverage	0.213	0.144	0.285	0.248	0.196	0.114	0.088***	0.135***
Net market leverage	0.174	0.069	0.245	0.204	0.157	0.026	0.088***	0.178***
Long-term market leverage	0.158	0.086	0.226	0.191	0.142	0.058	0.084***	0.133***
Imputed leverage								
Total book leverage	0.162	0.155	0.184	0.188	0.157	0.143	0.026***	0.045***
Net book leverage	0.107	0.068	0.124	0.118	0.103	0.041	0.021***	0.078***
Long-term book leverage	0.106	0.081	0.120	0.114	0.102	0.067	0.018***	0.047***
Total market leverage	0.148	0.124	0.175	0.168	0.142	0.107	0.033***	0.061***
Net market leverage	0.102	0.053	0.122	0.103	0.097	0.029	0.025***	0.074***
Long-term market leverage	0.095	0.063	0.113	0.100	0.091	0.048	0.022***	0.052***
Industry-adjusted leverage								
Total book leverage	0.051	0.011	0.080	0.067	0.044	0.000	0.036***	0.067***
Net book leverage	0.060	0.000	0.101	0.081	0.050	0.000	0.051***	0.081***
Long-term book leverage	0.055	0.008	0.092	0.073	0.046	0.000	0.046***	0.073***
Total market leverage	0.065	0.010	0.110	0.084	0.054	0.000	0.055***	0.084***
Net market leverage	0.072	0.000	0.123	0.086	0.060	0.000	0.063***	0.086***
Long-term market leverage	0.063	0.006	0.113	0.082	0.051	0.000	0.062***	0.082***
Nobs	93,892	93,892	18,051	18,051	75,841	75,841	93,892	93,892

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

2.4.2. Baseline Analysis

We move on with the formal regression analysis of the relation between corporate diversification and capital structure. We estimate the following equation:

$$IAL_{i,t} = \alpha + \beta \times D_{i,t} + X'_{i,t} \times \gamma + \eta_t + \epsilon_{i,t} \tag{2.1}$$

$IAL_{i,t}$ is the industry-adjusted leverage ratio of firm i in period t; $D_{i,t}$ represents our diversification measure, which equals one if firm i operates in two or more different four-digit SIC code industries in period t and zero otherwise; X refers to a set of observable firm-specific standard determinants of capital structure, including size, profitability, tangibility, the market-to-book ratio, R&D, and dividend payer status; η_t is a set of year fixed effects, which absorb time-varying shocks that all firms face; and $\epsilon_{i,t}$ is the error term. We cluster standard errors at the firm level to adjust for heteroscedasticity and possible dependence in the residuals over time (Petersen, 2009). The parameter β is the primary coefficient of interest and represents the difference in leverage for diversified versus standalone firms.

Table 2.2 (column (2)) reports the estimates of equation (1). The results indicate a strong positive relation between our variable of interest, $D_{i,t}$, and industry-adjusted leverage. The association is significantly different from zero at the 1% level of significance. The estimated coefficient $\hat{\beta}$ is of sizable economic magnitude. Corporate diversification is associated with an absolute increase in industry-adjusted book leverage of 3.8 percentage points. This result translates into additional debt of \$67.6 M (converted into 2015 dollars) for the median-sized diversified firm.[21] The sign and statistical significance of the remaining covariates in our baseline specification are consistent with the extant literature on capital structure determinants (see, e.g., Frank and Goyal, 2009; Graham et al., 2015): We observe that larger and more tangible firms have higher industry-adjusted leverage

[21] Using alternative measures of book and market leverage, the association between our variable of interest $D_{i,t}$ and $IAL_{i,t}$ even increases in size (see Appendix 2.D). As expected and consistent with Duchin (2010), who finds that standalone firms hold relatively more cash for precautionary reasons, we obtain the largest estimates using specifications with net cash leverage measures as the dependent variable.

(IAL). Dividend payers and more profitable firms as well as firms with higher market-to-book ratios and higher R&D intensity are negatively associated with leverage.

For robustness, we estimate a specification similar to that in column (2) but include firm-level cash flow volatility (column (3)). The availability of data on cash flow volatility reduces the sample size by approximately 30%, so we do not include it in most of our reported results. The estimated coefficient on $D_{i,t}$ is virtually unchanged and remains significantly different from zero at the 1% level. Finally, we present results from an alternative estimation strategy (columns (4)-(6)). We regress total book leverage on the covariates described above but include imputed leverage as an additional control. The regressions yield similar coefficients on the diversification dummy and confirm the positive relation between diversification and leverage.

In capital structure regressions, a frequent concern is that unobservable, time-invariant differences across firms can induce a fixed effect on firms' leverage outcomes. For instance, Lemmon et al. (2008) document that a large part of the variation in capital structure is due to firm-specific time-invariant factors, which suggests the inclusion of firm fixed effects and identification from a firm's time-series variation. The problem with the fixed effects estimator is that it not only removes the cross-sectional variation in both the explanatory and dependent variables but also requires time-series variation in the firm's organizational status. While the majority of firms (84%) never change their organizational status during the sample period, 16% of firms in our sample do (6% diversify once, 4% refocus once, and 6% change their status multiple times). Our baseline results continue to hold (see Table 2.2, columns (7)-(9)). The baseline association between diversification and leverage remains economically large and significantly different from zero, with an estimated coefficient that ranges from 2.1% to 3.3%.

Table 2.2: Baseline Regression

This table presents the results of regressing industry-adjusted total book leverage (columns (1)-(3), (7)-(9) and total book leverage (columns (4)-(6)) on a firm's organizational status, *Diversified*, and a vector of additional controls. Industry-adjusted total book leverage is the difference between a firm's total book leverage and its imputed total book leverage (the asset-weighted median leverage of standalone firms operating in the same industry and year). *Diversified* is a dummy that equals one if the firm operates segments in at least two different four-digit SIC code industries and zero otherwise. The sample period ranges from 1981 to 2015. All regressions include year fixed effects. Columns (7)-(9) extend the specification of columns (1)-(3) by including firm fixed effects. Standard errors (in brackets) are heteroscedasticity consistent and clustered at the firm level. See Appendix 2.A for detailed variable descriptions.

	Industry-Adjusted Total Book Leverage			Total Book Leverage			Industry-Adjusted Total Book Leverage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Diversified	0.037***	0.038***	0.036***	0.046***	0.037***	0.035***	0.033***	0.023***	0.021***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Imputed leverage				0.639***	0.452***	0.422***			
				(0.012)	(0.014)	(0.017)			
Firm size		0.013***	0.012***		0.015***	0.016***		0.027***	0.029***
		(0.001)	(0.001)		(0.000)	(0.001)		(0.001)	(0.002)
Profitability		−0.142***	−0.180***		−0.154***	−0.191***		−0.168***	−0.205***
		(0.007)	(0.010)		(0.007)	(0.009)		(0.007)	(0.009)
Tangibility		0.039***	0.024***		0.150***	0.139***		0.165***	0.127***
		(0.007)	(0.009)		(0.007)	(0.009)		(0.012)	(0.015)
Market-to-book		−0.008***	−0.006***		−0.013***	−0.013***		−0.004***	−0.003***
		(0.000)	(0.001)		(0.000)	(0.001)		(0.000)	(0.001)
R&D		−0.024***	−0.017***		−0.049***	−0.048***		−0.043***	−0.046***
		(0.003)	(0.006)		(0.003)	(0.006)		(0.004)	(0.006)
Dividend payer		−0.064***	−0.063***		−0.062***	−0.059***		−0.039***	−0.035***
		(0.003)	(0.003)		(0.003)	(0.003)		(0.003)	(0.003)
Cash flow volatility			−0.019***			−0.013**			0.014*
			(0.006)			(0.006)			(0.007)
Constant	0.012***	0.013***	0.021***	0.087***	0.090***	0.098***	−0.007*	−0.105***	−0.099***
	(0.003)	(0.005)	(0.006)	(0.004)	(0.005)	(0.006)	(0.003)	(0.008)	(0.011)
Year FE	X	X	X	X	X	X	X	X	X
Firm FE							X	X	X
Nobs	93,892	93,892	65,384	93,892	93,892	65,384	93,892	93,892	65,384
Adjusted R^2	0.02	0.06	0.07	0.17	0.25	0.23	0.03	0.08	0.08

Robust standard errors in parentheses

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

2.5. Natural Experiment and Identification Strategy: SFAS No. 131

2.5.1. Exogenous Shock on Diversification and Institutional Background

The ideal setting to test for the (causal) effect of corporate diversification on leverage would consist of a randomly assigned intervention that induces exogenous variation in corporate diversification in a controlled experiment. We could then easily measure the causal effect of a change in diversification on leverage. Because such an experiment is hardly feasible to implement, we exploit an exogenous policy shock that allows us to closely approximate such an ideal experiment. In June 1997, the US Financial Accounting Standard Board (FASB) issued the Statement of Financial Accounting Standards No. 131 (SFAS 131) to establish new standards for disclosures about reported business segments. Effective for fiscal years beginning after December 15, 1997, SFAS 131 forced firms to provide information about their reportable business segments consistent with the internal organization of the firm. It superseded SFAS 14, which allowed managers flexibility in defining their reportable segments. In particular, the old standard allowed firms to aggregate dissimilar lines of business into broad industry segments or even to report only a single line of business, although firms in fact ran businesses in more than one industry.[22]

We exploit this unique setting in a difference-in-differences framework to empirically evaluate the effect of corporate diversification on financial leverage. SFAS 131 forced some firms to reveal previously hidden information about their level of firm diversification to outsiders, allowing us to exploit plausibly exogenous variation in these firms' (publicly observed) diversification status. Other firms had already complied with SFAS 131 prior to its enactment, and we use a subset of these firms to control for common temporal trends. The *treatment group* contains firms that were self-proclaimed *standalone* firms under SFAS 14 but revealed (previously hidden) industry operations, i.e., diversification, upon adoption of the new standard. Hereafter, we label these firms as "*change firms*".

[22] Frequently referred examples are IBM or Xerox (see Ettredge et al., 2005; Berger and Hann, 2003). For instance, IBM restated from one industry segment ("*Information Handling-Systems*") to seven operating segments ("*Global Services*", "*Enterprise Investments*", "*Technology*", "*Server*", "*Personal Systems*", "*Global Financing and Software*") in five different industries (at the SIC 4 level) under the new standard.

We identify these firms based on a hand-collected database that contains restated SFAS 131 segment accounting data for the final SFAS 14 fiscal year using an algorithm proposed by Berger and Hann (2003). This algorithm allows us to distinguish the effect of revealed diversification from other changes in the adoption year (such as pooling acquisitions or discontinued operations). Firms with such changes are excluded from the sample because they may contaminate our results. For instance, observed leverage increases could be driven by firms' need to fund their diversifying long-term investments (Denis and McKeon, 2012).[23] As a result, our treatment group is a subset of all firms with $D_{i,t}$ changing from zero to one upon and only through introduction of SFAS 131.

We proxy the behavior of treated firms absent the shock with a group of standalone firms. This *control group* (labeled "*no-change firms*") serves as the counterfactual and contains standalone firms that had complied with SFAS 131 prior to its introduction. The segment reporting of these "real" standalone firms was unaffected by the new rule, and as we show in the robustness section further below, firms in the control group behaved similarly before the shock compared to those in the treatment group.[24] This procedure identifies 388 "*change firms*" and a control group of 1,052 "*no-change firms*".

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[23] Following Berger and Hann (2003), we hand-collect restated SFAS 131 segment data for the final SFAS 14 fiscal year, compare the sums of segment revenues (and earnings) from restated reports with the corresponding sum for the historical SFAS 14 year, and exclude firms when the historical and restated sums differ by more than 1%. For a detailed description of the sample screening procedure, see Berger and Hann (2003).

[24] Visual inspection of the debt levels across both groups (see Figure 2) already suggests parallel trends before the shock. We provide a formal statistical test and further support for the parallel trends assumption in Section 2.5.3.1.

2.5.2. Difference-in-Differences Strategy

To formally test the effect of (disclosed) diversification on financial leverage, we estimate the following difference-in-differences (DiD) specification:

$$
\begin{aligned}
IAL_{i,t} &= \alpha + \delta_{DiD} \times \textit{Change-firm}_i \times \textit{Post-SFAS}_{i,t} + \delta_{change} \times \textit{Change-firm}_i \\
&\quad + \delta_{post\text{-}SFAS} \times \textit{Post-SFAS}_{i,t} + \eta_t + \epsilon_{i,t}
\end{aligned}
\tag{2.2}
$$

, where $\textit{Change-firm}_i$ is an indicator that equals one if a firm belongs to the treatment group and zero otherwise; $\textit{Post-SFAS}_{i,t}$ is an indicator for the post-treatment period of firm i; η_t is a set of year fixed effects; and $\epsilon_{i,t}$ is the unobservable error term. We restrict the full sample to the four years before and after firms' adoption of SFAS 131. The coefficient of interest is δ_{DiD}, which measures the average leverage change in the treatment group compared to the change in the control group before and after the shock. A statistically significant and positive coefficient would provide support for the coinsurance hypothesis of diversification.[25]

Table 2.3 presents the estimates of the difference-in-differences specification described above. We report the results from regressions on the full sample in columns (1)-(3) and from a balanced sample (as defined by the presence of firms in each year during the DiD sample period) in columns (4)-(6). We estimate different regressions with and without covariates as well as with and without firm fixed effects for each of the two samples. All regressions have standard errors clustered at the firm level. Table 2.3 shows that leverage increases substantially after the shock for *change firms*. Across all specifications, the coefficient of interest $\hat{\delta}_{DiD}$ is uniformly positive, always economically large and statistically significant – in the full sample and the balanced sample. The magnitudes of the coefficients are similar to those in our baseline analysis (Section 2.4): In column (1), the specification

[25] There is a small group (17%) of treated firms with fiscal year end between June and November. These firms adopted SFAS 131 in 1999 instead of 1998. The index i in $\textit{Post-SFAS}_{i,t}$ accounts for this difference in time. We find economically and statistically similar results when we consider the two alternative strategies of either completely excluding this subgroup of treated firms from the sample or considering a modified pre- and post-treatment period that covers the years 1994 to 1997 (pre) and 1999 to 2002 (post) for all firms.

without covariates, the coefficient of interest $\hat{\delta}_{DiD}$ equals 4.1% and is statistically significant at the 1% level. The size of the estimated coefficient is also similar across alternative specifications, e.g., when we add the covariates from the OLS analysis (column (2): 3.9%) or firm fixed effects (column (3): 3%). For robustness, columns (4)-(6) repeat the analysis and present the estimated coefficients for the balanced sample. These regressions address the concern that changes in the sample composition in each group of firms could affect our results. The significance and magnitude of the estimates are similar to those in the full sample. In Appendix 2.E, we re-estimate all specifications for alternative leverage measures. All results are qualitatively similar to those in Table 2.3, with even slightly larger magnitudes than the ones presented here.

In Panel B of Table 2.3, we present results from the alternative estimation strategy of replacing the dependent variable with non-industry-adjusted total book leverage. With this analysis, we assess whether the results are affected by industry-adjusting our leverage measure.[26] In some of the specifications, we add imputed leverage as an additional control. Panel B of Table 2.3 shows that the coefficients of the interaction term, *Change-firm* × *Post-SFAS*, are consistently significant at the 1% level and virtually identical to those in the corresponding specifications in Panel A.

Overall, the results in Table 2.3 are consistent with the coinsurance hypothesis of diversification, suggesting that (observed) diversification allows firms to have higher leverage relative to comparable focused firms.

[26] We discuss the potential implications of the industry adjustment and provide more definite tests in Section 2.6.2.2.

Table 2.3: Difference-in-Differences Regression (DiD)

This table presents the results from estimating the following difference-in-differences (DiD) specification:

$$\begin{aligned} IAL_{i,t} = \alpha &+ \delta_{DiD} \times \textit{Change-firm}_i \times \textit{Post-SFAS}_{i,t} + \delta_{change} \times \textit{Change-firm}_i \\ &+ \delta_{post\text{-}SFAS} \times \textit{Post-SFAS}_{i,t} + \eta_t + \epsilon_{i,t} \end{aligned}$$

, where $IAL_{i,t}$ is industry-adjusted total book leverage (Panel A), which is the difference between a firm's total book leverage and its imputed leverage. In Panel B, the dependent variable is total book leverage, and imputed leverage is included as an additional control. $\textit{Change-firm}_i$ is an indicator that equals one if the disclosed organizational status of firm *i* changes from *standalone* to *diversified* after the adoption of SFAS 131 (treated firms) and zero otherwise (control firms). $\textit{Post-SFAS}_{i,t}$ is an indicator for the post-treatment period of firm *i*. The sample period ranges from 1994 to 2002 (four years before and after the adoption of SFAS 131). The regressions are estimated separately for the full sample in columns (1)-(3) and for a balanced sample in columns (4)-(6). All regressions include year fixed effects. Columns (3) and (6) extend the specification by including firm fixed effects. Standard errors (in brackets) are heteroscedasticity consistent and clustered at the firm level. See Appendix 2.A for all variable definitions.

Panel A. Regression of Industry-Adjusted Total Book Leverage

	Full Sample			Balanced Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Change-firm × Post-SFAS	0.041***	0.039***	0.030***	0.046***	0.042***	0.046***
	(0.010)	(0.009)	(0.009)	(0.014)	(0.013)	(0.013)
Change-firm	0.033***	0.033***		0.026	0.032*	
	(0.012)	(0.012)		(0.018)	(0.018)	
Post-SFAS	−0.009	−0.013	0.003	0.001	−0.007	0.005
	(0.013)	(0.012)	(0.007)	(0.016)	(0.016)	(0.008)
Firm size		0.015***	0.045***		0.019***	0.055***
		(0.002)	(0.005)		(0.003)	(0.008)
Profitability		−0.155***	−0.170***		−0.177***	−0.194***
		(0.030)	(0.021)		(0.046)	(0.029)
Tangibility		0.012	0.095***		0.000	0.083*
		(0.020)	(0.034)		(0.026)	(0.047)
Market-to-book		−0.011***	−0.004***		−0.011***	−0.007***
		(0.002)	(0.001)		(0.003)	(0.002)
R&D		0.053	−0.051		0.148**	−0.054
		(0.033)	(0.033)		(0.057)	(0.050)
Dividend payer		−0.056***	−0.020**		−0.051***	−0.016
		(0.009)	(0.009)		(0.012)	(0.013)
Constant	0.010	−0.010	−0.192***	−0.007	−0.048**	−0.243***
	(0.006)	(0.015)	(0.030)	(0.008)	(0.022)	(0.045)
Year FE	X	X	X	X	X	X
Firm FE			X			X
Nobs	8,432	8,432	8,432	4,246	4,246	4,246
Adjusted R^2	0.02	0.07	0.10	0.03	0.09	0.13

Panel B. Regression of Total Book Leverage

	Full Sample			Balanced Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Change-firm × Post-SFAS	0.040***	0.037***	0.026***	0.046***	0.043***	0.045***
	(0.009)	(0.009)	(0.008)	(0.013)	(0.012)	(0.012)
Change-firm	0.038***	0.033***		0.033*	0.031*	
	(0.011)	(0.011)		(0.018)	(0.017)	
Post-SFAS	−0.001	−0.004	0.006	0.013	−0.000	0.005
	(0.012)	(0.011)	(0.006)	(0.015)	(0.014)	(0.007)
Imputed leverage	0.603***	0.375***	0.236***	0.511***	0.282***	0.228***
	(0.032)	(0.039)	(0.028)	(0.046)	(0.055)	(0.037)
Firm size		0.020***	0.047***		0.024***	0.057***
		(0.002)	(0.005)		(0.003)	(0.008)
Profitability		−0.192***	−0.201***		−0.242***	−0.230***
		(0.029)	(0.021)		(0.042)	(0.029)
Tangibility		0.134***	0.109***		0.140***	0.097**
		(0.021)	(0.033)		(0.028)	(0.046)
Market-to-book		−0.019***	−0.008***		−0.017***	−0.010***
		(0.002)	(0.001)		(0.003)	(0.002)
R&D		−0.162***	−0.068**		−0.178***	−0.079
		(0.047)	(0.033)		(0.052)	(0.048)
Dividend payer		−0.056***	−0.017**		−0.048***	−0.019
		(0.008)	(0.008)		(0.010)	(0.013)
Constant	0.081***	0.065***	−0.063**	0.079***	0.043**	−0.110**
	(0.007)	(0.014)	(0.029)	(0.010)	(0.020)	(0.045)
Year FE	X	X	X	X	X	X
Firm FE			X			X
Nobs	8,432	8,432	8,432	4,246	4,246	4,246
Adjusted R^2	0.18	0.27	0.13	0.15	0.27	0.17

Robust standard errors in parentheses

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

2.5.3. Internal Validity of the Empirical Design and Threats to Identification

In this section, we address potential concerns about the interpretation of our results and the validity of the difference-in-differences design. In particular, we analyze pre-treatment leverage dynamics to assess the plausibility of the parallel trends assumption, potential self-selection into the treatment group and the control group and dependence on the functional form of the DiD estimator.

2.5.3.1. Identifying Assumption: Parallel Trends

A necessary condition for identification is the parallel trends assumption. In our case, this assumption requires that the evolution of leverage of *change firms* and *no-change firms* absent the shock would have followed common trends both before and after the shock. The potential leverage had the shock not happened is unobservable, so we cannot formally test whether this *parallel trends assumption* holds after the introduction of SFAS 131. We therefore test whether the trends in leverage are parallel before the shock.

To assess pre-shock trends, we estimate the following specification:

$$IAL_{i,t} = \alpha + \sum_{t=1993}^{2001} \beta_t \times \textit{Change-firm}_{i,t} + \gamma_i + \eta_t + \epsilon_{i,t} \tag{2.3}$$

, where $\textit{Change-firm}_{i,t}$ is an indicator variable that equals one for treated firms ("*change firms*") in period t and zero otherwise, γ_i are firm dummies and η_t is a set of year fixed effects. The coefficients of interest, β_t, are interactions between the change dummy and year fixed effects. Figure 2.3 plots the estimated coefficients and the 95% confidence intervals. We use 1992 as the reference year, for which the coefficient is zero by construction. As Figure 2.3 reveals, the estimated coefficients for the years prior to the shock are statistically indistinguishable from zero and economically small (between -0.8% and 0.8%). Therefore, we fail to reject that time trends prior to the introduction of SFAS 131 are similar across treated and control firms. There is no evidence that nonparallel trends could bias our estimates.

Figure 2.3: Parallel Pre-Treatment Trends

This figure plots the estimated coefficients and 95% confidence intervals for a set of leads and lags contained in the following equation:

$$IAL_{i,t} = \alpha + \sum\nolimits_{t=1993}^{2001} \beta_t \times \mathit{Change\text{-}firm}_{i,t} + \gamma_i + \eta_t + \epsilon_{i,t}$$

, where $\boldsymbol{\beta}_t$ represents the coefficient estimates of interactions between the treatment indicator and year fixed effects (with 1992 as the reference year).

2.5.3.2. Matched Difference-in-Differences Estimator

Even though the treatment group and the control group follow parallel trends prior to the introduction of SFAS 131, the DiD estimator can lead to biased inferences if post-treatment trends in leverage diverge for reasons unrelated to revealed diversification. Shocks common to both groups could coincide with the introduction of SFAS 131 and differentially affect temporal trends, even in the absence of revealed diversification. Such differential trends may result from firm characteristics that are unbalanced across treatment and control firms if firms systematically self-select into the treated group. We address this concern by matching treatment and control firms based on propensity scores prior to the introduction of SFAS 131 and then perform a matched, conditional DiD analysis. The matching procedure absorbs possible differential trends by assuring that we compare observationally similar firms on dimensions that are likely to affect treatment assignment and leverage. The downside of the matched DiD design is the loss of data, which may lead to larger standard errors compared to using a DiD on its own.[27]

To estimate the propensity scores, we first run a probit regression of *Change-firm* (the binary variable indicating whether a firm is in the treatment group) on variables that determine the outcome (i.e., leverage) as well as variables that likely predict treatment assignment. We use firm size, tangibility, profitability, dividend payments, R&D, market-to-book ratio (the control variables from our baseline leverage regression) and a set of characteristics that likely affect the incentives to withhold segment disclosures prior to the SFAS 131 introduction. Earlier work summarizes theories of segment (non-)disclosure into two nonmutually exclusive hypotheses: the proprietary costs of disclosure hypothesis and the agency cost hypothesis. For instance, Harris (1998) and Botosan and Stanford (2005) provide evidence suggesting that firms aggregate segments to conceal line-of-business information due to competitive concerns (the proprietary cost hypothesis). Detailed segment information about line-of-business profitability can reveal proprietary information (such as trade secrets or profitable customers and markets) that competitors may use to the disclosing firm's disadvantage. Other studies (e.g., Berger and Hann, 2007; Berger, 2011; Bens et al., 2011) suggest that firms with agency problems have incentives to withhold segment disclosure because nondisclosure weakens the effectiveness of external monitoring by shareholders (the agency cost hypothesis). Following the literature, we proxy for the firm's proprietary costs of disclosure using two variables that reflect different aspects of competition (see Harris, 1998): industry competitiveness and the speed of profit adjustment. The first measure of competition, industry competitiveness, is defined as one minus the asset-weighted average of the Herfindahl index of the industries in which the firm's segments operate. The second measure, speed of profit adjustment, is the asset-weighted average of the speed of adjustment for positive abnormal profits within each industry in which the

[27] Another possibility to absorb differential temporal trends would be to assume a functional form for the post-treatment time-series, e.g., by extending the main DiD specification in (2) with interaction terms of firm characteristics and year indicator variables. The propensity score matching procedure offers the advantage of reducing model dependence, i.e., the knowledge of the functional form of the parametric model.

firm's segments operate. The measure proxies for the persistence of abnormally high positive profits within an industry by estimating the reversal speed of abnormal positive profits to the industry mean. We use the percentage of shares held by institutional investors and the GIM index by Gompers et al. (2003) to proxy for the severity of unresolved agency problems between shareholders and managers.[28] For all matching variables, we use pre-treatment averages.

We then use the predicted probabilities from the probit estimation (i.e., the propensity scores) and explore different matching procedures: one-to-one matching without and with replacement, nearest neighborhood matching with different numbers of matches, and inverse probability weighting. These alternatives involve trade-offs between matching accuracy and efficiency reduction (see Smith and Todd, 2005; Caliendo and Kopeinig, 2008; Roberts and Whited, 2013).[29] The propensity scores of all firms (except for three control firms that we discard) lie in the common support region of estimated propensity scores (see Appendix 2.F).[30] Then, we rerun the main DiD test on the different propensity score matched samples, which we report in Table 2.4. Our results continue to hold, and statistical and economic significance are similar in magnitude (4.1-4.5%) compared to those obtained in our baseline DiD test. In untabulated analysis, we also repeat all other baseline DiD tests of Table 2.3, Panels A and B on the propensity score matched samples and find either qualitatively similar

[28] Using the entrenchment index (Bebchuk et al., 2009) as an alternative measure of agency provides similar results.

[29] One-to-one matching with replacement allows a control firm to be matched with more than one treated firm, which increases matching quality (and reduces bias) but also reduces the number of distinct firms that form the control group (which may lead to increased standard errors). Increasing the number of matches using nearest neighborhood matching with the n closest matches involves a similar bias-variance trade-off. Inverse probability weighting uses all observations with positive propensity scores and weights each observation with the inverse of the estimated propensity score (see Abadie and Cattaneo, 2018).

[30] The figure plots the distribution of propensity scores for both groups across twenty equal-length partitions of the propensity score distribution. There is only one partition with no overlap in the covariate distributions of the treatment and the control group, which suggests we are able to find sufficiently good matches in the control group (and our baseline DiD findings do not suffer from bias resulting from nonoverlapping supports). Moreover, we formally test whether firm characteristics are balanced after the matching process. In Appendix 2.G, we report the mean of the matching categories for firms in the control group and treated group. Column (7) tests the null hypothesis that the means across the two groups are equal. We cannot reject the null for any of the ten matching variables.

or economically even stronger results. Overall, these results indicate that heterogeneity across firm characteristics is unlikely to bias our results.

Table 2.4: Matched DiD Regression

This table presents the results from estimating difference-in-differences (DiD) regressions for matched samples of treated and control firms. The dependent variable is industry-adjusted total book leverage, which is the difference between a firm's total book leverage and its imputed leverage. *Change-firm*$_i$ is an indicator that equals one if the disclosed organizational status of firm *i* changes from *standalone* to *diversified* after adoption of SFAS 131 (treated firms) and zero otherwise (control firms). *Post-SFAS*$_{i,t}$ is an indicator for the post-treatment period for firm *i*. The sample period ranges from 1994 to 2002 (four years before and after the adoption of SFAS 131). Treated and control firms are matched based on one-to-one propensity score matching with replacement in column (1), without replacement in column (2), and nearest neighbor propensity score matching with different numbers of matches in columns (3)-(5). In column (6), treated and control firms are weighted by the inverse of their propensity score (IPW). Propensity scores are obtained from a probit regression of *Change-firm* on a set of ten matching variables, including firm size, profitability, tangibility, market-to-book ratio, R&D activity, dividend payer status, industry competitiveness, speed of profit adjustment, the GIM index, and the total share of institutional ownership. All regressions include year fixed effects and controls from prior regressions. Standard errors (in brackets) are heteroscedasticity consistent and clustered at the firm level. See Appendix 2.A for all variable definitions.

	One-to-one Matching		Nearest Neighbor Matching			IPW
	(1)	(2)	(3)	(4)	(5)	(6)
Change-firm × Post-SFAS	0.043***	0.045***	0.041***	0.042***	0.045***	0.043***
	(0.014)	(0.012)	(0.012)	(0.011)	(0.011)	(0.012)
Change-firm	0.019	0.033**	0.033**	0.038***	0.036***	0.017
	(0.016)	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)
Post-SFAS	−0.034	−0.042**	−0.033*	−0.024	−0.027	−0.038**
	(0.022)	(0.021)	(0.020)	(0.019)	(0.019)	(0.019)
Constant	−0.026	−0.034	−0.049**	−0.057**	−0.037	−0.017
	(0.028)	(0.027)	(0.024)	(0.024)	(0.023)	(0.020)
Controls	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Replacement	X	—				
Matches (N)	1	1	2	3	4	
Nobs	2,971	3,321	3,997	4,691	5,236	8,400
Adjusted R^2	0.08	0.09	0.09	0.10	0.10	0.09

Robust standard errors in parentheses

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

2.5.3.3. Functional Form Independence

We conduct further robustness checks to demonstrate the functional form independence of our results. The magnitude or even the sign of the DiD estimator may be sensitive to its functional form assumption when average outcomes for the treatment group and the control group are very different at baseline. We introduce a log-level difference-in-differences specification to study the shock in relative terms (instead of absolute terms). We use the natural log of total book leverage as the dependent variable on the left-hand side of equation (2) and include firms' imputed leverage ratio as an additional control.[31] Table 2.5 reports estimates for the coefficients of the log-level DiD specification. The results suggest that treatment firms increase their leverage ratio compared to control firms and after the adoption of SFAS 131 in relative terms – for the baseline DiD without controls by more than 26% (column (1)). The average effect of the treatment is similar if we add observed firm characteristics (column (2)) or firm fixed effects (column (3)) or run the same regressions on the balanced sample (columns (4)-(6)). Thus, our results continue to hold if we consider relative changes in debt levels instead of absolute changes in debt levels.

[31] We refrain from applying the log transformation to the main measure, industry-adjusted leverage (IAL), because all firms that are underlevered relative to their industries (i.e., IAL < 0) would be canceled out.

Table 2.5: Functional Form Independence

This table presents the results from estimating log-level difference-in-differences (DiD) regressions. The dependent variable is the natural log of total book leverage. *Change-firm*$_i$ is an indicator that equals one if the disclosed organizational status of firm *i* changes from *standalone* to *diversified* after the adoption of SFAS 131 (treated firms) and zero otherwise (control firms). *Post-SFAS*$_{i,t}$ is an indicator for the post-treatment period of firm *i*. *Imputed leverage*$_{i,t}$ is the asset-weighted median total book leverage of standalone firms operating in the same industry and year. The sample period ranges from 1994 to 2002 (four years before and after the adoption of SFAS 131). The regressions are estimated separately for the full sample in columns (1)-(3) and for a balanced sample in columns (4)-(6). All regressions include year fixed effects. Columns (3) and (6) extend the specification by including firm fixed effects. Standard errors (in brackets) are heteroscedasticity consistent and clustered at the firm level. See Appendix 2.A for all variable definitions.

	Full Sample			Balanced Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Change-firm × Post-SFAS	0.261***	0.220***	0.163***	0.299***	0.275***	0.317***
	(0.067)	(0.062)	(0.059)	(0.095)	(0.090)	(0.089)
Change-firm	0.385***	0.314***		0.322**	0.273**	
	(0.081)	(0.076)		(0.131)	(0.119)	
Post-SFAS	0.063	0.058	0.089*	0.142	0.039	0.041
	(0.097)	(0.089)	(0.051)	(0.131)	(0.119)	(0.066)
Imputed leverage	4.423***	2.196***	1.443***	3.786***	1.482***	1.506***
	(0.243)	(0.292)	(0.208)	(0.356)	(0.401)	(0.308)
Constant	1.515***	1.458***	0.548**	1.540***	1.284***	0.128
	(0.065)	(0.120)	(0.224)	(0.095)	(0.166)	(0.354)
Controls		X	X		X	X
Year FE	X	X	X	X	X	X
Firm FE			X			X
Nobs	8,432	8,432	8,432	4,246	4,246	4,246
Adjusted R^2	0.17	0.30	0.12	0.13	0.27	0.13

Robust standard errors in parentheses

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

2.6. Channels of Diversification and Alternative Explanations

2.6.1. The Coinsurance Channel

In this chapter, we aim to provide further evidence for a coinsurance channel through which *revealed diversification* affects leverage. Theory suggests that diversified firms enjoy the benefit of cross-divisional coinsurance in the presence of imperfectly correlated segment cash flows, as first noted by Lewellen (1971).[32] Therefore, if there is a coinsurance effect, we should find not only a relative leverage increase for the *change firms* compared to *no-change firms* after the shock but also that firms with more coinsurance (higher diversification) react more sensitively to treatment. Following the procedure proposed by Duchin (2010), we construct a direct measure of cash flow coinsurance using the volatilities and correlations of industry-level cash flows based on single-segment firms.[33] Specifically, we compute the sales-weighted industry cash flow portfolio standard deviation associated with the industries in which firm i engages with N segments in year t:

$$\sigma_{i,t}^{ind} = \sqrt{\sum_{m=1}^{N}\sum_{n=1}^{N}\omega_{m,t}\sigma_{m,t}\omega_{n,t}\sigma_{n,t}\rho_{m,n}} \tag{2.4}$$

, where $\sigma_{i,t}^{ind}$ is firm *i's* portfolio standard deviation across all its N segments in period t; $\omega_{m,t}$ is the weight of segment m's sales relative to the consolidated sales of the firm; $\sigma_{m,t}$ is the industry cash flow volatility of segment m; $\rho_{m,n}$ is the pairwise correlation between the industry cash flows of segment m and segment n. Industry cash flow volatilities $\sigma_{m,t}$ are based on the narrowest SIC grouping that includes at least five observations of standalone firms over a rolling time window of ten years.

---

[32] Related theoretical arguments are suggested by Leland (2007) and Banal-Estañol et al. (2013). However, these papers are concerned with the ex-ante propensity to integrate (or separate) projects and financing rather than with examining realized ex post financial synergies considered here.

[33] We obtain similar results using the sales-weighted portfolio correlation as an alternative measure for coinsurance (Hann et al., 2013).

We also calculate the segments' no-diversification portfolio standard deviation ($\overline{\sigma}_{i,t}^{ind}$) by setting the pairwise correlation between all segments to one. This provides us with a benchmark and allows us to assess the extent to which cash flow coinsurance comes into play:

$$\tau_{i,t} \quad = \quad \overline{\sigma}_{i,t}^{ind} - \sigma_{i,t}^{ind} \tag{2.5}$$

, where $\tau_{i,t}$ measures the difference between the portfolio volatility with and without correlation. Note that mechanically, $\tau_{i,t}$ is always greater than or equal to zero, and higher values imply lower correlation and higher levels of diversification.

We split our treatment sample into firms with high and low cash flow coinsurance and then re-estimate our DiD model for both types of firms. We classify a firm as having strong (low) coinsurance synergies if the firm's average value of $\tau_{i,t}$ in the post-treatment era exceeds (falls below) the sample median of treated firms. Table 2.6 presents the regression results of our DiD model separately for the subsamples of treated firms with high and low cash flow coinsurance. Note that *no-change firms* have zero diversification by construction, which implies that we cannot exploit within-group variation, e.g., in a triple-differences framework. Hence, all regressions use the same control group of standalone firms from Section 2.4. Column (1) of Table 2.6 shows the results of univariate regressions on industry-adjusted leverage for treated firms with strong cash flow coinsurance. The coefficient of the DiD estimator is 5.9% and thus increased by 1.8 percentage points (44%) relative to the coefficient of the entire treatment group. This result is statistically significant at the 1% level and remains similar if we add controls to the DiD model (see column (2)). In contrast, the same coefficient decreases substantially to 2.4% for the subsample of treated firms with low cash flow coinsurance (see columns (3) and (4)). The overall picture portrayed by the first four columns of Table 2.6 continues to hold if we use total book leverage as the dependent variable and augment the specification with a firm's imputed total book leverage as an additional control (see columns (5)-(8)). The evidence presented in Table 2.6 thus supports the notion that coinsurance gains of treated firms with a higher degree of diversification can also explain the increase in leverage after the adoption of SFAS 131 within the group of treated firms.

Table 2.6: Cash Flow Coinsurance Channel (Subsample Analysis)

This table presents the results from estimating difference-in-differences (DiD) regressions for subsamples of treated firms with a high and low degree of cash flow coinsurance. In columns (1)-(4), the dependent variable, $IAL_{i,t}$, is industry-adjusted total book leverage, defined as the difference between a firm's total book leverage and its imputed leverage. In columns (5)-(8), the dependent variable is total book leverage, and imputed leverage is included as an additional control. A treated firm is classified as having *high (low) coinsurance* if its degree of cash flow coinsurance exceeds (falls below) the median value of treated firms in fiscal years after adoption of SFAS 131. Cash flow coinsurance is the reduction of a (diversified) firm's total industry cash flow volatility due to imperfectly correlated cross-industry cash flows. $\textit{Change-firm}_i$ is an indicator that equals one if the disclosed organizational status of firm *i* changes from *standalone* to *diversified* after adopting SFAS 131 (treated firms) and zero otherwise (control firms). $\textit{Post-SFAS}_{i,t}$ is an indicator for the post-treatment period of firm *i*. The sample period ranges from 1994 to 2002 (four years before and after adoption of SFAS 131). All regressions include year fixed effects. Standard errors (in brackets) are heteroscedasticity consistent and clustered at the firm level. See Appendix 2.A for all variable definitions.

	Industry-Adjusted Total Book Leverage				Total Book Leverage			
	High Coinsurance		Low Coinsurance		High Coinsurance		Low Coinsurance	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change-firm × Post-SFAS	0.059***	0.055***	0.024*	0.024*	0.058***	0.053***	0.023*	0.021*
	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)	(0.013)	(0.012)	(0.012)
Change-firm	0.035**	0.040***	0.030*	0.029*	0.034**	0.035***	0.041**	0.034**
	(0.015)	(0.015)	(0.017)	(0.017)	(0.014)	(0.013)	(0.017)	(0.016)
Post-SFAS	−0.004	−0.006	0.000	−0.004	0.001	−0.001	0.009	0.005
	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)
Imputed leverage					0.619***	0.389***	0.616***	0.384***
					(0.033)	(0.041)	(0.033)	(0.041)
Constant	0.011*	−0.008	0.010*	−0.006	0.079***	0.063***	0.080***	0.068***
	(0.006)	(0.016)	(0.006)	(0.016)	(0.008)	(0.015)	(0.008)	(0.016)
Year FE	X	X	X	X	X	X	X	X
Controls		X		X		X		X
Nobs	7,640	7,640	7,656	7,656	7,640	7,640	7,656	7,656
Adjusted R^2	0.02	0.08	0.01	0.06	0.19	0.28	0.18	0.27

Robust standard errors in parentheses

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

2.6.2. Alternative Explanations and Threats to Identification

A threat to the internal validity of our identification strategy is that the mandatory adoption of SFAS 131 might affect capital structure through channels other than *revealed diversification*. We conduct several robustness tests to rule out alternative channels and corroborate our results.

2.6.2.1. The Information Disaggregation Channel

First, it is possible that our shock operates through increased information disaggregation, i.e., less opaqueness at the segment level (the transparency channel). Prior literature has shown that SFAS 131 increased the extent of segment reporting disaggregation (Berger and Hann, 2003; Herrmann and Thomas, 2000; Street et al., 2000). Then, more disaggregated information at the segment level instead of revealed diversification may explain the increase in leverage induced by the shock.

We construct two related tests that enable us to distinguish the effect of increased segment reporting transparency on firms' capital structure after the shock from the effect of revealed diversification. To proxy for the level of information disaggregation at the firm level, we use the "fineness" measure, *DISAGG,* introduced by Piotroski (2002) and Berger and Hann (2003). This measure is defined as the ratio of the number of reported segments to the number of reported four-digit SIC code industries.

The first test builds a placebo sample of firms that serves as pseudo-treatment group. This group consists of firms that reveal an increased number of operating segments under the new standard but operate in the same four-digit SIC code industry throughout the sample period (i.e., *Disagg* = 1 under SFAS 14, but *Disagg* > 1 under SFAS 131). These firms are *single*-segment, single-industry firms under SFAS 14 but become *multi*-segment, single-industry firms under the new standard. One example is Oshkosh Truck Corp., which operated in SIC code *3711* throughout the sample period and disclosed a single segment called "*specialized motor vehicles*" before the shock but three segments ("*commercial trucks*", "*fire and emergency trucks*" and "*defense tactical trucks*") under the new standard. We identify 113 such nondiversified placebo firms.

Then, we estimate a variant of equation (2), in which we replace the treatment assignment indicator, *Change-firm*$_i$, with an indicator variable, $Placebo_i$, that equals one if a firm belongs to the "placebo" group and zero if the firm is part of the control group (firms that are single-segment, single-industry throughout the sample period). If information disaggregation was an alternative channel, we would expect to find a relative increase in leverage for the placebo firms after the shock compared to the control group ($\delta_{DiD} > 0$). As we show in Table 2.7, the DiD estimate is insignificant and close to zero, indicating no change in leverage for placebo firms relative to control firms. This result suggests that it seems unlikely that disaggregation drives our results.

The second test proposes a triple-differences (difference-in-differences-in-differences) strategy that tests whether the relative leverage effect of the shock is larger for the group of *change firms* with a revealed increase in disaggregated reporting under SFAS 131 (i.e., $Disagg > 1$ under SFAS 131, 31% of *change firms*) compared to the group of treated firms with no such increase (69%). While the placebo test in the previous paragraph indicates that disaggregation did not affect the leverage ratio of persistently (pre- and post-SFAS 131) nondiversified firms, this test provides an assessment of whether our baseline difference-in-differences results (Section 2.5) are affected by the alternative channel.

To explore the incremental effects of the shock on leverage across all four subsamples of treated and control firms with and without disaggregation, we require a post-SFAS counterfactual for *change firms* with an increase in disaggregation. Therefore, we assign the previously defined placebo firms to the control group. By including the placebo group, we can properly differentiate between the common effect of disaggregation for all firms and the (possible) incremental effect of disaggregation within the group of treated firms. The firms in the original control group have no increase in disaggregation by construction and serve as the counterfactual for *change firms* without an increase in disaggregation.[34]

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[34] The alternative estimation strategy of using only the original control group of standalone firms without disaggregation produces qualitatively similar results.

Then, we estimate the triple-differences specification as described in equation (2.6):

$$
\begin{aligned}
IAL_{i,t} = \alpha &+ \delta_{DiDiD} \times Disagg_i \times Change\text{-}firm_i \times Post\text{-}SFAS_{i,t} \\
&+ \delta_1 \times Disagg_i \times Post\text{-}SFAS_{i,t} + \delta_2 \times Change\text{-}firm_i \times Post\text{-}SFAS_{i,t} \\
&+ \delta_3 \times Disagg_i \times Change\text{-}firm_i + \delta_4 \times Disagg_i + \delta_{change} \times Change\text{-}firm_i \\
&+ \delta_{post\text{-}SFAS} \times Post\text{-}SFAS_{i,t} + \eta_t + \epsilon_{i,t}
\end{aligned}
\tag{2.6}
$$

, where $Disagg_i$ is an indicator variable that equals one for firms with greater disaggregation under SFAS 131; $Change\text{-}firm_i$ is an indicator that equals one if a firm belongs to the treatment group; and $Post\text{-}SFAS_{i,t}$ is an indicator for the post-treatment period of firm i. This specification allows us to difference out two separate control effects during the pre- and post-treatment periods by accounting for three levels of differencing: *Change firms* versus *no-change firms*, disaggregation versus no disaggregation, and pre- versus post-SFAS 131. The main coefficient of interest is the triple-differences estimate δ_{DiDiD} on the interaction $Disagg_i \times Change\text{-}firm_i \times Post\text{-}SFAS_{i,t}$, which captures how different the leverage change is for *change firms* with increased disaggregation relative to *change firms* without this increase. If there is an effect of the disaggregation channel incremental to revealed diversification, we should expect a positive estimate, $\delta_{DiDiD}>0$. The second-level interactions control for changes after the shock common to all firms with greater disaggregation (δ_1), changes after the shock common to all treated firms (δ_2), and time-invariant characteristics of the *change firms* with greater disaggregation (δ_3).

Table 2.8 reports estimates for the coefficients in equation (4) across different specifications. The estimated coefficient of interest δ_{DiDiD} is negative, close to zero, and never statistically significant. This near-zero effect persists uniformly across all specifications. Across all specifications, Table 2.8 also shows positive, economically small, and statistically insignificant effects of the shock on the leverage of all firms with greater disaggregation (δ_1), which confirms the results of our placebo test. In summary, we find no evidence for an effect of information disaggregation beyond revealed diversification or, more generally, evidence in favor of an information disaggregation hypothesis of leverage.

Table 2.7: Information-Disaggregation Channel (Placebo Test)

This table presents the results from estimating the following difference-in-differences (DiD) specification for an alternative pseudo-treatment group (placebo firms):

$$IAL_{i,t} = \alpha + \delta_{DiD} \times Placebo_i \times Post\text{-}SFAS_{i,t} + \delta_{Placebo} \times Placebo_i + \delta_{post\text{-}SFAS} \times Post\text{-}SFAS_{i,t} + \eta_t + \epsilon_{i,t},$$

In columns (1)-(3), the dependent variable, $IAL_{i,t}$, is industry-adjusted total book leverage, defined as the difference between a firm's total book leverage and its imputed leverage. In columns (4)-(6), the dependent variable is total book leverage, and imputed leverage is included as an additional control. $Placebo_i$ is an indicator that equals one if firm i reveals an increased number of operating segments through the implementation of SFAS 131 while still operating in a single industry and zero otherwise. $Post\text{-}SFAS_{i,t}$ is an indicator for the post-treatment period of firm i. The sample period ranges from 1994 to 2002 (four years before and after the adoption of SFAS 131). All regressions include year fixed effects. Columns (3) and (6) extend the specification by including firm fixed effects. Standard errors (in brackets) are heteroscedasticity consistent and clustered at the firm level. See Appendix 2.A for all variable definitions.

	Industry-Adjusted Total Book Leverage			Total Book Leverage		
	(1)	(2)	(3)	(4)	(5)	(6)
Placebo × Post-SFAS	0.009	0.007	0.007	0.009	0.004	0.004
	(0.015)	(0.015)	(0.012)	(0.014)	(0.012)	(0.010)
Placebo	0.029*	0.032**		0.028*	0.033**	
	(0.015)	(0.015)		(0.014)	(0.013)	
Post-SFAS	0.009	0.007	0.023***	0.014	0.012	0.022***
	(0.013)	(0.013)	(0.007)	(0.013)	(0.012)	(0.006)
Imputed leverage				0.624***	0.386***	0.234***
				(0.032)	(0.040)	(0.029)
Firm size		0.013***	0.038***		0.018***	0.041***
		(0.002)	(0.005)		(0.002)	(0.005)
Profitability		−0.143***	−0.155***		−0.185***	−0.188***
		(0.031)	(0.022)		(0.029)	(0.022)
Tangibility		0.027	0.119***		0.152***	0.128***
		(0.020)	(0.036)		(0.022)	(0.035)
Market-to-book		−0.011***	−0.005***		−0.018***	−0.008***
		(0.002)	(0.001)		(0.002)	(0.001)
R&D		0.060*	−0.060		−0.138***	−0.068**
		(0.034)	(0.037)		(0.042)	(0.034)
Dividend payer		−0.061***	−0.012		−0.058***	−0.011
		(0.010)	(0.009)		(0.009)	(0.008)
Constant	0.011*	−0.005	−0.167***	0.079***	0.064***	−0.046
	(0.006)	(0.015)	(0.030)	(0.007)	(0.015)	(0.029)
Year FE	X	X	X	X	X	X
Firm FE			X			X
Nobs	7,532	7,532	7,532	7,532	7,532	7,532
Adjusted R^2	0.01	0.06	0.08	0.19	0.28	0.12

Robust standard errors in parentheses

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

Table 2.8: Information-Disaggregation Channel (Triple Differences)

This table presents the results from estimating the following triple differences (DiDiD) specification:

$$
\begin{aligned}
IAL_{i,t} = \alpha &+ \delta_{DiDiD} \times Disagg_i \times Change\text{-}firm_i \times Post\text{-}SFAS_{i,t} + \delta_1 \times Disagg_i \times Post\text{-}SFAS_{i,t} \\
&+ \delta_2 \times Change\text{-}firm_i \times Post\text{-}SFAS_{i,t} + \delta_3 \times Disagg_i \times Change\text{-}firm_i + \delta_4 \times Disagg_i \\
&+ \delta_{change} \times Change\text{-}firm_i + \delta_{post\text{-}SFAS} \times Post\text{-}SFAS_{i,t} + \eta_t + \epsilon_{i,t}
\end{aligned}
$$

, where $IAL_{i,t}$ is industry-adjusted total book leverage, which is the difference between a firm's total book leverage and its imputed leverage. $Disagg_i$ is an indicator that equals one for firms with greater segment information disaggregation under SFAS 131. $Change\text{-}firm_i$ is an indicator that equals one if the disclosed organizational status of firm i changes from *standalone* to *diversified* after adopting SFAS 131 (treated firms) and zero otherwise (control firms). $Post\text{-}SFAS_{i,t}$ is an indicator for the post-treatment period of firm i. The sample period ranges from 1994 to 2002 (four years before and after adoption of SFAS 131). All regressions include year fixed effects. Columns (3) and (4) extend the specification by including firm fixed effects. Standard errors (in brackets) are heteroscedasticity consistent and clustered at the firm level. See Appendix 2.A for all variable definitions.

	Industry-Adjusted Total Book Leverage			
	(1)	(2)	(3)	(4)
Disagg × Change-firm × Post-SFAS	−0.011	−0.006	−0.010	−0.012
	(0.026)	(0.025)	(0.023)	(0.023)
Change-firm × Post-SFAS	0.041***	0.039***	0.030***	0.030***
	(0.011)	(0.011)	(0.010)	(0.010)
Disagg × Post-SFAS	0.010	0.008	0.007	0.010
	(0.016)	(0.016)	(0.014)	(0.013)
Change-firm × Disagg	−0.009	−0.016		
	(0.027)	(0.026)		
Change-firm	0.027*	0.028**		
	(0.014)	(0.014)		
Disagg	0.029*	0.032**		
	(0.015)	(0.015)		
Post-SFAS	−0.007	−0.011	0.003	0.002
	(0.012)	(0.012)	(0.007)	(0.007)
Constant	0.010*	−0.011	0.012***	−0.185***
	(0.006)	(0.014)	(0.003)	(0.029)
Year FE	X	X	X	X
Controls		X		X
Firm FE			X	X
Nobs	9,147	9,147	9,147	9,147
Adjusted R^2	0.02	0.07	0.04	0.10

Robust standard errors in parentheses

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

2.6.2.2. The Industry Composition Channel

Another potential threat to our identification strategy could arise if treated firms conceal their pre-SFAS 131 segments' industry affiliation and systematically report their high-leverage industry segments during the pre-treatment era (while segments of low-leverage industries remain hidden under SFAS 14).[35] Then, SFAS 131 may reveal mandated changes in reported industry affiliation instead of diversification strategies, and specifications using industry-adjusted leverage as the dependent variable would mechanically overestimate the effect of revealed diversification. Moreover, even if there were no incentives to camouflage low-debt-capacity industries, firms' incentives to hide segments (e.g., to withhold information that could competitively disadvantage the firm) may impart bias to industry adjustment.[36] Technically, this "industry composition channel" may mechanically introduce nonparallel trends in the *post-SFAS 131* periods and confound our results. To formally address this concern, we examine whether the shock induced by SFAS 131 differentially affected the industry adjustment of leverage for *change firms* versus control firms. To do so, we rerun equation (2) but replace the dependent variable, *IAL*, with the firm's imputed leverage. This alternative difference-in-differences specification tests how SFAS 131 affects the imputed leverage of *change firms* compared to that of *no-change firms*. Recall that the imputed leverage of standalone firms is the leverage of the median firm in its industry, whereas the imputed leverage of diversified firms is the industry-matched, asset-weighted median leverage of the industries in which the firm operates. Our results, reported in Table 2.9, rule out that changes in industry composition may drive our results. The coefficient on the interaction *Change-firm* × *Post-SFAS* is close to zero and statistically insignificant across all specifications.

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[35] We note that SFAS 14 and SFAS 131 require firms to report the products and services from which each reportable segment derives its revenues but do not require firms to report SIC codes on a segment level. It is S&P Compustat that assigns four-digit segment SIC codes based on the descriptive information on segment activities (see Davis and Duhaime, 1992; Guenther and Rosman, 1994; Maksimovic and Phillips, 2007 for details on this iterative process). For convenience, we refer to "firms that report industries" throughout the chapter (instead of to "firms that report descriptive information about business activities, which Compustat uses to assign SICs").

[36] Botosan and Stanford (2005) find evidence that firms hide profitable segments in less competitive industries than their primary operations to appear as if they were underperforming their competition.

Table 2.9: Industry Composition Channel

This table presents the results from estimating the following difference-in-differences (DiD) specification:

$$\begin{aligned}\textit{Imputed-TBL}_{i,t} = {} & \alpha + \delta_{DiD} \times \textit{Change-firm}_i \times \textit{Post-SFAS}_{i,t} + \delta_{change} \times \textit{Change-firm}_i \\ & + \delta_{post\text{-}SFAS} \times \textit{Post-SFAS}_{i,t} + \eta_t + \epsilon_{i,t}\end{aligned}$$

, where $\textit{Imputed-TBL}_{i,t}$ is the firm's imputed total book leverage, which is the asset-weighted median total book leverage of standalone firms operating in the same industry year. Industry matching is based on the narrowest SIC grouping (beginning with four-digit SIC codes) that includes at least 10 standalone firms per industry and year. $\textit{Change-firm}_i$ is an indicator that equals one if the disclosed organizational status of firm *i* changes from *standalone* to *diversified* after adopting SFAS 131 (treated firms) and zero otherwise (control firms). $\textit{Post-SFAS}_{i,t}$ is an indicator for the post-treatment period of firm *i*. The sample period ranges from 1994 to 2002 (four years before and after the adoption of SFAS 131). All regressions include year fixed effects. Columns (3) and (4) extend the specification by including firm fixed effects. Standard errors (in brackets) are heteroscedasticity consistent and clustered at the firm level. See Appendix 2.A for all variable definitions.

	Imputed Total Book Leverage			
	(1)	(2)	(3)	(4)
Change-firm × Post-SFAS	−0.000	−0.004	−0.003	−0.003
	(0.005)	(0.005)	(0.004)	(0.004)
Change-firm	0.012	0.000		
	(0.007)	(0.006)		
Post-SFAS	0.020**	0.013**	0.003	0.003
	(0.008)	(0.006)	(0.003)	(0.003)
Firm size		0.008***		0.002
		(0.001)		(0.002)
Profitability		−0.058***		−0.040***
		(0.022)		(0.008)
Tangibility		0.194***		0.017
		(0.013)		(0.015)
Market-to-book		−0.012***		−0.004***
		(0.001)		(0.000)
R&D		−0.346***		−0.022**
		(0.084)		(0.010)
Dividend payer		0.000		0.004
		(0.005)		(0.004)
Constant	0.179***	0.120***	0.173***	0.168***
	(0.004)	(0.010)	(0.001)	(0.012)
Year FE	X	X	X	X
Firm FE			X	X
Nobs	8,432	8,432	8,432	8,432
Adjusted R^2	0.01	0.34	0.05	0.06

Robust standard errors in parentheses

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

2.6.2.3. The Agency Cost of Debt Channel

A final concern with our identification strategy is that SFAS 131 could have forced (some) firms to also reveal previously hidden inefficient cross-segment transfers, which may indicate unresolved within-firm agency problems and divisional rent-seeking.[37] Therefore, a natural question that we consider next is whether the revelation of within-firm agency problems associated with the distortion of capital allocation affects our results.

The most plausible explanation is that agency problems are negatively related to leverage because they restrict debt capacity by introducing frictions in the supply of debt to the firm (e.g., Stiglitz and Weiss, 1981; Tirole, 2006). Therefore, our shock-based research design could underestimate the effect of diversification on capital structure if some of the firms in our sample pursue agency motives. For example, if some firms not only disclose that they are diversified but also reveal agency problems, the positive effect on leverage may be mitigated by an alternative channel. The opposite story is that the revelation of agency problems is associated with a subsequent increase in leverage, e.g., if investors impose higher leverage to increase discipline on the firm (e.g., Jensen, 1986). In this case, our baseline DiD specification would provide an upward biased estimate of the magnitude and perhaps the wrong sign of the effect.

To examine this "agency cost channel", we first divide our treated group of *change firms* into two samples: one sample that includes firms that revealed pronounced (but previously hidden) cross-segment subsidization in capital allocation suggesting agency problems at the segment level and one sample that includes firms with no such revelation. We follow the literature and employ a common measure ("*Transfer*") introduced by Billett and Mauer (2003) and Berger and Hann (2007) to proxy for agency motives associated with inefficient cross-segment transfers. *Transfer* (described in

[37] A large body of empirical literature studies the (in)efficiency of capital allocation in diversified firms, see, e.g., Lamont, 1997; Shin and Stulz, 1998; Rajan et al., 2000; Maksimovic and Phillips, 2002; Billett and Mauer, 2003; Ozbas and Scharfstein, 2010; Matvos and Seru, 2014. Most of the theoretical literature suggests that inefficient within-firm capital allocations are indicative of rent-seeking at the division-manager level (e.g., Scharfstein and Stein, 2000; Rajan et al., 2000; Stein, 2003; Wulf, 2009).

Appendix 2.A) is an indicator variable that equals one if a *change firm* likely subsidizes underperforming segments. For the control group of *no-change firms*, we set the variable *Transfer* equal to zero.

To avoid possible bias if firms anticipate adverse financing effects resulting from the disclosure of agency problems, we exploit a unique feature of SFAS 131. SFAS 131 mandated firms to release restated segment information for the final SFAS 14 year (the lag adoption year), which implies that firms were forced to retroactively disclose investment behavior. Using this restated segment information, we are able to address the concern that firms strategically respond to the introduction of the new regulatory requirements by adjusting capital allocation prior to the release of the first SFAS 131 financial statement. Because the restated data are not available in commercial databases, we hand-collect them from the firms' first SFAS 131 10-K filings.

We then re-estimate our main difference-in-differences specification for the two subsamples and find evidence that leverage increased around the shock only in the subsample of firms without agency problems (Table 2.10, columns (1)-(4)). For the group of firms that revealed cross-segment transfers, we detect a near-zero and statistically insignificant effect of the shock (columns (5)-(8)). This result indicates that the net effect of revealed diversification for firms with agency problems is close to zero.

Table 2.10: Agency Motive Channel (Subsample Analysis)

This table presents the results from estimating the following difference-in-differences (DiD) specification for subsamples of treated firms with/without inefficient cross-segment transfers under SFAS 14:

$$IAL_{i,t} = \alpha + \delta_{DiD} \times \textit{Change-firm}_i \times \textit{Post-SFAS}_{i,t} + \delta_{change} \times \textit{Change-firm}_i$$
$$+ \delta_{post\text{-}SFAS} \times \textit{Post-SFAS}_{i,t} + \eta_t + \epsilon_{i,t}$$

, where $IAL_{i,t}$ is industry-adjusted total book leverage, which is the difference between a firm's total book leverage and its imputed leverage. A treated firm is classified as having inefficient cross-segment transfers if at least one underperforming segment received cross-segment transfers in the final fiscal year before the adoption of SFAS 131. $\textit{Change-firm}_i$ is an indicator that equals one if the disclosed organizational status of firm *i* changes from *standalone* to *diversified* after the adoption of SFAS 131 (treated firms) and zero otherwise (control firms). $\textit{Post-SFAS}_{i,t}$ is an indicator for the post-treatment period of firm *i*. The sample period ranges from 1994 to 2002 (four years before and after adoption of SFAS 131). All regressions include year fixed effects. Columns (3)-(4) and (7)-(8) extend the specification by including firm fixed effects. Standard errors (in brackets) are heteroscedasticity consistent and clustered at the firm level. See Appendix 2.A for all variable definitions.

	Efficient Firms				Inefficient Firms			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Change-firm × Post-SFAS	0.053***	0.052***	0.038***	0.037***	0.000	0.000	0.000	0.002
	(0.011)	(0.011)	(0.011)	(0.010)	(0.017)	(0.017)	(0.015)	(0.014)
Change-firm	0.026**	0.028**			0.055**	0.054**		
	(0.013)	(0.013)			(0.024)	(0.023)		
Post-SFAS	−0.010	−0.012	0.006	0.006	0.008	0.005	0.024***	0.023***
	(0.013)	(0.013)	(0.007)	(0.007)	(0.013)	(0.013)	(0.007)	(0.007)
Firm size		0.013***		0.044***		0.014***		0.038***
		(0.002)		(0.005)		(0.003)		(0.005)
Profitability		−0.160***		−0.166***		−0.137***		−0.156***
		(0.031)		(0.022)		(0.031)		(0.022)
Tangibility		0.014		0.102***		0.023		0.106***
		(0.020)		(0.035)		(0.021)		(0.036)
Market-to-book		−0.011***		−0.004***		−0.011***		−0.005***
		(0.002)		(0.001)		(0.002)		(0.001)
R&D		0.064*		−0.042		0.055		−0.044
		(0.035)		(0.035)		(0.034)		(0.034)
Dividend payer		−0.056***		−0.020**		−0.063***		−0.018*
		(0.009)		(0.009)		(0.010)		(0.009)
Constant	0.009	−0.004	0.008**	−0.194***	0.012*	−0.008	0.007*	−0.167***
	(0.006)	(0.015)	(0.004)	(0.030)	(0.006)	(0.016)	(0.004)	(0.031)
Year FE	X	X	X	X	X	X	X	X
Firm FE			X	X			X	X
Nobs	8,061	8,061	8,061	8,061	7,240	7,240	7,240	7,240
Adjusted R^2	0.02	0.07	0.05	0.10	0.01	0.06	0.03	0.08

Robust standard errors in parentheses

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

In our last analysis, we use the coinsurance measure as introduced in Section 2.6.1 and provide a more nuanced analysis of the (net) effect of revealed diversification conditional on revealed agency problems. We use a triple-differences framework similar to the one in Section 2.6.2.1. The variant of equation (2.6) that we estimate replaces $Disagg_i$ (which measures disaggregation under SFAS 131) with $Transfer_i$ (which measures disclosed agency problems). Similar to the triple-differences specification in Section 2.6.2.1, we assign the group of placebo firms to the control sample. Recall that placebo firms reveal an increased number of operating segments under the new standard, but all of them operate in the same four-digit SIC industry. The unique feature that we exploit here is that a subset of these placebo firms also disclose inefficient transfers and therefore serve as a post-SFAS counterfactual for *change firms* with inefficient transfers.

Table 2.11 presents the results. In columns (1) and (2), we first run the specification with and without covariates on the full sample. The estimates confirm that the (simultaneous) disclosure of agency problems dampens the baseline results (and does not drive them). The coefficient on the double interaction, *Change-firm* × *Post-SFAS*, is positive, economically large (5.2-5.4%) and increases in magnitude relative to the estimates in the baseline DiD (3.9-4.1%; Table 2.3, columns (1)-(2)). The reason can be seen from the triple interaction, *Transfer* × *Change-firm* × *Post-SFAS*, which is significant but negative and thus represents the offsetting impact of revealed agency problems. We observe the same pattern when we split the sample into firms with high and low coinsurance (columns (3)-(6)) and rerun the regression separately on the two subsamples: The double-differences coefficients increase in magnitude compared to those in the respective baseline DiD (Table 2.6, columns (1)-(4)), and the triple-differences coefficients are similar in size to the double-differences coefficients or slightly larger but with opposite signs. The triple-differences framework thus confirms our previous findings that firms with no (revealed) agency problems benefit from the revelation of diversification strategies, whereas firms with (revealed) agency problems are not able to utilize coinsurance synergies.

Table 2.11: Agency Motive Channel (Triple Differences)

This table presents the results from estimating the following triple-differences (DiDiD) specification for the full sample and subsamples of treated firms with a high and low degree of cash flow coinsurance:

$$IAL_{i,t} = \alpha + \delta_{DiDiD} \times \mathit{Transfer}_i \times \mathit{Change\text{-}firm}_i \times \mathit{Post\text{-}SFAS}_{i,t} + \delta_1 \times \mathit{Transfer}_i \times \mathit{Post\text{-}SFAS}_{i,t}$$
$$+ \delta_2 \times \mathit{Change\text{-}firm}_i \times \mathit{Post\text{-}SFAS}_{i,t} + \delta_3 \times \mathit{Transfer}_i \times \mathit{Change\text{-}firm}_i + \delta_4 \times \mathit{Transfer}_i$$
$$+ \delta_{change} \times \mathit{Change\text{-}firm}_i + \delta_{post\text{-}SFAS} \times \mathit{Post\text{-}SFAS}_{i,t} + \eta_t + \epsilon_{i,t}$$

, where $IAL_{i,t}$ is the industry-adjusted total book leverage, which is the difference between a firm's total book leverage and its imputed leverage. $\mathit{Transfer}_i$ is an indicator that equals one if at least one underperforming segment received cross-segment transfers in the final fiscal year before the adoption of SFAS 131 and zero otherwise. $\mathit{Change\text{-}firm}_i$ is an indicator that equals one if the disclosed organizational status of firm i changes from *standalone* to *diversified* after adopting SFAS 131 (treated firms) and zero otherwise (control firms). $\mathit{Post\text{-}SFAS}_{i,t}$ is an indicator for the post-treatment period of firm i. The sample period ranges from 1994 to 2002 (four years before and after the adoption of SFAS 131). All regressions include year fixed effects. Standard errors (in brackets) are heteroscedasticity consistent and clustered at the firm level. See Appendix 2.A for all variable definitions.

	Full Sample		High Coinsurance		Low Coinsurance	
	(1)	(2)	(3)	(4)	(5)	(6)
Transfer × Change-firm × Post-SFAS	−0.067**	−0.065**	−0.074**	−0.068*	−0.053*	−0.054*
	(0.028)	(0.026)	(0.037)	(0.035)	(0.032)	(0.030)
Change-firm × Post-SFAS	0.054***	0.052***	0.069***	0.066***	0.036**	0.037**
	(0.011)	(0.011)	(0.016)	(0.015)	(0.016)	(0.015)
Change-firm × Transfer	0.017	0.015	0.019	0.017	0.017	0.015
	(0.037)	(0.035)	(0.042)	(0.039)	(0.047)	(0.046)
Transfer × Post-SFAS	0.011	0.009	0.011	0.009	0.010	0.009
	(0.019)	(0.018)	(0.019)	(0.017)	(0.019)	(0.018)
Change-firm	0.024*	0.023*	0.028*	0.031*	0.019	0.017
	(0.013)	(0.013)	(0.016)	(0.016)	(0.019)	(0.019)
Transfer	0.012	0.010	0.012	0.011	0.012	0.011
	(0.026)	(0.024)	(0.026)	(0.024)	(0.026)	(0.024)
Post-SFAS	−0.007	−0.011	−0.001	−0.003	0.002	−0.002
	(0.012)	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)
Constant	0.013**	−0.007	0.014**	−0.005	0.014**	−0.003
	(0.006)	(0.015)	(0.006)	(0.015)	(0.006)	(0.015)
Year FE	X	X	X	X	X	X
Controls		X		X		X
Nobs	9,146	9,146	8,359	8,359	8,371	8,371
Adjusted R^2	0.02	0.07	0.02	0.07	0.01	0.06

Robust standard errors in parentheses

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

2.7. Conclusion

In this chapter, we show that diversified firms have higher leverage than standalone firms. Our results suggest economically large financing advantages of diversified firms, which allows them to borrow more than comparable focused firms. We identify causal effects in a novel shock-based difference-in-differences research design using the introduction of new segment reporting standards (SFAS No. 131) as a quasi-natural experiment. SFAS 131 forced some firms to reveal previously hidden information about their level of firm diversification to outsiders, allowing us to exploit plausibly exogenous variation in a firm's diversification status. Our findings identify the reduction of cash flow volatility as the main channel of the coinsurance effect. The effect of how diversification affects leverage is strongest in firms with high cross-divisional cash flow coinsurance but partially offset by the additional revelation of agency problems at the divisional level. These results add to our understanding of how firm boundaries affect financial policy.

Chapter 3 – The Role of Human Capital in Internal Resource Allocation

3.1. Introduction

Much of the extensive empirical literature on corporate diversification has revolved around the question of whether internal capital markets create or destroy value. Over the past few decades, this line of research has focused on the sensitivity of capital allocation to segment investment opportunities. The early literature on this subject finds that conglomerate investment patterns usually deviate from the predictions of the neoclassical model and therefore concludes that internal capital markets promote resource misallocation. Corporate investment, especially the investment behavior of multisegment firms, remains poorly understood; while most early (and to date influential) studies have pointed toward a dark side of internal capital markets, more recent articles have cautioned against drawing premature conclusions.

One possible reason for the lack of conclusive evidence is the standard practice of using *industry q* (i.e., the median Tobin's q of standalone firms in a segment's industry) as a proxy for unobservable segment investment opportunities. This approach implicitly emphasizes the relevance of the general technological and business environment in which the division operates but ignores the second essential ingredient needed to generate returns from investment: *human capital* (*ability, talent,* or *reputation*). This deficiency is also reflected in a discrepancy between the established criteria for measuring efficient investment and the factors that top managers consider important when making budgeting decisions. For example, in their large-scale survey, Graham et al. (2015) find that more than 71% of CEOs focus on the reputation of division managers when deciding how to allocate capital between divisions.[38] In particular, they come to the conclusion that "*CEOs focus more on*

[38] In a recent survey of CFOs, Hoang et al. (2021) find evidence that top management's assessment of division managers' abilities to deliver expected results plays a crucial role in the budgeting process.

the person … rather than on the division the manager represents", suggesting that the literature's focus on *industry q* in assessing (unobservable) segment investment opportunities is at odds with the practice in reality.

This chapter seeks to fill this gap by examining the human capital aspect of internal capital budgeting. Using a large and unique data set of division managers at multisegment firms included in the S&P 1500 index in the 2000-2018 period, we investigate the effect of *division-manager ability* on the internal allocation of financial resources. We find that conglomerate investment patterns strongly reflect what theorists have called "winner-picking": superior managers receive substantially larger capital allocations than their less able peers. Moreover, our results suggest that the omission of the human capital component may lead to severely biased conclusions about investment efficiency.

A likely reason why this subject has been unexplored in the empirical literature is the absence of a convincing ability metric at the divisional level and the dearth of data on division managers. We address this deficiency by adapting the managerial ability score ("*MA-Score*") developed by Demerjian et al. (2012) to develop an ability measure for division managers. The *MA-Score* of Demerjian et al. measures the efficiency of operations, especially with respect to the generation of revenues, and then controls for factors outside the manager's control to isolate managerial contributions. The *MA-Score* has several advantages over other frequently used ability measures (such as ROA, tenure, media mentions, education, or manager fixed effects) because it is a multidimensional measure with flexible weights for each dimension.[39] To the best of our knowledge, the *MA-Score* has thus far been used exclusively for measuring top management ability. Taking advantage of the recent advances in segment reporting, we modify the *MA-Score* to measure division-manager ability. In the first stage, we use data envelopment analysis (DEA) to estimate divisional efficiency scores and then use second-stage regressions to control for division-specific drivers of efficiency. Following Demerjian et al. (2012), our single output is segment revenue. Due to the limited

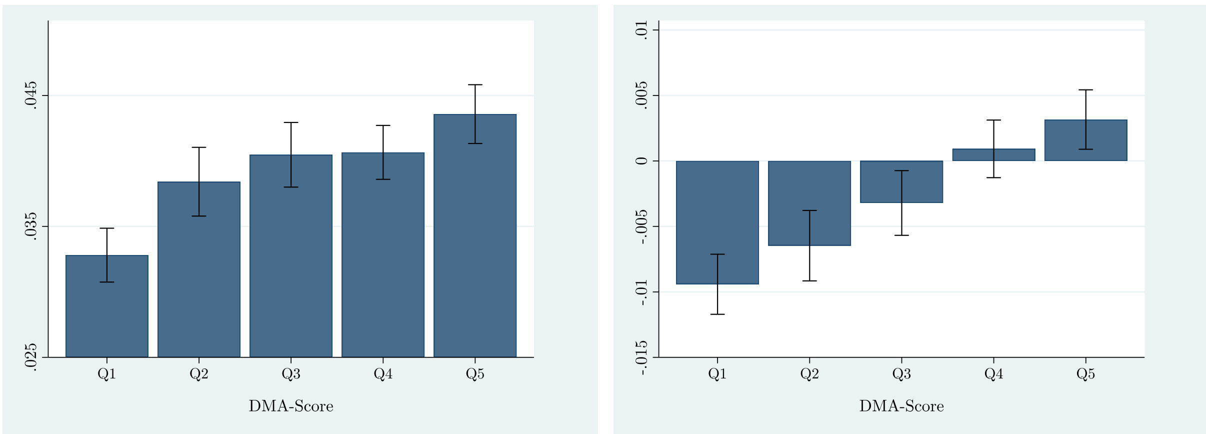
[39] Additional benefits of the score are that it is widely available (which is not the case for media mentions or press releases) and that it does not reflect factors outside of the manager's control (such as stock returns).

availability of segment data, we employ two inputs for the DEA program in the first stage: segment assets and segment operating expenses.[40] Next, we run second-stage regressions of divisional efficiency on four covariates: *segment size*, *segment market share*, *segment free cash flow*, and *business segment concentration*. The residual from the second-stage regression is our proposed division-manager ability score (*DMA-Score*). Figure 3.1 illustrates the strong positive association between managerial ability and capital allocation, which is the main result of this chapter.

Figure 3.1: 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 segment investment (capital expenditures scaled by book assets). Panel B shows the average industry-adjusted segment investment. Division-manager ability is the *DMA-Score* described in Section 3.3.4. For each bin, the graphs report 95% confidence intervals around the mean. Detailed variable definitions are provided in Appendix 3.A.

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



Panel A shows the average segment investment (the ratio of capital expenditures scaled by book assets) for quintile groups of increasing managerial 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 4.4%, which is an economically meaningful difference of 38% in relative terms. A similar

[40] Although these variables are not as granular as those used in Demerjian et al. (2012), they still capture much of the same information at the segment level. A detailed explanation of the *DMA-Score* is provided in Section 3.3.4.

pattern emerges for industry-adjusted segment investment (Figure 3.1, Panel B) and industry-firm-adjusted segment investment (see Appendix 3.C). Overall, these stylized facts indicate that internal capital markets tend to move financial resources toward segments of relatively more able division managers. In the empirical section, we conduct formal tests of this relation. Our results rule out that conventional determinants of capital allocation known from the literature explain the association observed in Figure 3.1.

In the baseline analysis, we run segment-level regressions of capital allocation on division-manager ability (the *DMA-Score*) and a rich set of controls, including segment- and firm-level characteristics (e.g., industry q, segment size, firm size, segment cash flow) and managerial attributes (e.g., tenure, age, gender, educational background).[41] The effect of division-manager ability is uniformly positive and statistically significant across all of the above measures of capital allocation. The economic magnitude slightly decreases relative to the univariate results but remains large: division managers in the top quintile of the ability distribution receive 24% larger capital allocations than their peers in the bottom quintile. On average, this difference translates into $22 M in extra funds per year and $139 M over the tenure of a division manager. This magnitude remains stable after we account for time-invariant heterogeneity across firms, industries and divisions, suggesting that unobservable characteristics correlated with division-manager ability are unlikely to drive our results. In further robustness checks, we rule out potential alternative explanations related to endogenous matching of managers to divisions and social connections to the CEO. In all our regression specifications, we find that division-manager ability has predictive power for internal capital allocation. In contrast, the estimated coefficient on *industry q* is statistically insignificant and close to zero. Taken together, the results suggest that internal capital markets strongly engage in a form of winner-picking that operates predominantly by selecting for human capital productivity. Put colloquially, top management tends to bet on the "*jockey*" (i.e., the division's management) rather than on the "*horse*" (i.e., the division itself).

[41] Our segment-level approach is similar to that introduced by Shin and Stulz (1998).

To gain further insight into the underlying economic mechanisms of this relationship, we investigate several nonmutually exclusive hypotheses. We first examine whether our baseline results are sensitive to the quality of corporate governance structures (the *governance channel*). If human capital-oriented investment is aligned with shareholder interests, one should expect that better-governed firms place greater emphasis on division-manager ability in financial resource allocation. We test this conjecture by examining the interplay of segment investment, division-manager ability and different measures of corporate governance that capture the strength of both internal and external governance structures. The results strongly support the hypothesis that better-governed firms focus more strongly on the human capital-based dimension of winner-picking.

We further hypothesize that investment decisions are more strongly affected by human capital considerations if informational asymmetries between headquarters and divisions are relatively large (the *information asymmetry channel*). This channel captures the notion that top management's assessment of division managers' abilities to deliver expected results helps mitigate potential frictions related to opacity at the divisional level. We explore this hypothesis by employing different measures of segment diversity and operational complexity. Consistent with our hypothesis, we find that segment investment is more sensitive to division-manager ability as information asymmetries become larger. This evidence suggests that headquarters' knowledge about division managers' abilities to deliver expected results is most valuable in situations where internal capital markets are more likely to fail.

A complementary hypothesis that remains is that capital allocation decisions are affected by headquarters' learning over time about division managers' abilities (the *employer learning channel*). If top management relies on performance histories to reveal division-manager ability over time, the effect of (perceived) managerial ability on capital allocation should become stronger over the course of a division manager's tenure. Our results lend support to this view.

Finally, we examine the value consequences of human capital-based winner picking in capital budgeting. Even though the results of our segment-level analysis suggest that allocating extra funds to more highly skilled managers is value enhancing, we also conduct direct tests of this assumption at the firm level. Inspired by the seminal work of Rajan et al. (2000), we apply a novel measure of internal capital market efficiency that operates by gauging the sensitivity of segment investment to division-manager ability. Our results corroborate the notion that firms create value when they tilt capital allocation toward more able managers.

This chapter has three main goals. The first goal is a conceptual one. By providing a novel measure of division-manager ability (the *DMA-Score*), we present a tool to more accurately capture the economic role of corporate managers with direct responsibility for businesses (assets) of comparable size to standalone firms. The second goal is to shed more light on the functioning of internal capital markets. In particular, we provide new evidence on how top management makes capital budgeting decisions and what role the human capital of division managers has in the process. While survey results already allude to the potential importance of managerial human capital in the budgeting process, the analysis presented in this chapter is the first to provide evidence based on archival data. The third goal of Chapter 3 is to address the ongoing debate about whether internal capital markets maintained by conglomerate firms facilitate efficient resource allocation. Specifically, the chapter analyzes the value consequences of human capital-oriented winner-picking in capital allocation. Thus, we inform the debate about the crucial role of heterogeneity in human capital productivity for the efficiency of internal capital markets. In summary, our results provide strong evidence that allocating more capital to better managers creates value.

The remainder of the chapter is organized as follows. Section 3.2 discusses related literature. Section 3.3 describes the data and introduces the *DMA-Score* – our proposed measure of division-manager ability. Sections 3.4 and 3.5 examine the effect of managerial ability on capital allocation and analyze economic channels. Section 3.6 studies investment efficiency and firm value. Section 3.7 provides robustness tests. Section 3.8 concludes.

3.2. Related Literature

3.2.1. Managerial Features

In the neoclassical model of the firm, the role of the manager is to select in the given set of feasible production plans those that achieve the objectives of firm owners (see Hart, 1989). In this rigid framework, there is no role for managers' individual features, characteristics, or preferences. Consequently, the empirical literature in accounting, finance, and economics has long focused predominantly on firm-, industry-, or market-level variables when studying corporate activities and outcomes. However, both theory, more recent archival work, and managerial surveys recognize that managers are heterogeneous in their skills, beliefs and preferences and that those heterogeneous characteristics matter for corporate behavior and outcomes. For an early example of the important influence of skill on corporate variables, Rosen (1981) presents a model where "Superstars" are differentiated from others and receive large economic benefits. Murphy et al. (1991) describe how managerial talent positively affects the production of employees, leading to economic growth.

Bertrand and Schoar (2003) explore the influence of individual managers on a variety of firm policies. Their approach is based on a manager-firm matched panel data set (i.e., they track top managers who switch firms during their sample period). One benefit of such a "switching sample" is that it allows the estimation of manager fixed effects. Using a fixed effects research design, Bertrand and Schoar (2003) show that individual manager fixed effects provide incremental explanatory power for several corporate policies, including payout and investment policies.

Bertrand and Schoar (2003) initiated a new stream of literature using their fixed effects research design. For instance, Bamber et al. (2010) identify systematic long-lived differences in managers' unique disclosure styles (*manager fixed effects*), even after controlling for known economic determinants of disclosure and firm- and time-specific effects. Similarly, Ge et al. (2011) find that CFO fixed effects are correlated with various financial reporting features, including income smoothing and the aggressiveness of firm accounting policy. Dyreng et al. (2010) find that manager fixed effects are associated with tax avoidance. These papers, and others, collectively suggest that heterogeneity in individual managers affects different accounting and tax policies and outcomes. Other empirical studies focus on specific features of executives using small samples. Kaplan et al. (2012) examine general managerial talent as well the manager's leadership style ("resolute" vs. "empathetic") for a sample of 316 executives hired following buyouts; they find that talent is related to better performance, as is managerial resoluteness. Adams et al. (2005) find that companies whose executives have more power experience more variable performance, consistent with a concentration of decision making leading to more extreme financial outcomes.

The influential fixed effect structure used in Bertrand and Schoar (2003) is also subject to several limitations. First, inferences rely on managers switching firms, which means that the analysis must focus on a relatively small subsample of mobile managers. To the extent that there are idiosyncratic drivers of management changes, the results of these studies may not be generalizable. Second, the statistical tests provide relatively rudimentary evidence on the effects of managers on the policy or outcome under study.[42]

A separate stream of literature attempts to measure the skill or ability of managers or management teams directly. These studies use a variety of metrics, including industry-adjusted stock returns (Fee and Hadlock, 2003) and media mentions (Rajgopal et al., 2006). Demerjian et al. (2012) develop the *MA-Score*, a measure of top management ability. This score measures the efficiency of firm operations (specifically, the efficiency with which the firm produces revenue) and then controls for firm features to isolate the effect of managers. Conceptually, the score is built on the idea that some aspects of firm performance are attributable to the background, skill, and decision-making acumen of the manager, while other aspects of performance will be driven by factors outside of the manager's control, such as inherent features of the firm or industry in which the firm operates.

A large empirical literature has used the *MA-Score*. Topics include earnings quality (Demerjian et al., 2013), earnings forecasts (Baik et al., 2011), tax avoidance (Koester et al., 2017), audit fees

[42] These studies typically use F-tests and incremental R^2s, both of which assess the joint significance of managers but say little about their individual significance.

(Krishnan and Wang, 2015), credit ratings (Bonsall et al., 2017; Cornaggia et al., 2017), and earnings smoothing (Demerjian et al., 2020).

We adapt the method of Demerjian et al. (2012) to measure the ability of division managers. This two-stage method (described in detail in Section 3.3.4) has several advantages relative to other measures used to assess the influence of managers on firm outcomes and policies. First, the score is *interpretable*; a drawback of the results from the fixed effects method is that it can be challenging to identify the impact of individual managers. Second, it is *widely available*. Contrast this with ability assessed by media mentions, which is only available for only a subset of firms. Third, it *does not reflect factors outside of the manager's control*. Both media mentions and stock returns also reflect the information, preferences, and biases of parties external to the firm (the media and investors, respectively), making these noisy metrics of managerial ability. Fourth, the score is *closely related to the overarching goal of profit maximization* as opposed to education-based measures or tenure.

3.2.2. Internal Capital Allocation

The focus of this chapter is on the managerial level just below top management: the division managers responsible for the firm's business units (divisions or segments). *Division managers* are key agents of a firm, driving the results and the development of their segments. Business segments are often viewed as functioning similarly to standalone entities under the division manager's leadership but with top management acting as the single provider of capital and holding total and unconditional economic control rights (see Gertner et al., 1994).[43]

Theoretical papers emphasize the importance of division managers for corporate value enhancement, both by division managers providing superior information and for value destruction due to agency problems caused by division managers pursuing private interests (see, e.g., Harris and Raviv, 1996; Scharfstein and Stein, 2000; Stein, 2002; Marino and Matsusaka, 2005; Roper and Ruckes, 2012). Despite the volume of theory in this area, empirically, the role of division managers remains relatively

[43] For treatments of control rights, see Grossman and Hart (1986), Hart and Moore (1990), and Hart (1995).

underexplored. While recent survey evidence supports the relevance of division-manager ability for capital allocation (Graham et al., 2015; Hoang et al., 2021), we are not aware of any large-scale empirical work that studies this relation. Glaser et al. (2013) find that division-manager influence affects the distribution of cash windfalls across the divisions of a large multinational conglomerate. Gaspar and Massa (2011) and Duchin and Sosyura (2013) provide evidence that professional and social connections between division managers and CEOs are highly relevant for capital allocation. More implicitly, the relevance of division managers is evident in Xuan (2009), who finds that recently appointed CEOs allocate more capital to segments through which they did not advance.

A potentially important advantage of multisegment firms compared to standalone firms is the possibility of redistributing resources toward segments where they can be most profitably employed (Gertner et al., 1994; Stein, 1997). It has been of longstanding interest to empirically evaluate whether multisegment firms actually take advantage of such winner-picking opportunities because otherwise external capital markets are likely more efficient in allocating financial resources to businesses.[44] To assess the efficiency of internal capital markets, the literature has developed a number of metrics that relate the actual segment investment to its investment opportunities (Scharfstein, 1998; Shin and Stulz, 1998; Rajan et al., 2000). Whereas segment investment is observable, segment investment opportunities are not. As a proxy for segment investment opportunities, the literature nearly universally relies on *industry q*'s derived from standalone firms to approximate the q's of conglomerate divisions.[45] The majority of these studies find that conglomerate investment is insufficiently responsive to segment investment opportunities, suggesting that internal capital markets engage in inefficient cross-subsidization of weak divisions at the expense of those with good opportunities (see, e.g., Lamont, 1997; Shin and Stulz, 1998; Rajan et al., 2000; Ahn and Denis, 2004; Ozbas and Scharfstein, 2010). The notion that capital allocation in multisegment firms is structurally flawed serves one of the most popular explanations for the finding

[44] The literature surveys by Stein (2003) and Maksimovic and Phillips (2007) provide comprehensive reviews of the bright and dark sides of internal capital markets.

[45] One exception is Boguth et al. (2021), who estimate conglomerate-implied *industry q*'s by mimicking standalone firms with portfolios composed only of conglomerates.

by Lang and Stulz (1994) and Berger and Ofek (1995) that diversified conglomerates trade at a discount relative to matched portfolios of standalone firms (see Stein, 2003). There is, however, evidence for more efficient investment of multisegment firms during times of adverse circumstances (Khanna and Tice, 2001; Matvos and Seru, 2014; Kuppuswamy and Villalonga, 2016).

While there has been concern about using *industry q* as a proxy for unobservable segment investment opportunities related to selection and measurement issues (Whited, 2001; Maksimovic and Phillips, 2002; Çolak and Whited, 2007), the concept itself is widely accepted. A major shortcoming of the entire analysis based on *industry q* is that it is implicitly assumed that segment investment opportunities are determined exclusively by the general and industry environments. However, investment opportunities should be interpreted as a function of both real capital and human capital productivities. Our results show that internal capital markets operate predominantly by selecting for human capital productivity. More importantly, firms may strongly enhance value when they allocate more capital to more able division managers, suggesting that the omission of the human capital component may lead to severely biased conclusions about internal capital market efficiency.

Few papers emphasize the complementarity of human capital below the top management level and financial capital for corporate success. Giroud and Mueller (2015) and Tate and Yang (2015) document that multisegment firms facilitate the reallocation of workers across plants and industries, respectively.[46] A likely reason multisegment firms focus on human capital productivity in the budgeting process is because this form of winner-picking can provide performance incentives for division managers. Hoang et al. (2021) find that top management is aware of agency problems at the division level and uses its private assessment of division managers' abilities in the budgeting process to counteract managerial opportunism. Our results suggest that human capital-driven winner-picking reduces the scope for rent-seeking behavior at the divisional level.

[46] While the focus of these studies is on the allocation of nonmanagerial human capital, it is management decisions (including those by division managers) that determine these allocations.

3.3. Data and Variables

3.3.1. Sample Selection

Our initial sample includes all multisegment firms in the S&P 1500 index between 2000 and 2018. We restrict the analysis to this period because the data in BoardEx, which is our main source for the division manager information, are incomplete for years before 2000.[47] 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); these firms' financial policies are subject to specific regulations, and their accounting information can differ from that 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 nonmissing and nonnegative segment data on (1) capital expenditures, (2) assets, (3) net sales, and (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 be within 5% of the 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 division managers, as we discuss in more detail in Section 3.3.3. Our final sample consists of 329 firms, 1,137 divisions, and 5,101 segment-year observations for the period 2000-2018.[48] This sample is substantially larger than the samples used in previous studies based on division manager data (e.g., Duchin and Sosyura, 2013; Duchin et al., 2017; Cichello et al., 2009). Table 3.1 summarizes the sample selection steps and provides the number of firms, divisions, and observations retained after each selection step.

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[47] In addition, the segment data before and after 1997 are not directly comparable due to the introduction of SFAS 131 (see, e.g., Berger and Hann, 2003; Cho, 2015).

[48] Our sample is reduced by 2,070 segment-year observations due to the one-year lag requirement for our *DMA-Score* and control variables.

Table 3.1: 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.

	# Firms	# Firm-Years	# Segments	# Segment-Years
S&P 1500 firms with two or more segments	1,588	17,464	9,864	58,867
Less:				
Financial firms and utilities (and firms with segments in these sectors)	313	3,748	2,402	15,539
Incomplete or anomalous financial data at firm or segment level	248	3,747	1,887	12,160
Firms with functional or geographic organizational structure; missing correspondence between Compustat segments and division manager information; unavailability of division manager information	643	6,788	4,214	23,997
Full sample	384	3,181	1,361	7,171
One-year lag requirement for DMA-Score and control variables	55	697	224	2,070
Final sample	329	2,484	1,137	5,101

Table 3.2: 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 for firms represents the number of firm-years, and the number of observations for segments and division managers represents the number of segment-years. See Appendix 3.A for detailed variable descriptions.

Panel A. Firms and Segments						
Variable	Mean	Median	Std.	25^{th} Perc.	75^{th} Perc.	Nobs
Firms						
Number of segments	3.225	3.000	1.106	2.000	4.000	2,484
Number of industries (SIC 3)	2.241	2.000	1.026	2.000	3.000	2,484
Log(Size)	8.049	7.948	1.358	7.104	8.843	2,484
Sales ($ millions)	8,240	2,671	15,455	1,233	6,829	2,484
Capital expenditure/assets	0.039	0.031	0.03	0.02	0.048	2,484
Tobin's q	1.563	1.472	0.493	1.209	1.803	2,280
Cash flow	0.137	0.135	0.054	0.101	0.168	2,484
Profitability	0.103	0.098	0.067	0.058	0.142	2,484
Book leverage	0.244	0.247	0.129	0.158	0.327	2,484
Segments						
Segment investment	0.039	0.029	0.034	0.016	0.050	5,101
Industry-adj. segment investment	−0.003	−0.006	0.036	−0.021	0.013	5,101
Industry-firm-adj. segment investment	0.001	0.000	0.027	−0.012	0.013	5,101
Sales ($ millions)	2,364	909	3,765	381	2,420	5,101
Assets ($ millions)	2,298	927	3,467	344	2,588	5,101
Industry q	1.417	1.358	0.554	1.029	1.750	5,101
Segment cash flow	0.138	0.126	0.093	0.079	0.185	5,101
Panel B. Division Managers						
DMA-Score	0.021	0.016	0.118	−0.059	0.096	5,101
Age	54.253	54.000	6.014	50.000	58.000	5,101
Male indictor	0.948	1.000	0.223	1.000	1.000	5,101
Tenure (position)	6.441	6.000	3.757	4.000	8.000	5,101
Salary ($ thousands)	445	420	165	325	532	3,375
Salary + bonus ($ thousands)	578	485	336	371	650	3,375
Bachelor	0.787	1.000	0.410	1.000	1.000	5,101
Master	0.504	1.000	0.500	0.000	1.000	5,101
MBA	0.332	0.000	0.471	0.000	1.000	5,101
PhD	0.061	0.000	0.239	0.000	0.000	5,101

Panel A of Table 3.2 reports descriptive (segment- and firm-level) statistics for our final sample. On average, the firms in our sample operate 3.23 business segments in 2.24 different three-digit SIC code industries. The average (median) business segment owns book assets valued at $2,298 million ($927 million), generates sales of $2,364 million ($909 million) and has a segment investment rate (capital expenditures to assets ratio) of 3.9% (2.9%).

3.3.2. Capital Allocation and Internal Capital Market Efficiency

To empirically investigate the relationship between managerial ability and capital allocation, we employ two different approaches. The first approach is to run 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 (Section 3.4), we use three different measures of capital allocation known from the literature: (1) segment investment defined as the ratio of capital expenditures scaled by beginning-of-year book assets, (2) industry-adjusted segment investment and (3) industry-firm-adjusted segment investment. Detailed descriptions of these variables appear in Appendix 3.A.

The second approach is to directly measure internal capital market efficiency (with respect to the *DMA-Score*) *at the firm level*. We do this by using a variant of the *relative value added* (RVA) measure introduced by Rajan et al. (2000).[49] 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 analysis, in turn, benefits from a larger sample size due to less restrictive conditions imposed on the data.

[49] See Appendix 3.E for a detailed explanation of our human capital-based variant of the RVA measure.

3.3.3. Division Managers

The crucial challenge for our analysis is that detailed information on division managers is not available from archival sources. We therefore use a combination of textual analysis and hand collection to identify division managers and then assign them to corporate segments. Division manager information is drawn mainly from BoardEx, Form 10-K reports, and DEF-14a proxy statements.

Broadly speaking, manager-segment matching works in two steps: (Step 1) Division managers typically have the title of *division president*, *executive vice president*, *senior vice president*, or a combination 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) To validate the algorithmic division-manager matches, we retrieve executive information from the firms' annual Form 10-K reports and DEF-14a proxy statements gathered from EDGAR as well as a few 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 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 1,431 division managers. Panel B of Table 3.2 provides descriptive statistics for the sample of division managers. A majority are male (95%), 79% hold a bachelor's degree, 50% hold a master's degree, and 6% have a PhD. On average, division managers are 54.2 years old, have a tenure of 6.4 years, and earn a base salary of $445 K.

3.3.4. Measure of Division-Manager Ability

To quantify the managerial ability of division managers, the main variable of interest in our analysis, we follow the general structure of the *managerial ability score* (*MA-Score*) introduced by Demerjian et al. (2012). This measure captures the efficiency with which the firm's top management team (and in particular, the CEO) uses the firm's resources in generating revenue. We start by describing the method used in Demerjian et al. (2012) and follow this with a discussion of how we modify their method to measure the ability of division managers.

Estimation of MA-Score. Demerjian et al. (2012) use a two-stage procedure to measure managerial ability. In the first stage, Demerjian et al. (2012) measure *firm efficiency* using DEA (data envelopment analysis). DEA is a nonparametric optimization technique that calculates relative efficiency. The key innovation of DEA, relative to other efficiency measurement methods, is that DEA allows for flexible, observation-level weights in the efficiency calculation rather than researcher-imposed weights. This allows for observation-level variation in the optimal input–output mix. Demerjian et al. (2012) use a single output, sales revenue, and seven inputs: net property, plant, and equipment; capitalized operating leases; capitalized research and development expenditures; goodwill; other intangibles; cost of goods sold; and selling, general, and administrative costs. Demerjian et al.'s interpretation of firm efficiency rests on the idea that the most efficient firms will maximize their sales revenue for a given level of capital inputs.

The second stage in Demerjian et al. (2012) uses regression to purge firm efficiency of firm features that either aid or hinder efficient operations. The covariates include total assets, market share, firm age, free cash flow, business segment concentration, and an indicator for foreign currency transactions. The residual from the regression of firm efficiency on these six covariates is Demerjian et al.'s *MA-Score*. Because Demerjian et al. (2012) interpret the residual as the manager's contribution to firm efficiency, their assumption is that any firm efficiency not related to firm features is attributed to the skill and ability of the manager.

We adopt a conceptually similar design: in the first stage, we run a modified DEA program to estimate *division-level efficiency scores* and then use second-stage regressions to control for division-specific drivers of efficiency. The residual is our proposed *division-manager ability score (DMA-Score).*

Estimation of Division-Manager Ability. Replicating the Demerjian et al. (2012) design at the division level presents several practical implementation challenges due to the limitations of segment data. The first-stage DEA program, as developed in Demerjian et al. (2012), described above, uses revenue as the sole output and a set of seven capital and expense quantities as inputs. At the segment level, however, several of these inputs are either not reported (e.g., leases, goodwill, intangible assets) or sparsely populated (e.g., PP&E, COGS, R&D expenses).[50] Therefore, we develop an economically similar but modified specification of the DEA estimator adapted to the segment level.[51] 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 all capitalized expenditures of the division. The second input is the segment's operating expenses (labeled *opex*). This variable captures expenditures that are not afforded balance sheet recognition but rather immediately expensed and recognized on the income statement. We construct this variable by subtracting (*ops*) and depreciation (*dps*) from segment sales (*sales*). We then estimate division-level efficiency scores separately by year over the period from 1999 to 2018 for all reported business segments with nonmissing input and output data.[52] We present detailed summary statistics on the division efficiency measure in Appendix 3.B.

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[50] Only five segment-level variables – sales, total assets, operating profit, capital expenditures, and depreciation – have data broadly available on Compustat (Botosan et al., 2021)

[51] Demerjian (2017) emphasizes the importance of sufficiently large calculation groups for calculating DEA efficiency. In our setting, we benefit from the fact that most firms have multiple segments (and thus multiple observations per year). Therefore, limited availability of segment data does not impose significant restrictions on calculation group sizes.

[52] 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

The first-stage DEA analysis yields a measure of *division efficiency*, analogous to firm efficiency from Demerjian et al. (2012). Certain features outside of the division manager's control are likely to make a division more or less efficient. To isolate the effects of the division manager from these features, in the second-stage analysis, we regress division efficiency on a set of variables that should aid or hinder a division from operating efficiently. Our second-stage covariates adapt those from Demerjian et al. (2012) to the divisional setting. As described earlier, Demerjian et al. (2012) use six covariates to control for firm-level drivers of efficiency: firm size, market share, an indicator for free cash flows, firm age, business segment concentration, and an indicator for foreign currency transactions. Size, market share, free cash flows, and firm age all enhance firm efficiency and have a positive association with firm efficiency; business segment concentration and foreign currency transactions make firms more complex and more difficult to run efficiently, leading to a predicted negative association with firm efficiency.[53]

In our second-stage analysis, we include four segment-level covariates drawn from firm-level analogs in Demerjian et al. (2012).[54] The first division-level covariate is *segment size*, which follows firm size. We expect larger segments to be more efficient than smaller segments due to economies of scale. The second covariate is *segment market share*, which is measured like firm market share but with segment sales (rather than firm sales) scaled by total sales for 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; we expect that more free cash flows facilitate investment and operating flexibility, leading to higher efficiency. The fourth covariate is *business segment concentration*, measured as the segment sales scaled by the aggregated segment sales of the firm during the year. This variable measures diversification within

to calculate current-period efficiency scores, which may introduce look-ahead bias (Demerjian, 2017). We obtain very similar results from year- and industry-calculated DEA efficiency.

[53] Demerjian et al. (2012) find the predicted relations for all covariates except business segment concentration.

[54] We do not use segment analogs for two of their variables due to lack of data; we do not have data to determine the age of a segment or whether the segment has foreign currency transactions.

the firm. We include it to control for differences in efficiency between single-segment firms and multisegment firms. Since conglomerates are known to operate larger and more profitable segments than standalone firms (Kuppuswamy and Villalonga, 2016; Hund et al., 2016), we expect *business segment concentration* to be negatively associated with segment efficiency.

In terms of estimation, we run annual Tobit regressions with *division efficiency* as the dependent variable and *segment size*, *segment market share*, *segment free cash flow*, and *business segment concentration* as the independent variables. We further include industry fixed effects (represented by three-digit SIC codes) to control for cross-industry variation in efficiency. Table 3.3 presents the average coefficients across the different year estimations and reports the standard errors produced by the Fama-MacBeth procedure. We first analyze each explanatory variable separately based on univariate specifications. The results confirm the predicted relations for all covariates (Table 3.3, columns (1)-(4)).

Column (6) reports the results when we run the full model. The residual from this estimation (i.e., the difference between the actual and predicted efficiency of the division) is our proposed *division-manager ability score* (*DMA-Score*). As column (6) shows, the Fama-MacBeth t-statistic is no longer significant for the variables *segment size* and *business segment concentration* when we run the full model. The reason can be seen from column (5): the average effect of segment size is absorbed by the other explanatory variables, and the average effect of *business segment concentration* is absorbed by the inclusion of industry fixed effects. However, this does not mean that these variables have no explanatory power at all. The last column of Table 3.3 shows the percentage of significant coefficients (the number of coefficients that are statistically significant at the 10% level across the 20 year regressions) with respect to the full model (column (6)). We find that the coefficients of *segment size* and *business segment concentration* are statistically significant in more than 50% of the underlying year estimations. We therefore retain them in the model.

Table 3.3: Second-Stage Estimation of Managerial Ability

This table presents the results from second-stage Tobit regressions of division efficiency. Regressions are estimated by year over the period from 1999 to 2018 for all reported business segments listed on Compustat with nonmissing data on division efficiency and explanatory variables. Division efficiency is measured using DEA based on the vectors described in Section 3.3.4. 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 3.3.4. See Appendix 3.A for detailed variable descriptions.

Dep. Var.:	Division Efficiency							
	Predicted Sign	Average Coefficient (Fama-MacBeth SE)						Proportion Significant
Model		(1)	(2)	(3)	(4)	(5)	(6)	(6)
Segment size	+	0.018***				0.003	−0.000	0.80
		(0.004)				(0.003)	(0.004)	
Segment market share	+		2.126***			1.271***	1.985***	1.00
			(0.151)			(0.090)	(0.111)	
Segment free cash flow	+			0.129***		0.145***	0.118***	1.00
				(0.010)		(0.010)	(0.008)	
Business segment concentration	−				−0.009***	−0.006**	0.001	0.50
					(0.004)	(0.002)	(0.004)	
Industry FE		X	X	X	X		X	
Year estimations		20	20	20	20	20	20	
Nobs		74,384	74,384	74,384	74,384	74,384	74,384	

Robust standard errors in parentheses

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

3.4. Empirical Analysis

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

This section presents baseline tests of the relation between division-manager ability and resource allocation in internal capital markets. The unit of observation is a segment-year. The dependent variable is segment-level capital allocation. In our baseline analysis, we employ three different measures of capital allocation: (1) segment investment (the ratio of capital expenditures scaled by beginning-of-year book assets), (2) industry-adjusted segment investment and (3) industry-firm-adjusted segment investment. The variable of interest is the one-period-lagged *DMA-Score* described in Section 3.3.4. The baseline model further includes a vector of established segment- and firm-level determinants of capital allocation (*industry q*; cash flow; size) and manager-specific characteristics (age; gender; tenure on position; educational background) as controls. In addition, we include year fixed effects in all regressions to account for time-varying shocks that all firms face. Standard errors are clustered by firm to account for possible cross-segment dependencies of investment outcomes. Detailed variable definitions appear in Appendix 3.A.

Table 3.4 presents the results. We begin the analysis with univariate and multivariate regressions of (unadjusted) segment investment (see columns (1) and (2)). Both specifications include industry-year fixed effects to account for cross-sectional variation in high- and low-ability manager representation across industries and cross-industry heterogeneity in capital investment.[55] As expected, there is a strong and positive association between managerial ability and internal capital allocation. The coefficient on the one-period-lagged *DMA-Score* equals 2.8% in the multivariate specification and is statistically significant at the 1% level (see Table 3.4, column (2)).

To put this magnitude in perspective, division managers in the top quintile of the ability distribution (*DMA-Score*: 0.194) receive 24% larger capital allocations (0.9 percentage points) than managers in

[55] Note that *industry q* (the standard proxy for unobservable segment investment opportunities) has no within-industry variation in a given year and is therefore absorbed by the addition of industry-year fixed-effects.

the bottom quintile (*DMA-Score*: -0.143). This translates into \$22 M additional funds per year for the average-sized division in our data and \$139 M over the average tenure of a division manager (6.4 years $\times$ \$22 M per year).

We next augment the previous specification with firm fixed effects to remove unobserved firm-specific factors that remain constant over time, such as access to external financing, industry composition or geographic location. This extension helps us address the possibility that better managers self-select into "better" firms. Column (3) shows that the positive association between managerial ability and capital allocation continues to hold with a similar magnitude (2.4%), suggesting that unobserved heterogeneity at the firm level is unlikely to drive our results.

In columns (4) to (6) of Table 3.4, we present results from the alternative estimation strategy of replacing the dependent variable with industry-adjusted segment investment. Industry adjustment has the advantage of removing unobserved industry heterogeneity in capital intensity based on more complete out-of-sample information from the industry in which the division operates. A potential concern with this approach, however, is that demeaning the dependent variable can lead to distorted estimates (Gormley and Matsa, 2014).[56] We repeat all previous tests. Columns (4)-(6) show that the magnitudes and significance of the coefficients on the *DMA-Score* are very similar to those obtained from previous regressions that include industry-year fixed effects (see Table 3.4, columns (1)-(3)). Therefore, we conclude that industry adjustments do not have a substantive effect on the results that we report in our analysis.

Using a third measure of capital allocation, we perform regressions of industry-firm-adjusted segment investment (Rajan et al., 2000). The additional firm adjustment allows us to differentiate cross-segment transfers from net additions to all segments of a firm. Across all specifications, the estimated coefficients on our ability measure are uniformly positive and statistically significant, with

[56] Note that our main explanatory variable, *DMA-Score*, is also industry adjusted by construction. This can be seen from the fact that we (1) calculate the score on a year-by-year basis and (2) include industry fixed effects in the 2[nd]-stage regressions (see Section 3.3.4).

magnitudes ranging from 1.6% to 2.1% (see Table 3.4, columns (7)-(9)). This evidence indicates that the above results are largely attributable to resource transfers from less to more able division managers.

In summary, we find that division-manager ability plays an important role in the allocation of financial resources to segments in all our regression specifications. The analysis of manager controls suggests that most individual-specific characteristics only play a subordinate role in explaining conglomerate investment behavior. One exception is *gender*. In line with recent evidence by Duchin et al. (2021) on the existence of a gender gap in internal capital allocation, the coefficient on the male indicator is generally positive, but the significance of this result varies across specifications. The reason for this is likely the relatively small number of only 87 female division managers in our sample.[57]

The analysis of the firm and division control variables confirms the importance of firm and segment cash flow in explaining capital allocation (Shin and Stulz, 1998). However, the estimated coefficient on *industry q* is negative close to zero and statistically insignificant, suggesting that winner-picking activities in internal capital markets operate predominantly via selection for human capital productivity.[58] Put colloquially, top management tends to bet on the "*jockey*" rather than on the "*horse*".

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[57] Chapter 4 of this dissertation provides a comprehensive analysis of women's representation in division management. In particular, Chapter 4 shows that female underrepresentation in division management is an ongoing and widespread phenomenon.

[58] Note that *industry q* is mechanically absorbed by specifications that include industry-year fixed effects (see Table 3.4, columns (1) and (2)). In unreported tests, we estimate alternative specifications in which industry and year fixed effects are separately included in the regression. The coefficient on *industry q* is always insignificant and close to zero.

Table 3.4: Baseline Regression

This table presents OLS and fixed effects regressions of internal capital allocation on division-manager ability and a vector of additional controls. The sample period ranges from 2000 to 2018. The dependent variable is segment investment in columns (1)-(3), industry-adjusted segment investment in columns (4)-(6), and industry-firm-adjusted segment investment in columns (7)-(9). *DMA-Score* is the measure of division-manager ability described in Section 3.3.4. Explanatory variables are lagged one year, and continuous variables are winsorized at the extreme 1%. Standard errors (in brackets) are clustered at the firm level. See Appendix 3.A for detailed variable descriptions.

Dep. Var.:	Segment Investment			Industry-Adjusted Segment Investment			Industry-Firm-Adjusted Segment Investment		
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DMA-Score	0.036***	0.028***	0.024***	0.037***	0.026***	0.022***	0.021***	0.016***	0.021***
	(0.008)	(0.008)	(0.009)	(0.007)	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)
Division controls									
Industry q					−0.001	−0.002		−0.001	−0.003**
					(0.002)	(0.002)		(0.001)	(0.001)
Segment cash flow		0.017*	0.031***		0.032***	0.041***		0.030***	0.032***
		(0.009)	(0.010)		(0.010)	(0.011)		(0.010)	(0.011)
Segment size		−0.000	0.000		−0.001	−0.000		−0.001	−0.001
		(0.002)	(0.002)		(0.001)	(0.001)		(0.001)	(0.001)
Firm controls									
Firm cash flow		0.055***	0.058***		0.071***	0.073***		−0.032**	−0.029***
		(0.017)	(0.021)		(0.019)	(0.021)		(0.015)	(0.014)
Firm size		−0.000	−0.002		0.001	−0.001		0.001	0.001
		(0.001)	(0.003)		(0.002)	(0.003)		(0.002)	(0.002)
Number of segments		−0.001	0.001		−0.002	0.000		−0.000	0.000
		(0.006)	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
Manager controls									
Male		0.006	0.006		0.001	0.005		0.004**	0.005*
		(0.004)	(0.004)		(0.003)	(0.003)		(0.002)	(0.003)
Age		0.001	0.000		0.000	0.000		0.000	0.000
		(0.001)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Tenure		−0.000	0.000		−0.001*	−0.000		−0.000	−0.000
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)	(0.000)
Bachelor		0.001	−0.003		−0.000	−0.001		−0.000	0.001
		(0.003)	(0.003)		(0.003)	(0.003)		(0.002)	(0.002)
Master		0.004	0.000		−0.000	0.002		0.002	0.002
		(0.003)	(0.003)		(0.003)	(0.003)		(0.002)	(0.003)
MBA		0.003	−0.002		−0.001	−0.001		−0.001	0.001
		(0.003)	(0.002)		(0.003)	(0.003)		(0.002)	(0.002)
Constant	0.038***	0.021*	0.034	−0.001	−0.019	−0.021	0.005	−0.005	0.012
	(0.004)	(0.012)	(0.022)	(0.005)	(0.011)	(0.025)	(0.004)	(0.009)	(0.016)
Year FE				X	X	X	X	X	X
Industry-Year FE	X	X	X						
Firm FE			X			X			X
Nobs	5,101	5,101	5,101	5,101	5,101	5,101	5,101	5,101	5,101
Adjusted R^2	0.46	0.47	0.58	0.02	0.04	0.28	0.01	0.03	0.08

Robust standard errors in parentheses

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

3.4.2. Validation Tests

In this section, we introduce different sets of fixed effects and their high-dimensional combinations that help alleviate residual concerns about the interpretation of results.

3.4.2.1. Unobservable Characteristics of Divisions, Managers and CEOs

While we control for established determinants of internal capital allocation and managerial attributes in our baseline tests, additional unobservable factors might confound our inferences. To mitigate concerns about the issue of correlated omitted variables, we extend our baseline model by adding different groups of fixed effects. Division fixed effects address the concern that our proposed *DMA-Score* may to some extent reflect measurement error caused by additional unidentified division characteristics. This could be the case if some division-specific drivers of divisional efficiency are unobservable and therefore not captured by the second-stage model reported in Section 3.3.4. Manager fixed effects absorb unobservable persistent differences across managers outside the realm of managerial ability, such as preferences or risk aversion, that may coincide with our main variable of interest. CEO fixed effects account for the possibility that differences across CEOs (e.g., attitudes or leadership styles) drive the results.[59]

Table 3.5 presents the results. The dependent variable is industry-adjusted segment investment.[60] In columns (1)-(3), we sequentially add the abovementioned groups of fixed effects. All specifications include year fixed effects and the time-varying controls from prior regressions (see Table 3.5). The results confirm that capital allocation is sensitive to division-manager ability. The estimated coefficients on the one-period-lagged *DMA-Score* are similar in size to those in our baseline analysis (2.3-2.8%) and significantly different from zero at the 1% level of significance. In column (4) of Table 3.5, we jointly include the three groups of fixed effects and find economically even stronger results

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[59] Prior research emphasizes the importance of CEO traits as a key determinant of corporate investment policies (see, e.g., Bertrand and Schoar, 2003; Frank and Goyal, 2007; Malmendier et al., 2011; Graham et al., 2012; Custódio et al., 2013; Bennedsen et al., 2020).

[60] Appendix 3.D replicates the analysis for the other measures of capital allocation mentioned in our baseline analysis. The results are very similar.

(3.0%). This evidence mitigates the scope for alternative explanations related to omitted variables and measurement error in our main variable of interest.

3.4.2.2. Endogenous Matching of Managers to Divisions and CEO Favoritism

Next, we examine two alternative explanations for our findings. First, it is possible that endogenous matching of superior managers to capital-rich divisions confounds the interpretation of our results. For example, better-skilled managers could select themselves into divisions where they expect to receive more capital in the future. We address this concern by augmenting our baseline regression model with (division $\times$ division manager) fixed effects. This strategy allows us to exploit time-series variation during a manager's tenure in a specific division. Column (5) of Table 3.5 reports the results. We find that capital allocation is highly sensitive to a division manager's performance on his or her current division. The coefficient on division-manager ability remains statistically significant and economically large (2.8%). This evidence suggests that endogenous assignment of managers to divisions cannot explain our results.

Another potential concern is that division managers and capital allocation may be subject to CEO favoritism. This channel is based on the notion that managers might perform better and receive more capital if they are favored by the CEO for reasons outside of job performance. Better-performing division managers might in fact simply benefit from strong social ties to the CEO (e.g., via shared backgrounds, joint club memberships, or prior employment in the same firm) and therefore receive larger capital allocations.[61] To address this concern, we exploit the fact that social ties between individuals are typically time-invariant in the short and medium term. Accordingly, we extend our baseline model with (CEO $\times$ division manager) fixed effects. Column (6) of Table 3.5 shows that our results hold robustly with similar magnitude (2.9%) and statistical significance (1% level). Accordingly, we rule out CEO favoritism driving our results.

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[61] Prior work has documented that division managers with strong social connections to the CEO receive more capital (see, e.g., Xuan, 2009; Gaspar and Massa, 2011; Duchin and Sosyura, 2013; Glaser et al., 2013).

Table 3.5: Unobservable Factors, Endogenous Matching of Managers, and CEO Favoritism

This table presents fixed effects regressions on the relation between internal capital allocation and division-manager ability. The sample period ranges from 2000 to 2018. The dependent variable is industry-adjusted segment investment. *DMA-Score* is the measure of division-manager ability described in Section 3.3.4. Control variables include the same characteristics of the division, firm, and manager used in Table 3.4. Explanatory variables are lagged one year, and continuous variables are winsorized at the extreme 1%. Standard errors (in brackets) are clustered at the firm level. See Appendix 3.A for detailed variable descriptions.

Dep. Var.:	Industry-Adjusted Segment Investment					
Model	(1)	(2)	(3)	(4)	(5)	(6)
DMA-Score	0.025***	0.028***	0.023***	0.030***	0.028***	0.029***
	(0.008)	(0.009)	(0.009)	(0.010)	(0.008)	(0.008)
Constant	0.031	0.032	−0.000	0.110	0.084*	0.091*
	(0.032)	(0.067)	(0.028)	(0.064)	(0.049)	(0.048)
Controls	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Division FE	X			X		
Manager FE		X		X		
CEO FE			X	X		
Division * Manager FE					X	
CEO * Manager FE						X
Nobs	5,101	5,101	5,101	5,101	5,101	5,101
Adjusted R^2	0.48	0.49	0.32	0.37	0.53	0.52

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

3.5. 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.

3.5.1. The Governance Channel

Corporate governance and internal capital market efficiency are closely intertwined topics. Since top management acts as an agent of outside investors, it does not bear the (full) costs of inefficient allocation of resources (Bolton and Scharfstein, 1998). Theoretical arguments suggest that ineffective governance at the top of the organization may lead to misallocation of internal capital at the expense of shareholder wealth (see Stein, 2003 for a review). The reason for this is that poorly governed firms may provide agency-prone CEOs with discretion to engage in inefficient cross-subsidization to derive private benefits, e.g., from empire-building (Jensen, 1986), pursuit of entrenchment or wasteful pet projects (Shleifer and Vishny, 1989), or rent-payment to division managers (Scharfstein and Stein, 2000). Several studies find evidence for a positive link between the quality of corporate governance at the top of the organization and the efficiency of internal resource allocation (see, e.g., Anderson et al., 2000; Durnev et al., 2004; Datta et al., 2009; Sautner and Villalonga, 2010; Chen and Chen, 2012; Hoechle et al., 2012). If human capital-oriented segment investment is value-creating for shareholders, we would expect relatively better-governed firms to engage more strongly in this form of winner-picking.

To examine this hypothesis, we interact our key variable of interest, *DMA-Score*, with different measures of internal and external governance: (1) board independence, the fraction of outside directors on the board, is a proxy for the board's ability to monitor management decisions; (2) CEO equity-based pay captures CEO incentives for efficient investment and value maximization; and (3) the percentage of shares held by institutional investors proxies for the effectiveness of large and sophisticated investors in limiting top management's discretion to pursue its own objectives. To facilitate comparison, we standardize each governance measure (i.e., the mean is zero, and the standard deviation is one).

Table 3.6 presents the results. The dependent variable is industry-adjusted segment investment. The variable of interest is the interaction between division-manager ability (the one-period-lagged *DMA-Score*) and corporate governance. The even- and odd-numbered columns report regressions with and without controls from prior regressions. Columns (1)-(6) of Table 3.6 sequentially estimate the interaction between managerial ability and governance for each of the abovementioned governance measures. The coefficients on the interaction are uniformly positive and statistically significant across all specifications. The magnitudes of these coefficients are also economically large (1.7-4.0%). For example, a one-standard-deviation increase in institutional ownership increases the effect of division-manager ability on capital allocation by 1.7 percentage points (or 60% in relative terms).[62] This evidence suggests that when allocating capital, well-governed firms engage more strongly in winner-picking activities based on division managers' abilities.

We also present estimates from the alternative empirical strategy of interacting division-manager ability with a composite index of the standardized governance measures mentioned above (see Appendix 3.A). The composite index has the advantage of allowing us to exploit complementarity relations between the different governance mechanisms, thus providing a more holistic view of the interplay between managerial ability, governance and capital allocation.[63] The results of these tests corroborate our previous findings (see Table 3.6, columns (7)-(8)). The coefficient on the interaction term *DMA-Score* $\times$ *Composite Index* is positive, significantly different from zero and economically large (3.9-4.0%), while the coefficient on the uninteracted *DMA-Score* is close to zero and insignificant. Again, the evidence is consistent with the hypothesis that well-governed firms winner-pick based on human capital considerations, while poorly governed firms do not.

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[62] The coefficient on the *DMA-Score* is 2.9% (see Table 3.6, column (5)). All governance measures are standardized. Hence, a one-standard-deviation increase in total ownership increases the association by approximately 60% ($\sim\frac{1.7\%}{2.9\%}$).

[63] Prior research highlights the importance of the interdependence among different governance mechanisms in assessing their impact on firm performance (see Agrawal and Knoeber, 1996).

Table 3.6: The Governance Channel

This table presents OLS regressions of internal capital allocation on the interaction between division-manager ability and corporate governance. The sample period ranges from 2000 to 2018. The dependent variable is industry-adjusted segment investment. All governance measures are standardized to have zero mean and unit variance. *DMA-Score* is the measure of division-manager ability described in Section 3.3.4. Control variables include the same characteristics of the division, firm, and manager used in Table 3.4. Explanatory variables are lagged one year and continuous variables are winsorized at the extreme 1%. All regressions include year fixed effects. Standard errors (in brackets) are clustered at the firm level. See Appendix 3.A for detailed variable descriptions.

Governance measure	Board Independence		Equity-Based Pay		Institutional Ownership		Composite Index	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DMA-Score × Governance	0.039***	0.040***	0.023***	0.022***	0.017*	0.019**	0.039***	0.040***
	(0.010)	(0.010)	(0.007)	(0.006)	(0.009)	(0.009)	(0.009)	(0.009)
DMA-Score	0.018**	0.007	0.018**	0.008	0.029***	0.016**	0.002	−0.009
	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)
Governance	0.000	0.001	−0.001	−0.001	0.001	0.001	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	−0.002	−0.017	−0.001	−0.019	−0.001	−0.020*	−0.002	−0.018
	(0.005)	(0.011)	(0.005)	(0.012)	(0.005)	(0.012)	(0.005)	(0.011)
Year FE	X	X	X	X	X	X	X	X
Controls		X		X		X		X
Nobs	5,101	5,101	5,101	5,101	5,101	5,101	5,101	5,101
Adjusted R^2	0.03	0.07	0.03	0.06	0.02	0.06	0.03	0.07

Robust standard errors in parentheses

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

3.5.2. The Information Asymmetry Channel

Our second hypothesis postulates that capital allocation decisions rely more strongly on human capital-related signals if lines of business are relatively diverse and informational asymmetries between divisions and the corporate center are potentially large. Theory suggests that the informational disadvantage of headquarters relative to division managers exacerbates the potential for a second type of agency conflict inside the firm, which may lead to underinvestment and resource misallocation (see, e.g., Antle and Eppen, 1985; Harris and Raviv, 1996; Scharfstein and Stein, 2000; Bernardo et al., 2001; Wulf 2009). Theoretical arguments by Hoang and Ruckes (2015) suggest that private information of top management is prevalent in the budgeting process. A recent survey by Hoang et al. (2021) finds that firms are aware that divisions' investment proposals may be biased and organize the budgeting process to counteract managerial opportunism. Their results further indicate that firms use information only residing at headquarters, in particular top management's assessment of divisional managers' abilities, to mitigate agency problems at the division level. In this spirit, we hypothesize that firms operating in informationally opaque environments engage more strongly in human capital-oriented winner-picking when allocating capital.

To test this hypothesis, we estimate regressions of industry-adjusted segment investment on the interaction between division-manager ability (one-period-lagged *DMA-Score*) and various measures of information asymmetry between headquarters and divisions from the literature: (1) the number of reported segments, (2) the dispersion of operations across divisions (Herfindahl index of sales), and (3) R&D intensity (the ratio of R&D expenditures to firm sales).[64] We again standardize each measure to unit standard deviation so that we can compare the coefficients and assess economic magnitude. Table 3.7 reports the results.

We find positive, statistically significant, and economically large (1.3-3.3%) coefficients on the interaction between division-manager ability and information asymmetry for each of the above measures and across specifications with and without covariates (see Table 3.7, columns (1)-(6)).

[64] See, e.g., Aboody and Lev (2000), Datta et al. (2009) or Duchin and Sosyura (2013).

Again, we also present results from the alternative strategy of using a composite index that incorporates the three measures. The results continue to hold with similar magnitude (1.9-2.2%) and statistical significance (see Table 3.7, columns (7)-(8)).[65] Consistent with the above predictions, this finding suggests that informationally opaque firms rely more strongly on division-manager ability in the budgeting process.

3.5.3. The Employer Learning Channel

We also examine whether temporal dynamics and intertemporal learning in assessing the effective ability of division managers affect our results. It is reasonable to assume that informational asymmetries may also affect headquarters' capacity to discern more able division managers from their less able peers. The longer a division manager's professional tenure, however, the more information that headquarters can draw upon in assessing the manager's ability to deliver the expected results (see, e.g., Waldman, 1984; Baker et al., 1994). If employer learning mitigates frictions in the assessment of division managers' individual abilities, our results should become stronger over the course of a division manager's tenure.

Columns (9)-(10) of Table 3.7 present estimates from univariate and multivariate regressions of industry-adjusted segment investment on the interaction between division-manager ability (the one-period-lagged *DMA-Score*) and a division manager's tenure (measured in years) on his or her current position. As expected, the association between segment investment and managerial ability increases over the course of a division manager's tenure. The interaction coefficient (*DMA-Score* $\times$ *Tenure*) is significantly different from zero (1% level) and economically large (0.6%), suggesting that an additional year in office increases the association between (perceived) ability and capital allocation by 0.6 percentage points, holding the other covariates constant. Thus, our results support the hypothesis that employer learning facilitates the selection of "winners" in internal capital markets.

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[65] The composite index equals the sum of the (standardized) measures of information asymmetry. To facilitate comparison of results, the index is standardized to unit standard deviation as well.

Table 3.7: The Information Asymmetry Channel and the Employer Learning Channel

This table presents OLS regressions of internal capital allocation on the interaction between division-manager ability and information. The sample period ranges from 2000 to 2018. The dependent variable is industry-adjusted segment investment. The main variable of interest is the double interaction term *DMA-Score* $\times$ *M*, where *M* refers to different measures of information asymmetry and employer learning. All measures of information asymmetry are standardized to have zero mean and unit variance. *DMA-Score* is the measure of division-manager ability described in Section 3.3.4. Control variables include the same characteristics of the division, firm, and manager used in Table 3.4. Explanatory variables are lagged one year, and continuous variables are winsorized at the extreme 1%. All regressions include year fixed effects. Standard errors (in brackets) are clustered at the firm level. See Appendix 3.A for detailed variable descriptions.

	Information Asymmetry								Employer Learning	
Measure (M)	No. of Segments		R&D Expense		Inverted HHI of Sales		Composite Index		Tenure on Position	
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DMA-Score × M	0.015**	0.013**	0.032*	0.033*	0.022***	0.020**	0.022***	0.019***	0.006***	0.006***
	(0.006)	(0.006)	(0.020)	(0.018)	(0.008)	(0.008)	(0.008)	(0.007)	(0.002)	(0.002)
M	−0.002**	−0.002**	0.004	0.005	−0.002	0.000	−0.002*	0.003	−0.001	−0.001*
	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.004)	(0.000)	(0.000)
DMA-Score	0.029***	0.019**	0.038***	0.028***	0.023**	0.013	0.024***	0.015*	0.009	0.001
	(0.009)	(0.009)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)
Constant	−0.001	−0.022**	−0.001	−0.017	−0.017	−0.006	−0.000	−0.009	0.001	−0.017
	(0.005)	(0.011)	(0.005)	(0.011)	(0.011)	(0.008)	(0.005)	(0.010)	(0.005)	(0.011)
Year FE	X	X	X	X	X	X	X	X	X	X
Controls		X		X		X		X		X
Nobs	5,101	5,101	5,101	5,101	5,101	5,101	5,101	5,101	5,101	5,101
Adjusted R^2	0.03	0.06	0.03	0.06	0.03	0.06	0.03	0.06	0.03	0.06

Robust standard errors in parentheses

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

3.6. Managerial Ability, Investment Efficiency and Firm Value

The above results suggest that firms with active internal capital markets tilt capital allocation toward superior division managers. In this section, we study the valuation consequences of this behavior to evaluate whether human capital-based winner-picking reflects efficient investment. To examine this question, we run firm-level regressions of excess value on a novel measure of internal capital market efficiency based on the sensitivity of segment investment to managerial ability. The firm-level approach has the advantage of allowing us to directly estimate the value consequences of allocating extra funds to segments of more able division managers. The downside is a loss of data: for a firm-year to be included, one-period-lagged *DMA-Scores* must be available for all division managers of the firm. Therefore, fiscal years are mechanically removed in the presence of (1) division manager turnover or (2) changes in the number of reported segments, e.g., due to restructuring or changes in segment reporting.[66] Even though this condition reduces the sample size, the sample remains large (1,455 firm-years) in comparison to those of previous studies on division managers.

Measures of Excess Value. Following Berger and Ofek (1995), we calculate excess value as the natural log of the ratio of a firm's actual value to the sum of the imputed values of its segments. We calculate the imputed value of a segment by multiplying the segment's assets (sales) by the median market-to-assets (market-to-sales) ratio of standalone firms operating in the segment's industry.

Measure of Investment Efficiency. Our main variable of interest is a novel measure of internal capital market efficiency that captures how strongly firms engage in winner-picking activities with respect to managerial ability. In essence, we use a human capital-based variant of the *relative value added* (RVA) from internal capital allocation, defined by Rajan et al. (2000). RVA is a correlation-based measure of investment efficiency that operates by gauging the sensitivity of cross-segment investment to segment investment opportunities (proxied by *industry q*). At its core, the RVA metric

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[66] Some firms also report a segment labeled "other" that comprises miscellaneous entities of the firm that are too small for separate disclosure. For completeness, we also account for investments and *DMA-Scores* related to these segments when calculating our firm-level measure of investment efficiency. The results are similar if we remove these segments.

captures the effect of capital allocation (or more precisely, the reweighting of segment assets through capital allocation) on the asset-weighted average of all the segments' *industry q*'s. Building on this intuition, we create an ability-based variant of the RVA metric that measures how capital allocation alters the asset-weighted average of all the division managers' *DMA-Scores*. In technical terms, our measure (henceforth "*RVA-ABILITY*") is the asset-weighted covariance between cross-segment investment and division-manager ability.[67] Accordingly, positive (negative) values of *RVA-ABILITY* reflect transfers of assets from less to more (more to less) able division managers. Full details on the construction of the *RVA-ABILITY* measure are provided in Appendix 3.E.

Table 3.8 presents the results from regressions of excess value on *RVA-ABILITY*. All regressions include year fixed effects, and standard errors are clustered at the firm level. To facilitate interpretation of our results, we standardize all variables by subtracting the mean and dividing by the standard deviation. We begin our analysis with a univariate regression of excess value based on assets (see Table 3.8, column (1)). As the column shows, we find that a one-standard-deviation increase in *RVA-ABILITY* is associated with a 6.8-percentage-point-higher excess value. This relation is significantly different from zero at the 1% level of significance and continues to hold after we control for size, profitability, book leverage, and capital expenditures (see Table 3.8, column (2): 6.8%). We next augment the specification with firm fixed effects. The coefficient on *RVA-ABILITY* remains economically and statistically significant (see Table 3.8, column (3): 3.7%). For robustness, we also estimate our results after including the RVA measure (with respect to *industry q*) as defined in Rajan et al. (2000) as an additional control (column (4)). The estimated coefficient on *RVA-ABILITY* is virtually unchanged. Finally, we repeat the analysis for excess value based on sales multiples (see Table 3.8, columns (5)-(8)). The results are similar to those mentioned above, with slightly larger magnitudes (4.3-7.6%). Taken together, these results confirm our previous conclusions that human capital-based winner picking is value-enhancing.

[67] A benefit of this approach is that we circumvent the empirical concerns about measurement error related to *industry q* mentioned in Çolak and Whited (2007).

Table 3.8: Managerial Ability, Investment Efficiency and Firm Value

This table presents estimates from OLS and fixed effects regressions at the firm level. The sample consists of S&P 1500 multisegment firms during the period 2000 to 2018. 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). The excess value measure is based on asset multiples in columns (1)-(4) and on sales multiples in columns (5)-(8). The main variable of interest, *RVA-ABILITY*, is a human capital-based variant of the *relative value added (RVA)* measure (Rajan et al., 2000), which equals the firm-specific asset-weighted covariance between industry-adjusted segment investment and division-manager ability. All regressions include year fixed effects. Standard errors (in brackets) are clustered at the firm level. See Appendix 3.A for detailed variable descriptions.

	Excess Value (Asset-Multiples)				Excess Value (Sales-Mulitples)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RVA-Ability	0.068***	0.068***	0.037***	0.037***	0.075***	0.076***	0.043***	0.043***
	(0.016)	(0.016)	(0.014)	(0.014)	(0.024)	(0.023)	(0.017)	(0.017)
Firm size		-0.061***	-0.110**	-0.110**		-0.004	0.164**	0.164**
		(0.020)	(0.050)	(0.050)		(0.039)	(0.067)	(0.067)
Profitability		0.222***	0.164***	0.164***		0.277***	0.137***	0.137***
		(0.022)	(0.027)	(0.028)		(0.039)	(0.029)	(0.029)
Book Leverage		-0.047**	-0.018	-0.018		-0.008	0.022	0.023
		(0.022)	(0.026)	(0.026)		(0.038)	(0.029)	(0.030)
Capital Expenditures		0.018	0.046**	0.046**		-0.013	0.009	0.010
		(0.017)	(0.020)	(0.020)		(0.026)	(0.024)	(0.024)
RVA				0.012				0.001
				(0.010)				(0.014)
Constant	-0.009	0.138*	-0.009***	-0.014***	-0.183***	0.168*	-0.183***	-0.188***
	(0.027)	(0.076)	(0.000)	(0.000)	(0.043)	(0.095)	(0.000)	(0.000)
Year FE	X	X	X	X	X	X	X	X
Firm FE			X	X			X	X
Nobs	1,455	1,455	1,455	1,455	1,455	1,455	1,455	1,455
Adj. R2	0.02	0.26	0.67	0.66	0.01	0.19	0.73	0.73

Robust standard errors in parentheses

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

3.7. Additional Evidence

In this section, we conduct validity tests of our proposed ability measure (the *DMA-Score*) to demonstrate that it has a manager-specific element that is valued by the firm. Specifically, we examine the association between division managers' ability scores and reward outcomes in the form of wage increases or internal promotions to CEO.

We expect our ability score to be positively associated with division managers' cash compensation.[68] To test this conjecture, we run regressions of cash compensation (salary and salary plus bonus) on the one-period-lagged *DMA-Score*.[69] Table 3.9 presents the results. The unit of observation is a segment-year. In column (1), the dependent variable is the log of salary. Explanatory variables include the one-period-lagged *DMA-Score*, controls from prior regressions and year fixed effects. As the column shows, the coefficient on the *DMA-Score* is positive (0.225) and statistically different from zero at the 1% level of significance. The effect is also economically significant and becomes even stronger if we include industry fixed effects, represented by three-digit SIC codes (0.268; see Table 3.9, column (2)). In terms of economic significance, a one-standard-deviation increase in the *DMA-Score* is associated with an additional 3.2% (0.268 $\times$ 0.118) increase in salary, holding the other covariates constant. The result also holds, with smaller magnitude, if we extend the specification by including firm fixed effects (column (3): 0.135).[70]

The results from control variables confirm prior findings on the positive relation between remuneration and segment size, firm size and the age of an executive (see, e.g., Hall and Liebman,

[68] We exclude stock-based compensation from the analysis. Stock and option holdings are usually linked to the global performance of the firm rather than the local performance of division managers (see Aggarwal and Samwick, 2003; Wulf, 2007).

[69] We obtain data on executive compensation from the ExecuComp database, because BoardEx mainly covers directors and has very limited coverage on executives at hierarchy levels directly below the boardroom. We are able to collect compensation data for approximately two-thirds of the division managers in our sample (Nobs = 3,375; see Table 3.2).

[70] This decrease is consistent with the notion that better managers are attracted by (or select into) firms that pay more (Fee and Hadlock, 2003).

1998; Gabaix and Landier, 2008; Frydman and Saks, 2010). For robustness, columns (4)-(6) repeat the analysis and present the estimated coefficients after replacing the dependent variable with the log of total cash compensation (salary plus bonus). The regressions yield similar coefficients on the *DMA-Score* and confirm the positive relation between our ability measure and division managers' cash compensation.

As a second validity check, we examine the link between the *DMA-Score* and the likelihood of being promoted internally to CEO.[71] Columns (7)-(9) of Table 3.9 present estimates of a linear probability model, where the dependent variable is one if an executive is getting promoted internally to the CEO position after serving as a division manager.[72] Using information about an individual's employment history drawn from the BoardEx database, we find that 95 (6.6%) of the 1,431 division managers in our sample were selected to become CEOs of their organization. As independent variables, we include our ability measure and the controls from prior regressions. Again, we sequentially augment the specification with year fixed effects, industry fixed effects and firm fixed effects. The coefficient on the main variable of interest, the *DMA-Score*, is always positive and statistically significant. The magnitude of the coefficient ranges between 0.108 and 0.152, suggesting that a one-standard-deviation increase in the *DMA-Score* increases the likelihood of being promoted to the top of the organization by 1.3-1.8 percentage points (or 19-27% in relative terms).

Overall, these findings demonstrate that our proposed ability measure is predictive of reward outcomes in the form of wage increases and internal promotions to CEO. This evidence indicates that the *DMA-Score* has a manager-specific element that is valued by the firm.

[71] Theory predicts that firms assign employees to positions at higher levels in the corporate hierarchy based on their ability (see, e.g., Rosen, 1981; Waldman, 1984; Gibbons and Waldman, 1999, 2006). Empirically, division manager promotions remain relatively underexplored. One exception is Cichello et al. (2009) who find that promotions of division managers are significantly positively related to divisional accounting performance.

[72] We use the linear probability model for ease of interpretation. The results are very similar if we use a logit specification.

Table 3.9: Managerial Ability, Executive Pay, and Promotion Opportunities

This table presents the results from OLS and fixed effects regressions. The sample period ranges from 2000 to 2018. The dependent variable is the log of salary in columns (1)-(3) and the log of salary plus bonus in columns (4)-(6). In columns (7)-(9), the dependent variable is an indicator that equals one if an executive was promoted internally to CEO after serving as a division manager and zero otherwise. *DMA-Score* is the measure of division-manager ability described in Section 3.3.4. Explanatory variables are lagged one year, and continuous variables are winsorized at the extreme 1%. All regressions include year fixed effects. Standard errors (in brackets) are clustered at the firm level. See Appendix 3.A for detailed variable descriptions.

Dep. Var.:	Log(Salary)			Log(Salary + Bonus)			Promotion to CEO		
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
DMA-Score	0.225***	0.268***	0.135***	0.232***	0.307***	0.119*	0.131***	0.152***	0.108**
	(0.065)	(0.056)	(0.043)	(0.082)	(0.074)	(0.061)	(0.045)	(0.048)	(0.052)
Division controls									
Industry q	0.007	−0.010	0.007	−0.007	0.003	0.034	0.009	0.007	0.006
	(0.026)	(0.017)	(0.015)	(0.028)	(0.024)	(0.022)	(0.015)	(0.014)	(0.014)
Segment cash flow	0.146**	0.044	0.035	0.212**	0.125	0.079	0.029	0.059	0.066
	(0.068)	(0.062)	(0.044)	(0.083)	(0.084)	(0.061)	(0.049)	(0.050)	(0.052)
Segment size	0.076***	0.088***	0.072***	0.087***	0.085***	0.065***	0.045***	0.043***	0.047***
	(0.011)	(0.012)	(0.012)	(0.013)	(0.015)	(0.015)	(0.009)	(0.011)	(0.014)
Firm controls									
Firm cash flow	0.009	0.072	0.048	0.129	0.244	0.174	0.020	−0.018	0.023
	(0.186)	(0.136)	(0.115)	(0.220)	(0.180)	(0.161)	(0.093)	(0.095)	(0.092)
Firm size	0.114***	0.113***	0.047***	0.148***	0.158***	0.083**	−0.053***	−0.052***	−0.064***
	(0.016)	(0.015)	(0.025)	(0.020)	(0.011)	(0.035)	(0.012)	(0.013)	(0.021)
Number of segments	0.016	−0.000	−0.005	0.032**	0.011	−0.002	0.007	0.005	−0.008
	(0.012)	(0.011)	(0.012)	(0.014)	(0.013)	(0.016)	(0.007)	(0.007)	(0.009)
Manager controls									
Male	−0.059	0.053*	0.040	−0.071	0.030	0.021	0.019	0.011	0.001
	(0.066)	(0.030)	(0.027)	(0.069)	(0.047)	(0.042)	(0.022)	(0.027)	(0.032)
Age	0.007***	0.005***	0.003**	0.007***	0.005***	0.003*	−0.003**	−0.003***	−0.003**
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Tenure	−0.002	−0.000	0.006***	0.002	0.003	0.008***	−0.002	−0.000	0.000
	(0.005)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
Bachelor	−0.007	0.016	0.011	−0.002	0.023	0.037	0.051***	0.046**	0.042*
	(0.022)	(0.020)	(0.018)	(0.028)	(0.029)	(0.026)	(0.020)	(0.021)	(0.024)
Master	0.018	0.035	0.008	0.035	0.047	0.033	0.024	0.009	0.003
	(0.027)	(0.026)	(0.025)	(0.036)	(0.036)	(0.036)	(0.019)	(0.024)	(0.034)
MBA	0.017	0.029	0.014	0.021	0.025	0.025	0.055***	0.046**	0.045*
	(0.021)	(0.019)	(0.018)	(0.028)	(0.026)	(0.023)	(0.018)	(0.020)	(0.026)
Constant	4.160***	4.153***	4.905***	3.928***	3.903***	4.765***	0.239***	0.307***	0.423***
	(0.141)	(0.109)	(0.197)	(0.176)	(0.163)	(0.275)	(0.081)	(0.081)	(0.185)
Year FE	X	X	X	X	X	X	X	X	X
Industry FE		X	X		X	X		X	X
Firm FE			X			X			X
Nobs	3,375	3,375	3,375	3,375	3,375	3,375	5,101	5,101	5,101
Adjusted R^2	0.59	0.73	0.84	0.56	0.65	0.77	0.04	0.12	0.26

Robust standard errors in parentheses

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

3.8. Conclusion

In this chapter, we show that winner-picking activities in internal capital markets operate predominantly by selecting for human capital productivity. Division managers have first-order effects on corporate investment decisions. Using a novel measure of division-manager ability, we find that better managers receive substantially larger capital allocations. Human capital-based winner-picking is more strongly pronounced in better-governed firms and in the presence of informational asymmetries between headquarters and divisions.

Do conglomerate structures have the potential to add value, or are they on balance inefficient organizational forms created and maintained by a breakdown in corporate governance? This chapter sheds new light on the puzzling evidence found in prior work on this subject. In particular, we show that managerial ability is an important channel through which corporate investment decisions may create value. With heterogeneously skilled division managers within and across firms, investment opportunities cannot be satisfactorily approximated by *industry q*, and the omission of the human capital component may lead to severely biased conclusions about internal capital market efficiency. Overall, these findings provide new evidence on the functioning of internal capital markets and highlight a largely unexplored bright side of diversification.

Chapter 4 – A Look Below the Glass Ceiling: Female Representation in Division Management

4.1. Introduction

Gender imbalances are omnipresent in the upper echelons of corporate America and around the world. Over the past few decades, the debate on diversity and inclusion in organizations has received considerable academic and policy attention. In the broad literature on the career advancement of women in business, a commonly used explanatory metaphor is the "glass ceiling" (Kanter, 1977; Morrison et al., 1987), which describes an invisible barrier that keeps women from rising above a certain level in the executive hierarchy *because they are women*.[73] Strictly speaking, the glass ceiling metaphor implies an intensification of the disadvantages that women face relative to men as they move up the corporate hierarchy that takes the form of a step function (Baxter and Wright, 2000). This view suggests that gender barriers become most severe (and thus most relevant) at the top echelons of organizations. Consequently, most studies in the field focus on studying the inequality of gender participation in boardrooms, but little progress has been made in analyzing women's representation in the obviously largest group of a firm's top management: the group of *division managers*.[74]

The purpose of this chapter is to extend prior literature by providing new insights from the universe of US firms about women's representation in division management in the past two decades. I focus on division managers because it is the most senior top management position below the executive board and, therefore, the talent pool for both the executive board and the board of directors. Moreover, the general movement toward flatter organizations has led to greater authority being

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[73] See Oakley (2000) for a review of the major barriers that retard women's progress in management.

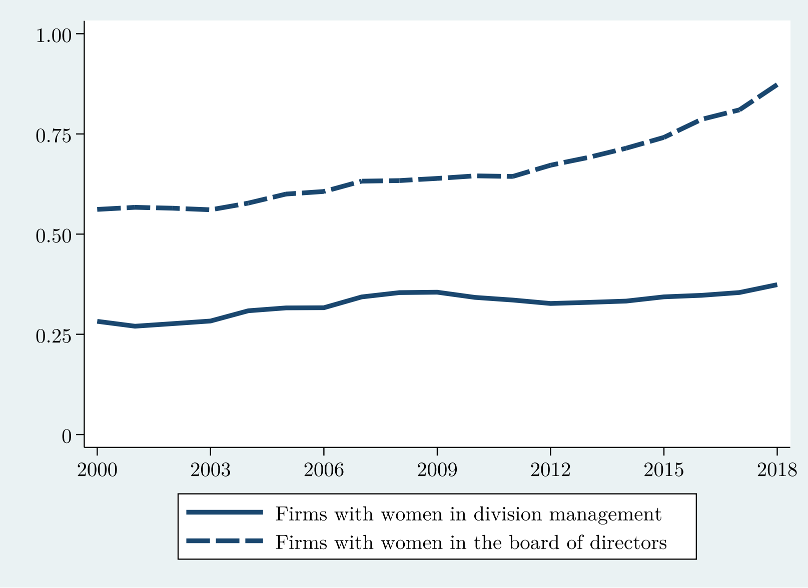
[74] Baxter and Wright (2000) find that barriers to women's advancement may exist at different levels of the organization and produce a cumulative glass ceiling effect as one moves to the top.

allocated to division managers in recent decades, which makes this position an even more important route to the boardroom (see Rajan and Wulf, 2006; Guadalupe and Wulf, 2010).

Using a comprehensive sample of 1,363 publicly traded US firms with available information about division managers in BoardEx, I find that only 2,452 (14%) of the 17,020 division managers who served at these firms in the 2000-2018 period were women. Figure 4.1 provides a striking illustration of the highly noticeable underrepresentation of women in division management.[75] As the figure shows, only approximately one-third of the firms have female division managers in a given year (solid line), and this magnitude has remained largely stagnant over the past decade. In contrast, the fraction of firms with at least one female director on the board has substantially increased over time, from 56% in 2000 to 87% in 2018.

Figure 4.1: Female Representation in Division Management over Time

This figure plots the fraction of firms with (i) one or more female division managers (solid line) and (ii) one or more female directors on the board (dashed line). The sample consists of 1,363 US public firms that operate two or more business segments in the period from 2000 to 2018.



[75] The figure is based on the full sample described in Section 4.1. To address potential concerns about survivorship bias, Appendix 4.C repeats the analysis for a balanced sample of firms. The results are qualitatively similar.

Moreover, and as I will show in my analysis below, a substantial fraction of 40% never have a single woman among their division managers in any year of the firm. Consistent with prior evidence on the slow-changing nature of established corporate cultures (Roland, 2004; Alesina et al., 2013) and, in particular, gender cultures that perpetuate male domination (Adams et al., 2021), this evidence suggests that the nonrepresentation of women in division management is not only a widespread phenomenon but also a persistent one. Firms with constant female participation, in contrast, represent a comparatively small group (approximately 10%). Overall, these stylized facts suggest that women face systematic obstacles in entering division management.

This chapter takes a first step toward understanding and assessing these patterns. I begin the analysis by studying the differential characteristics of firms with and without female representation in division management based on a rich set of covariates. Most interestingly, I find that firms led by female CEOs and firms with female directors on the board are significantly more inclined to appoint female division managers. The analysis also reveals that firms with and without female representation in division management differ across additional firm-specific characteristics. In particular, gender-diverse firms are substantially larger and have stronger governance structures. Taken together, these results are consistent with the notion that gender diversity in division management emerges as part of a well-functioning governance system.

In my analysis, I also examine how female representation in division management varies across industries. I find that female representation is particularly low in energy and mining, manufacturing, and durable consumer goods (e.g., cars, furniture, household appliances) and relatively high in telecom, health, wholesale and retail trade, and nondurable consumer goods (e.g., food, textiles, apparel). These results suggest that female representation in division management is driven to some extent by industry-specific factors. Nevertheless, there is a significant fraction of firms with exclusively male-led divisions in each industry, indicating that underrepresentation of women in division management is a widespread rather than a local phenomenon.

In the formal regression analysis, I investigate the relationship between female representation in division management and firm value, as proxied by Tobin's q. The results indicate that greater gender balance is associated with superior performance. On average, a firm generates 2.6% more firm value with at least one woman among its division managers in a given year than without. For the median firm in the sample, this effect is associated with roughly $72 million in additional firm value (in 2018 dollars). I estimate these magnitudes after controlling for a broad array of firm-level, CEO-level, and board-level characteristics (including female representation in the boardroom) and after accounting for time and industry fixed effects. Moreover, the relation is strongest in firms that persistently have women among their division managers, suggesting that the benefits of gender diversity unfold over time and become larger in more diverse organizations.[76]

The remainder of Chapter 4 is organized as follows. Section 4.2 describes the data and the definitions of important variables. Section 4.3 presents empirical results and characterizes the gender dimension of division management. Section 4.4 analyzes the link between female (non)representation in division management and firm performance. Section 4.5 concludes.

[76] I do not make *causal* claims concerning the effect of female representation in division management on firm performance. In addition, another natural question to ask about this result is: What is the channel through which female representation in division management affects firm value? One possible explanation is that gender diversity broadens the talent pool for executives (Adler and Izraeli, 1994; Adams and Ferreira, 2009), which may improve the human capital productivity of the firm. To analyze this question in detail, however, I would need a database that assigns the division managers of the sample firms directly to the firms' divisions or business segments. Such an ideal database would allow me to exploit publicly available division (more precisely: segment) accounting information in the empirical analysis. A detailed analysis of these questions is left for future research.

4.2. Data and Variables

4.2.1. Sample Selection

To construct the sample, I start with the universe of US public firms with coverage in Compustat North America in the period from 2000 to 2018.[77] From Compustat's Segment file, I retrieve the number of operating segments and additional segment accounting information. For a firm-year observation to be included, the firm must report at least two different business segments.[78] Segments with anomalous accounting data (zero or negative book assets/sales) or missing primary SIC codes (e.g., corporate accounts and allocation adjustments) are removed from consideration. This requirement yields an initial sample of 5,563 firms (42,720 firm-years).

Following the corporate finance literature, I eliminate observations from financial firms (SIC 6000-6999), utilities (SIC 4900-4999), and government agencies (SIC above 8999) because their accounting information can differ from that of other sectors of the economy. Moreover, I exclude firms with total sales of less than $20 million or missing financial data for the relevant variables in the multivariate analysis. The remaining sample consists of 27,820 firm-year observations that meet these criteria.

Finally, I collect information on the division managers who served at these firms during the sample period. From the BoardEx database, I extract detailed information on an individual's professional career as well as biographic information such as age, gender, and educational background. To identify division managers and assign them to firms, I use individual-specific data on the appointment dates and end dates, job titles, and detailed job descriptions of the positions listed in an executive's BoardEx profile. Division managers typically have titles such as *division president*, *executive vice*

[77] The sample period begins with 2000 because data coverage is very limited in BoardEx (the main source of the division manager information) for years prior.

[78] Single-segment firms frequently use functional or geographic structures, where managers are assigned on the basis of functional roles or regional markets.

president or *senior vice president*.[79] Firms with unavailable information on division managers are excluded. Finally, I require each firm to have a minimum of five firm-year observations in which the firm meets all of the above selection criteria.

Table 4.1 provides an overview of the sample construction. The resultant sample consists of 1,363 firms and 14,527 firm-year observations. The sample relates to a total of 17,020 division managers who served at these firms during the sample period. The average number of observations per firm is 10.7 firm-years. To address potential concerns about sample attrition, most results are also reported for an almost balanced sample defined by the presence of firms in 17 or more years during the sample period.[80]

Table 4.1: Sample Selection

This table documents the sample selection procedure and provides the retained number of firms and observations after each selection step. The sample consists of US public firms that operate two or more business segments. The sample period ranges from 2000 to 2018.

	# Firms	# Firm-Years
US public firms with two or more segments	5,563	42,720
Less		
Firms with missing financial information in Compustat	530	5,687
Financial firms, utilities and government agencies	835	6,358
Firms with less than $20 million total sales	534	2,855
Firms with missing information on division managers	1,418	10,237
Firms with less than five observations	883	3,056
Full sample	1,363	14,527

[79] Appendix 4.B provides an overview of the job titles of the division managers in the final sample and gives examples of specific roles associated with these job titles.

[80] The balanced sample consists of 316 firms and 5,334 firm-year observations.

4.2.2. Empirical Strategy and Measures

The empirical analysis consists of two different parts. The first part presents univariate and multivariate results on the differential characteristics of firms with and without female division managers. The second part tests for the existence of a relationship between female representation and firm value.

Measure of Female Representation. Since the majority of firms have almost exclusively male division managers (see Figure 4.1), female representation in division management is measured with indicator variables rather than percentage metrics. The first and most basic measure of female representation, *FR*, is an indicator that takes the value of one if the firm has at least one woman among its division managers in a given year. However, since the lion's share of the overall variation in *FR* (approximately two-thirds) is cross-firm variation, I also use the following time-invariant measures of female (non)representation: *Persistent-FR* is an indicator that equals one if the firm has one or more female division managers in any given year of the sample period, and *Never-FR* is an indicator that takes the value of one if the firm never has a single woman among its division managers during the sample period.

Measure of Firm Value. Following common practice, I use Tobin's q to measure firm performance. Tobin's q is defined as the ratio of the market value of assets (common equity plus the book value of assets minus the book value of common equity and balance sheet deferred taxes) divided by the book value of assets.

Control Variables. In multivariate regressions, I control for a rich set of firm, CEO and board characteristics. Firm characteristics include size (natural log of total book assets), firm age, profitability, capital expenditures, and tangibility. CEO attributes include a CEO's age, gender, tenure in position, and equity-based pay. Board characteristics include board size, board independence (the fraction of outside directors), and a female director dummy. Detailed definitions of these variables appear in Appendix 4.A.

4.3. Descriptive Evidence

4.3.1. Female Representation in Division Management

I start the empirical analysis by presenting descriptive statistics for the sample. Table 4.2 presents univariate comparisons (t-tests) between firms with and without female division managers in a given period. The observational unit is a firm-year. The sample consists of 14,527 firm-year observations, including 4,674 (32%) observations from firms with one or more female division managers. The average firm in the sample reports 3.2 business segments and operates in 2.2 different segment industries.

As Panel A of Table 4.2 reports, firms with and without women in division management differ across firm-specific characteristics. Most notably, firms with female representation (*FR=1*) are substantially larger (i.e., they have more total assets), have higher Tobin's q values and are more profitable than their peers with exclusively male-led divisions. Perhaps surprisingly, FR firms are not younger than their male-dominated peers and hold lower tangible assets, which may indicate that women, on average, select into less capital-intensive industries (an explicit analysis of female representation across industries is provided in Section 4.3.2).

The table also indicates significant disparities across selected CEO and board characteristics (see Panels C and D). Firms with female representation tend to have stronger governance structures, such as larger boards, greater board independence and higher CEO equity pay. In addition, these firms have significantly more women in top leadership positions and in the boardroom.[81] For example, the fraction of firms with a female CEO, while still low, is approximately twice as large (4.6% vs. 2.4%) in the group of firms with female representation in division management.[82] Firms

[81] This result aligns well with prior evidence from Adams and Ferreira (2009) who find that gender-diverse boards allocate more effort to monitoring.

[82] The full sample contains 452 observations (3.1%) from firms with female CEOs. Firms with persistent female representation in division management have the largest fraction of female CEOs (7.8%). The smallest fraction is observed for firms that never have female division managers (1.6%).

with female representation in division management also have higher fractions of female directors (15.5% vs. 9.5%).

Finally, Panel D of Table 4.2 shows summary statistics for the division managers who served in the sample firms between 2000 and 2018. On average, division managers are 52.1 years old and have a tenure of 6.6 years. More than half of the managers have a graduate degree (master's degree, doctorate, or law degree), 32% hold an MBA, and 9.7% received their degree from an *Ivy League* university.

The average (median) firm in the sample has 4.7 (3.0) division managers. As the Panel shows, firms with female representation in division management are not only larger in terms of total assets but also have larger division manager teams. The average (median) FR firm has 8.0 (6.0) division managers, while the average (median) firm without women representation has 3.1 (3.0) division managers. Therefore, it is important that I control for size differences in the multivariate regression analysis to account for the possibility that larger division manager teams are more likely to have women.

In the full sample, women make up an average of approximately 11% of a firm's division manager team. Notably, a substantial fraction of 40% of the firms in the full sample never have a single woman among their division managers during the sample period (i.e., *Never-FR*=1). This evidence suggests that the nonrepresentation of women in division management is not only a widespread but also a persistent phenomenon. In the subsample of FR firms, women make up an average of approximately one-third of a firm's division manager team. However, only a small fraction of the firms in this group (29%; approximately 10% of the full sample) have women among their division managers on a permanent basis (*Persistent-FR=1*). Overall, these results suggest that women face systematic obstacles in entering division management.

Table 4.2: Descriptive Statistics

This table reports descriptive statistics for the sample of firms with and without female representation in division management. The sample period ranges from 2000 to 2018. *FR* is an indicator equal to one if the firm has one or more female division managers in a given year and zero otherwise. All continuous variables are winsorized at the extreme 1%. Detailed variable definitions appear in Appendix 4.A.

	Total		(a) FR = 1		(b) FR = 0		(a)-(b)
Variable	Mean	Median	Mean	Median	Mean	Median	Mean
A. Firms							
# Business segments	3.245	3.000	3.488	3.000	3.130	3.000	0.358***
# Industries	2.183	2.000	2.320	2.000	2.119	2.000	0.201***
Log(Size)	7.292	7.267	8.118	8.170	6.899	6.917	1.219***
Tobin's q	1.557	1.398	1.647	1.482	1.514	1.358	0.133***
Excess value	−0.043	−0.053	0.007	−0.027	−0.067	−0.066	0.074***
Profitability	0.126	0.124	0.137	0.131	0.121	0.120	0.016***
Log(Age)	3.151	3.219	3.266	3.332	3.097	3.135	0.169***
Capex intensity	0.044	0.032	0.041	0.031	0.045	0.032	−0.004***
Tangibility	0.246	0.183	0.223	0.166	0.256	0.191	−0.033***
B. CEOs							
Female CEO	0.031	0.000	0.046	0.000	0.024	0.000	0.022***
Age, years	57.93	58.00	57.99	58.00	57.90	58.00	0.089
CEO tenure	8.950	7.000	8.421	7.000	9.201	8.000	−0.780***
CEO equity pay	0.337	0.370	0.419	0.496	0.299	0.271	0.120***
C. Directors							
Board size	8.738	9.000	9.598	9.000	8.330	8.000	1.268***
Board independence	0.676	0.833	0.728	0.857	0.651	0.833	0.077***
# Female directors	1.076	1.000	1.543	1.000	0.854	1.000	0.689***
Fraction female directors	0.115	0.111	0.155	0.143	0.095	0.100	0.060***
D. Division Managers							
# Division managers	4.657	3.000	8.032	6.000	3.057	3.000	4.975***
Fraction female managers	0.107	0.000	0.333	0.250	0.000	0.000	0.333***
Persistent-FR	0.095	0.000	0.294	0.000	0.000	0.000	0.294***
Never-FR	0.402	0.000	0.000	0.000	0.593	1.000	−0.593***
Age, years	52.057	52.167	51.281	51.500	52.437	52.667	−1.156***
Tenure (position)	6.564	5.750	6.039	5.571	6.813	6.000	−0.774***
Graduate degree	0.592	0.625	0.594	0.625	0.590	0.667	0.004
MBA	0.317	0.250	0.317	0.316	0.317	0.200	0.000
Ivy League	0.097	0.000	0.121	0.056	0.086	0.000	0.035***
Nobs	14,527	14,527	4,674	4,674	9,853	9,853	14,527

4.3.2. Female Representation and Industries

Before I proceed with the formal regression analysis, I examine how female representation in division management varies across industries. Column (1) of Table 4.3 reports the distribution of firms with at least one female division manager in a given year across major industries (based on the Fama-French 12-industry classification scheme).[83] On average, firms with female representation (*FR=1*) make up roughly one-third of all firm-years. However, there is indeed considerable variation in the fraction of these firms across industries: from 15% in the energy and mining sector to 53% in the telecom sector. Female representation is also particularly low in manufacturing and in durable consumer goods (e.g., cars, furniture, household appliances) and relatively high in the health sector, in wholesale and retail trade, and in nondurable consumer goods (e.g., food, textiles, apparel).

A very similar pattern emerges for the smaller subset of firms with persistent female representation in division management (*Persistent-FR=1*): these firms make up 9.5% of the entire sample, but their fraction varies from 1.2% in energy and mining and 1.6% in manufacturing to 19.6% in nondurable consumer goods and 32% in the telecom sector (see Table 4.3, column (2)). Firms that never have women among their division managers (*Never-FR=1*) make up 40.2% of the entire sample (Table 4.3, column (3)). These firms are most strongly represented in energy and mining, durable consumer goods and the manufacturing sector. Overall, these findings add to recent evidence from other studies on women's representation across industries. For example, Duchin et al. (2021) find in a smaller sample of 375 S&P 1500 firms during the 2000-2008 period that women are significantly more (less) likely to run divisions in healthcare products and nondurable consumer goods (energy and heavy manufacturing). Hebert (2020) documents that startups and small private firms with the largest (smallest) fraction of women in leadership roles are located in the healthcare (energy and mining) sector.

[83] I focus on the firm's major industry because there is no direct correspondence between division managers and segment industries in the data.

In summary, these results indicate that female representation in division management appears to be driven at least to some extent by industry-specific factors. However, the table also shows that there are significant fractions of firms with exclusively male-led divisions in all industries, which indicates that underrepresentation of women in division management is a widespread rather than a local phenomenon. Nevertheless, in the formal regression analysis, I account for cross-industry variation in female representation among division managers by adding industry dummies for a firm's major industry.

Table 4.3: Cross-Industry Variation in Female Representation

This table reports the distribution of firms with and without female representation in division management by industry groups (based on the Fama-French 12-industry classification scheme). The sample period ranges from 2000 to 2018. *FR* reports the fraction of firms with one or more female division managers in a given year. *Persistent-FR* reports the fraction of firms with one or more female division managers in any given year of the sample period. *Never-FR* reports the fraction of firms that never have women among their division managers during the sample period.

	FR (1)	Persistent-FR (2)	Never-FR (3)	Nobs (4)
All firms	32.2	9.5	40.2	14,527
FF12-Industry				
Telecom	53.4	32.0	24.8	622
Consumer Non-Durables	45.0	19.6	27.2	1,237
Healthcare	40.9	15.7	32.3	1,032
Shops	36.0	15.5	36.7	1,548
Chemicals	35.6	6.7	27.7	668
Technology	33.8	9.3	41.0	2,625
Other	32.1	6.0	37.3	2,856
Manufacturing	21.5	1.6	51.6	2,679
Consumer Durables	15.1	3.7	63.8	520
Energy and Mining	15.0	1.2	55.5	740

4.3.2. Multivariate Regression

To further explore the properties of firms with and without female division managers, Table 4.4 presents the estimates from linear probability regressions of female representation (i.e., the binary measures introduced in Section 4.2.2).[84] Independent variables include the firm-level, CEO-level, and board-level characteristics from the univariate analysis. All regressions include year fixed effects to account for temporal variation in the overall female representation. The even- and odd-numbered columns report regression estimates from specifications with and without industry fixed effects (based on the FF48 industry classification scheme), respectively. Standard errors are clustered by firm to address potential within-firm serial correlation of the error term.

In column (1) of Table 4.4, the dependent variable, *FR*, takes the value of one if a firm has at least one female division manager among its executives in a given year. Most notably, I find that firms with female representation in division management are more likely to have a female CEO and female directors on the board. The coefficients on these variables are also economically significant. Having a female CEO (female directors on the board) is associated with an increase in the propensity to have female representation in division management (i.e., *FR*=1) by 14.9% (8.9%). The coefficients on the other variables indicate that FR firms are significantly larger and have fewer tangible assets.[85] In column (2), I augment the specification with industry fixed effects. The results are economically similar. One exception is tangibility: the coefficient on tangibility is fully absorbed by industry fixed effects, which is consistent with the notion that women are less likely to select into highly tangible industries such as manufacturing, energy and mining or durable consumer goods. In columns (3) and (4), I repeat the analysis for the alternative measure *Persistent-FR*, which equals one for all firms with at least one female division manager in any available sample period; the results are similar. For robustness, I also estimate the regression for the opposite type of firm, which permanently has only

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[84] I report the estimates from linear probability models for ease of interpretation. Logit regressions, shown in Appendix 4.D, produce qualitatively similar results.

[85] I obtain very similar results when I use the number of division managers employed by the firm to control for size.

male division managers (see Table 4.4, columns (5)-(6)). The previous results continue to hold with reversed signs, statistical significance and similar magnitudes. Moreover, the results suggest that firms with permanent nonrepresentation of women have less effective governance structures, as indicated by the negative coefficients on CEO equity pay and board independence, but the significance of this result varies across specifications.

Table 4.4: Determinants of Female Representation in Division Management

This table reports the results of linear probability regressions of female representation in division management. The sample period ranges from 2000 to 2018. *FR* is an indicator equal to one if the firm has one or more female division managers in a given year; *Persistent-FR* is an indicator equal to one if a firm has one or more female division managers in any given year of the sample period; *Never-FR* is an indicator equal to one if the firm never has women among its division managers during the sample period. Standard errors (in brackets) are clustered at the firm level. Significance levels are indicated as follows: * = 10%, ** = 5%, *** = 1%. Detailed variable definitions appear in Appendix 4.A.

Dep. Var.:	FR		Persistent-FR		Never-FR	
Model	(1)	(2)	(3)	(4)	(5)	(6)
Log(Size)	0.073***	0.084***	0.038***	0.042***	−0.083***	−0.096***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Log(Age)	−0.013	0.026**	−0.012	0.008	0.020	−0.026
	(0.013)	(0.012)	(0.011)	(0.011)	(0.018)	(0.018)
Profitability	0.098	−0.026	0.036	−0.018	−0.083	0.067
	(0.087)	(0.081)	(0.073)	(0.072)	(0.112)	(0.104)
Capex intensity	0.273*	0.113	0.157	−0.027	−0.014	0.035
	(0.165)	(0.154)	(0.116)	(0.116)	(0.225)	(0.203)
Tangibility	−0.282***	−0.072	−0.137***	0.008	0.245***	0.124
	(0.056)	(0.058)	(0.042)	(0.046)	(0.079)	(0.087)
Female CEO	0.149***	0.087*	0.156***	0.116**	−0.190***	−0.126***
	(0.049)	(0.049)	(0.049)	(0.046)	(0.049)	(0.044)
CEO tenure	0.000	0.001	0.002*	0.002*	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
CEO equity pay	0.311	−0.047	0.115	−0.041	−0.700**	−0.238
	(0.202)	(0.191)	(0.188)	(0.182)	(0.273)	(0.261)
Board independence	0.024	0.035	−0.032	−0.022	−0.050	−0.063*
	(0.026)	(0.024)	(0.022)	(0.021)	(0.035)	(0.033)
Female director dummy	0.089***	0.059***	0.048***	0.033***	−0.098***	−0.064***
	(0.009)	(0.008)	(0.009)	(0.008)	(0.011)	(0.011)
Year FE	X	X	X	X	X	X
Industry FE		X		X		X
Nobs	14,527	14,527	14,527	14,527	14,527	14,527
Adjusted R^2	0.16	0.24	0.11	0.19	0.19	0.30

4.4. Female Representation and Firm Value

This section explores the association between female representation in division management and firm value. Following standard practice in the literature, I use the log transformed Tobin's q of the firm as the main dependent variable to reduce skewness and to ease interpretation of the results.[86] The main variable of interest is the indicator of female representation in division management. The model further includes a broad array of controls to account for the possibility of (observable) factors that may affect firm value and that are unbalanced across firms with and without gender-diverse division manager teams. Finally, I account for women's and men's selection into industries (industry fixed effects) and time-series variation in female representation (year fixed effects).[87] Standard errors are clustered by firm to address potential within-firm serial correlation of the error term.

Table 4.5 (column (2)) presents the results obtained from the estimation of the full regression model. The coefficient of interest is that on the *FR* indicator, which equals one if a firm has at least one female division manager in a given year. The results show a strong positive relation between female representation in division management and firm value. The estimated coefficient on female representation equals 0.026 and is significantly different from zero at the 5% level of significance, which means that Tobin's q is approximately 2.6% higher with female representation in division management than without. At the midpoint of the data (the median-sized FR firm), this result implies that, ceteris paribus, female representation is associated with an increase of $72 million in firm value (in 2018 dollars).[88] The evidence from the control variables yields the expected signs. More profitable firms, firms with a higher level of CEO equity pay, and firms that invest more are associated with higher valuations, while older and more tangible firms have lower Tobin's q values.

[86] The semi-log formulation yields coefficients on independent variables that approximate percentage changes in firm performance.

[87] I do not include firm fixed effects because the lion's share of the variation in female representation (around two-thirds) is cross-firm variation and more than half of the firms have no within-firm variation at all.

[88] The median-sized FR firm has book assets of $1.87 billion (in 2018 dollars) and a Tobin's q of 1.48. Thus, female representation leads to an increase in firm value of approximately $72 million (= 0.026 × 1.48 × $1.87 billion).

In line with prior work on the value-relevant impact of gender inclusion in corporations, the analysis presented thus far suggests that women's integration in division management has a positive effect on firm value, even after controlling for various measures of governance.[89] Accordingly, one might expect that the effect is particularly strong in firms that have women among their division managers on a permanent basis. Conversely, the discount associated with the nonrepresentation of women is likely to be amplified for firms whose divisions were run exclusively by men throughout the sample period. To examine this conjecture, I augment the specification in column (2) with indicators for persistent (non)representation of women in division management (Table 4.5, column (3)). In fact, the coefficient on *Persistent-FR* increases in magnitude (0.060, +131%) and statistical significance, reinforcing the hypothesis that benefits associated with gender diversity become largest in firms with permanent female participation. The coefficient on *Never-FR* is negative, statistically significant and economically large (-0.036), suggesting that permanent nonrepresentation of women in division management is associated with pronounced performance losses.

A potential concern with regressions on the full sample is that changes over time in the composition of firms could affect the results.[90] To address this uncertainty, I repeat the analysis for the balanced sample in Panel B of Table 4.5. The results corroborate the strong positive association between female representation and firm value, with an even larger magnitude (3.7%; see Table 4.5, column (5)). Finally, there is evidence of a similar pattern of pronounced increases (declines) in performance for firms with persistent (non)representation of women in division management (see Table 4.5, column (6)).[91]

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[89] Contributions to this literature include Adler (2001), Carter et al. (2003), Adams and Ferreira (2009), Dezsö and Ross (2012), Adams and Funk (2012), Lückerath-Rovers (2013), Griffin et al. (2021).

[90] To be included in the full sample, a firm must have a minimum of five firm-year observations in which the firm meets all the selection criteria mentioned in Section 4.2.1.

[91] For robustness, Appendix 4.E repeats the analysis in Table 4.5 using excess value (the natural log of the ratio of a firm's actual value to the sum of the imputed values of its segments using the industry multiplier approach described in Berger and Ofek, 1995) as the dependent variable. This alternative approach takes into account cross-sectional variation in segment values across industries. All results are qualitatively similar to those in Table 4.5.

Table 4.5: Female Representation and Firm Value

This table reports the results of firm-level regressions on the relation between female representation in division management and firm value. The sample period ranges from 2000 to 2018. The dependent variable is the log transformed Tobin's q of the firm. *FR* is an indicator equal to one if the firm has one or more female division managers in a given year; *Persistent-FR* is an indicator equal to one if a firm has one or more female division managers in any given year of the sample period; *Never-FR* is an indicator equal to one if the firm never has women among its division managers during the sample period. The regressions are estimated separately for the full sample in columns (1)-(3) and for a balanced sample in columns (4)-(6). Standard errors (in brackets) are clustered at the firm level. Significance levels are indicated as follows: * = 10%, ** = 5%, *** = 1%. Detailed variable definitions appear in Appendix 4.A.

	A. Full Sample			B. Balanced Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
FR	0.063***	0.026**	−0.001	0.090***	0.037**	0.006
	(0.014)	(0.011)	(0.011)	(0.023)	(0.015)	(0.014)
Persistent-FR			0.060***			0.057**
			(0.022)			(0.027)
Never-FR			−0.036**			−0.079***
			(0.014)			(0.022)
Log(Size)		−0.009	−0.011**		0.016**	0.010
		(0.005)	(0.005)		(0.008)	(0.008)
Profitability		2.074***	2.076***		2.953***	2.960***
		(0.098)	(0.097)		(0.188)	(0.185)
Log(Age)		−0.038***	−0.038***		−0.066***	−0.066***
		(0.009)	(0.009)		(0.017)	(0.017)
Capex intensity		0.783***	0.791***		0.236	0.272
		(0.134)	(0.134)		(0.279)	(0.269)
Tangibility		−0.447***	−0.448***		−0.494***	−0.490***
		(0.047)	(0.046)		(0.110)	(0.105)
Female CEO		0.008	0.000		−0.059*	−0.059*
		(0.034)	(0.034)		(0.034)	(0.032)
CEO age		−0.004***	−0.004***		−0.002**	−0.002**
		(0.001)	(0.001)		(0.001)	(0.001)
CEO tenure		0.002**	0.002**		0.001	0.001
		(0.001)	(0.001)		(0.001)	(0.001)
CEO equity pay		0.115***	0.113***		0.092***	0.089***
		(0.018)	(0.018)		(0.027)	(0.026)
Board size		0.002	0.001		0.001	0.002
		(0.003)	(0.003)		(0.003)	(0.003)
Board independence		0.005	0.005		0.025	0.014
		(0.018)	(0.018)		(0.026)	(0.026)
Female director dummy		0.031**	0.029**		0.038*	0.029
		(0.012)	(0.012)		(0.020)	(0.020)
Year FE	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Nobs	14,527	14,527	14,527	5,334	5,334	5,334
Adjusted R^2	0.15	0.42	0.42	0.23	0.59	0.60

4.5. Conclusion

The glass ceiling metaphor is a central theme in the literature explaining the dearth of women in top leadership roles. However, little empirical evidence is available concerning the gender barriers (glass ceiling effects) that constrain women's representation in the obviously largest group of a firm's top management, namely, within the group of *division managers*. Chapter 4 takes a step toward addressing this deficiency by documenting the widespread and persistent underrepresentation of women in division management during the past two decades in the United States. Women's near total exclusion from positions with direct responsibility for operational units (assets) reflects the reality in a majority of firms, while there is only a small group of firms with permanent representation of women in division management. The main implication that emerges from this analysis is that glass ceiling effects appear to be prevalent and also persistent at the hierarchy level directly below the boardroom.

As a first step toward understanding these patterns, Chapter 4 explores the differential characteristics of firms with and without female representation in division management. Most notably, firms led by female CEOs and firms with female directors on the board are significantly more inclined to appoint female division managers. Another takeaway is that gender-diverse firms are substantially larger, hold lower tangible assets and appear to have stronger governance structures than firms with exclusively male-led divisions.

Finally, the chapter shows that gender diversity in division management appears to have meaningful economic links with firm value. More research that further explores the economic mechanisms that drive this relationship will be helpful for our understanding of whether and how gender diversity in division management affects firm outcomes.

Chapter 5 – Concluding Remarks

In corporate finance, one of the most fundamental questions about corporate diversification is whether and how this form of organization (and the associated creation of an internal capital market) affects financial outcomes. The empirical literature is mixed on this question and provides inconclusive results. While theory offers competing hypotheses regarding the specific costs and benefits inherent to the conglomerate form of organization, empirical evaluation of these arguments has proven remarkably difficult. Tantalizing evidence from prior studies related to the existence of a "diversification discount" has been criticized as being indirect and tainted by endogeneity bias. A major obstacle to progress in this line of research is the correct identification of causal effect signs and magnitudes related to diversification. This dissertation contributes to the existing literature by providing new evidence on the financial impact inherent to the conglomerate form of organization and the associated creation of internal capital markets.

Chapter 2 sheds new light on the funding benefits of corporate diversification, one of the basic financing-related synergies associated with this sort of integration. Specifically, the chapter systematically examines the relationship between corporate diversification and external financing, in particular capital structure. The results suggest economically large and persistent financing advantages of diversified firms relative to comparable standalone firms. As a central contribution, the chapter identifies causal effects in a novel shock-based research design using the introduction of new segment reporting standards as a quasi-natural experiment. The evidence obtained from these tests strongly supports the hypothesis that coinsurance across imperfectly correlated businesses facilitates access to external financing and allows diversified firms to carry higher financial leverage. These findings underscore the importance of organizational structure for financial policy and may help to deepen our understanding of how firm boundaries are set.

Chapter 3 is concerned with the second financing-related way that value can be created by bringing together multiple businesses under one corporate umbrella: efficient internal capital allocation. One of the distinctive features of multisegment firms is the existence of an internal capital market that provides headquarters with the authority to reallocate investment funds across operating units. In this context, Chapter 3 fills an important gap in the literature by illuminating the largely unexplored role of managerial human capital in capital budgeting. This analysis reveals a striking new perspective on internal capital market efficiency by showing that budgeting decisions strongly reflect what theorists have called “winner-picking”: superior managers receive substantially larger capital allocations than their less able peers. This evidence reconciles the apparent contradiction that conglomerate investment patterns usually deviate from the predictions of the neoclassical model. In fact, managerial ability is an important channel through which internal capital markets may create value, and its omission may lead to severely biased conclusions about the efficiency of investment. Altogether, these findings contribute to our understanding of the functioning of internal capital markets and highlight a largely unexplored bright side of diversification.

While the focus of this dissertation is on examining the potential benefits associated with the conglomerate form of organization, Chapter 4 touches upon the ongoing debate on diversity and gender inclusion in organizations. Most notably, the chapter provides a striking illustration of the highly noticeable underrepresentation of women in division management. The vast majority of firms do not have a single woman among their division managers, suggesting that women face systematic obstacles in entering division management. The main implication that emerges from this analysis is that glass ceiling effects appear to be prevalent and also persistent at the hierarchy level directly below the boardroom.

Chapter 4 takes a first (exploratory) step toward analyzing these patterns by studying the differential characteristics of firms with and without female representation in division management. Moreover, the chapter shows that women’s representation appears to have meaningful economic links with firm value. Overall, the findings of Chapter 4 offer a point of departure toward developing a better understanding of women’s integration in division management and its impact on firm outcomes.

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Appendices

Appendix 2.A. Variable Definitions

Variable	Definition
Diversified	Indicator variable that equals one if a firm reports multiple segments in at least two different four-digit SIC code industries (sics1) and zero otherwise.
Firm size	The natural logarithm of the book value of assets (at).
Profitability	Operating income before depreciation (oibdp) scaled by the book value of assets (at).
Tangibility	Property, plant and equipment (ppent) scaled by the book value of assets (at).
Market-to-book	Total debt (dlc + dltt) + market value of common equity (prcc_f × csho) – preferred stock (pstkl) scaled by the book value of assets (at).
R&D	Research and development expenditures (xrd) scaled by total firm sales (sale).
Dividend payer	Indicator that equals one if a firm pays dividends (dvc>0) and zero otherwise.
Cash flow volatility	Rolling standard deviation of cash flow (oibdp/at) over a window of 10 years with a minimum requirement of 5 years of nonmissing data.
Total book leverage	Total debt (dlc + dltt) scaled by the book value of assets (at).
Net book leverage	Total debt (dlc + dltt) – cash and short-term investments (che) scaled by the book value of assets (at).
Long-term book leverage	Long-term debt (dltt) scaled by the book value of assets (at).
Total market leverage	Total debt (dlc + dltt) scaled by the market value of assets (dlc + dltt + prcc_f × csho + pstkl).
Net market leverage	Total debt minus cash and short-term investments (dlc + dltt – che) scaled by the net market value of assets (dlc + dltt – che + prcc_f × csho + pstkl).
Long-term market leverage	Long-term debt (dltt) scaled by the market value of assets (dlc + dltt + prcc_f × csho + pstkl).
Imputed leverage	Asset-weighted median leverage of standalone firms operating in the same industry and year. The industry matching is based on the narrowest SIC grouping (beginning with four-digit SIC codes) that includes at least 10 standalone firms per industry and year.

Transfer	Indicator that equals one if at least one underperforming segment received cross-segment transfers in the final fiscal year before the adoption of SFAS 131. A segment is classified as an "underperforming segment" if the segment's ROS (ops/sales) is less than the sales-weighted average ROS of the remaining segments. Segments are classified as receiving cross-segment transfers if their excess capital expenditures exceed the excess capital expenditures of their firm. Segment (firm) excess capital expenditures are measured as follows: 1) Segment excess capex = *max*{capxs – (ops + dps), 0} 2) Firm excess capex = *max*{capx – (ebit + dp), 0}
Industry cash flow volatility	The segments' sales-weighted cash flow volatility assuming a pairwise correlation of one between all industries. Segments' cash flow volatility is measured as the volatility of the median standalone firm operating in the narrowest SIC code grouping (beginning with four-digit SIC codes) over the past 10 years with at least 5 years of nonmissing data.
Cash flow coinsurance	The difference between industry cash flow volatility and the industry cash flow volatility obtained after accounting for the cross-industry cash flow correlations.
Industry competitiveness	One minus the asset-weighted Herfindahl index of industry sales in which the firm's segments operate in year *t*. Industry sales are calculated at the two-digit SIC code level.
Speed of profit adjustment	The asset-weighted average of the estimated speed of profit adjustment of the two-digit SIC code industries in which the firm's segments operate. Industry-specific speed of profit adjustment is calculated by estimating the following equation for all standalone firms operating in industry *j* and year *t*: $\overline{ROA}_{ijt} = \beta_{0j} + \beta_{1j}(D_p \times \overline{ROA}_{ijt-1}) + \beta_{2j}(D_n \times \overline{ROA}_{ijt-1}) + \varepsilon_{ijt}$, where $\overline{ROA}_{ijt}$ is the difference between firm *i*'s ROA (ebit/at) and the median ROA of its industry *j* in period *t*. D_p (D_n) is an indicator variable that equals one if ROA_{ijt-1} is positive (not positive) and zero otherwise. The coefficient β_{1j} is the estimated speed of profit adjustment in industry *j*.

Appendix 2.B. Evolution of Leverage over Time

This figure presents the evolution of book and market measures of leverage (y-axis) of diversified firms (solid lines) and standalone firms (dashed lines). The sample period ranges from 1981 to 2015. *Diversified firms* operate segments in at least two different four-digit SIC code industries. *Total book (market) leverage* is total debt scaled by book (market) value of assets. *Net book (market) leverage* is total debt minus cash and short-term investments scaled by book (market) value of assets. *Long-term book (market) leverage* is long-term debt scaled by the book (market) value of assets.

Appendix 2.C. Evolution of Industry-adjusted Leverage over Time

This figure presents the evolution of industry-adjusted book and market measures of leverage (y-axis) of diversified firms (solid lines) and standalone firms (dashed lines). The sample period ranges from 1981 to 2015. *Diversified firms* operate segments in at least two different four-digit SIC code industries. Industry-adjusted leverage is the difference between a firm's actual leverage and its imputed leverage (the asset-weighted median leverage of standalone firms operating in the same industry). Industry matching is based on the narrowest SIC grouping (beginning with four-digit SIC codes) that includes at least 10 standalone firms per industry and year. *Total book (market) leverage* is total debt scaled by book (market) value of assets. *Net book (market) leverage* is total debt minus cash and short-term investments scaled by book (market) value of assets. *Long-term book (market) leverage* is long-term debt scaled by the book (market) value of assets.

Appendix 2.D. Alternative Measures of Leverage: Baseline Regression

This table presents the results of regressing industry-adjusted book and market measures of leverage (Panel A) on a firm's organizational status, *Diversified*, and a vector of additional controls. Industry-adjusted leverage is the difference between a firm's total book leverage and its imputed total book leverage (the asset-weighted median leverage of standalone firms operating in the same industry and year). In Panel B, the dependent variable is the firm's actual leverage ratio, and imputed leverage is included as an additional control. *Total book (market) leverage* is total debt scaled by the book (market) value of assets. *Net book (market) leverage* is total debt minus cash and short-term investments scaled by book (market) value of assets. *Long-term book (market) leverage* is long-term debt scaled by book (market) value of assets. *Diversified* is a dummy that equals one if the firm operates segments in at least two different four-digit SIC code industries and zero otherwise. The sample period ranges from 1981 to 2015. All regressions include year fixed effects. Standard errors (in brackets) are heteroscedasticity consistent and clustered at the firm level. Detailed variable descriptions are provided in Appendix 2.A.

Panel A. Regressions of Industry-Adjusted Book and Market Leverage

	Industry-Adjusted Total Book Leverage		Industry-Adjusted Net Book Leverage		Industry-Adjusted Long-Term Book Leverage		Industry-Adjusted Total Market Leverage		Industry-Adjusted Net Market Leverage		Industry-Adjusted Long-Term Market Leverage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Diversified	0.037***	0.038***	0.051***	0.048***	0.047***	0.032***	0.055***	0.047***	0.062***	0.053***	0.062***	0.040***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Firm size		0.013***		0.009***		0.019***		0.010***		0.008***		0.017***
		(0.001)		(0.000)		(0.000)		(0.001)		(0.001)		(0.000)
Profitability		−0.142***		−0.107***		−0.050***		−0.169***		−0.137***		−0.075***
		(0.007)		(0.007)		(0.006)		(0.007)		(0.006)		(0.005)
Tangibility		0.039***		0.053***		0.030***		0.034***		0.053***		0.042***
		(0.007)		(0.007)		(0.007)		(0.007)		(0.007)		(0.006)
Market-to-book		−0.008***		−0.011***		−0.006***		−0.040***		−0.034***		−0.029***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
R&D		−0.024***		−0.043***		0.002		−0.033***		−0.046***		−0.009***
		(0.003)		(0.002)		(0.003)		(0.002)		(0.002)		(0.002)
Dividend payer		−0.064***		−0.056***		−0.047***		−0.078***		−0.070***		−0.056***
		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)		(0.003)
Constant	0.012***	0.013***	0.024***	0.031***	0.018***	−0.025***	0.035***	0.100***	0.045***	0.095***	0.038***	0.034***
	(0.003)	(0.005)	(0.003)	(0.005)	(0.002)	(0.004)	(0.004)	(0.006)	(0.004)	(0.006)	(0.003)	(0.004)
Year FE	X	X	X	X	X	X	X	X	X	X	X	X
Nobs	93,892	93,892	93,892	93,892	93,892	93,892	93,892	93,892	93,892	93,892	93,892	93,892
Adjusted R^2	0.02	0.06	0.01	0.06	0.02	0.07	0.02	0.15	0.02	0.12	0.03	0.13

Panel B. Regressions of Book and Market Leverage												
	Total Book Leverage		Net Book Leverage		Long-Term Book Leverage		Total Market Leverage		Net Market Leverage		Long-Term Market Leverage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Diversified	0.046***	0.037***	0.058***	0.045***	0.052***	0.028***	0.063***	0.045***	0.068***	0.051***	0.066***	0.036***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Imputed lev.	0.639***	0.452***	0.632***	0.423***	0.660***	0.404***	0.711***	0.464***	0.701***	0.474***	0.743***	0.439***
	(0.012)	(0.014)	(0.012)	(0.013)	(0.013)	(0.015)	(0.012)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Firm size		0.015***		0.012***		0.023***		0.013***		0.011***		0.021***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
Profitability		−0.154***		−0.121***		−0.063***		−0.184***		−0.152***		−0.090***
		(0.007)		(0.006)		(0.005)		(0.006)		(0.006)		(0.005)
Tangibility		0.150***		0.166***		0.153***		0.130***		0.143***		0.142***
		(0.007)		(0.007)		(0.007)		(0.007)		(0.007)		(0.007)
Market-to-book		−0.013***		−0.016***		−0.010***		−0.048***		−0.040***		−0.034***
		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)		(0.000)
R&D		−0.049***		−0.069***		−0.016***		−0.059***		−0.067***		−0.026***
		(0.003)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)
Dividend payer		−0.062***		−0.055***		−0.048***		−0.075***		−0.068***		−0.055***
		(0.003)		(0.003)		(0.002)		(0.003)		(0.003)		(0.002)
Constant	0.087***	0.090***	0.078***	0.077***	0.066***	0.013***	0.108***	0.203***	0.102***	0.164***	0.081***	0.092***
	(0.004)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)	(0.004)	(0.004)
Year FE	X	X	X	X	X	X	X	X	X	X	X	X
Nobs	93,892	93,892	93,892	93,892	93,892	93,892	93,892	93,892	93,892	93,892	93,892	93,892
Adjusted R^2	0.17	0.25	0.18	0.26	0.17	0.26	0.22	0.36	0.19	0.32	0.20	0.34

Robust standard errors in parentheses

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

Appendix 2.E. Alternative Measures of Leverage: Difference-in-Differences Regression

This table presents the results from estimating the following difference-in-differences (DiD) specification:

$$IAL_{i,t} = \alpha + \delta_{DiD} \times \textit{Change-firm}_i \times \textit{Post-SFAS}_{i,t} + \delta_{change} \times \textit{Change-firm}_i$$
$$+ \delta_{post\text{-}SFAS} \times \textit{Post-SFAS}_{i,t} + \eta_t + \epsilon_{i,t}$$

, where $IAL_{i,t}$ is industry-adjusted leverage (Panel A), i.e., the difference between a firm's actual leverage and its imputed leverage. In Panel B, the dependent variable is the firm's actual leverage ratio, and imputed leverage is included as an additional control. *Total book (market) leverage* is total debt scaled by book (market) value of assets. *Net book (market) leverage* is total debt minus cash and short-term investments scaled by book (market) value of assets. *Long-term book (market) leverage* is long-term debt scaled by the book (market) value of assets. $\textit{Change-firm}_i$ is an indicator that equals one if the disclosed organizational status of firm *i* changes from *standalone* to *diversified* after adoption of SFAS 131 (treated firms) and zero otherwise (control firms). $\textit{Post-SFAS}_{i,t}$ is an indicator for the post-treatment period of firm *i.* The sample period ranges from 1994 to 2002. All regressions include year fixed effects. Standard errors (in brackets) are heteroscedasticity consistent and clustered at the firm level. Detailed variable descriptions are provided in Appendix 2.A.

Panel A. Regressions of Industry-Adjusted Book and Market Leverage

	Industry-Adjusted Total Book Leverage		Industry-Adjusted Net Book Leverage		Industry-Adjusted Long-Term Book Leverage		Industry-Adjusted Total Market Leverage		Industry-Adjusted Net Market Leverage		Industry-Adjusted Long-Term Market Leverage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Change-firm × Post-SFAS	0.041***	0.039***	0.048***	0.046***	0.033***	0.032***	0.048***	0.040***	0.049***	0.042***	0.034***	0.028***
	(0.010)	(0.009)	(0.011)	(0.010)	(0.009)	(0.009)	(0.012)	(0.011)	(0.013)	(0.012)	(0.011)	(0.010)
Change-firm	0.033***	0.033***	0.040***	0.037***	0.037***	0.031***	0.044***	0.039***	0.047***	0.041***	0.045***	0.035***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)	(0.013)	(0.012)	(0.013)	(0.013)	(0.011)	(0.011)
Post-SFAS	−0.009	−0.013	−0.012	−0.015	−0.012	−0.016	−0.005	−0.002	−0.006	−0.004	−0.005	−0.004
	(0.013)	(0.012)	(0.013)	(0.013)	(0.011)	(0.011)	(0.015)	(0.014)	(0.015)	(0.014)	(0.013)	(0.012)
Firm size		0.015***		0.012***		0.021***		0.005*		0.006*		0.015***
		(0.002)		(0.002)		(0.002)		(0.003)		(0.003)		(0.002)
Profitability		−0.155***		−0.129***		−0.057**		−0.256***		−0.224***		−0.121***
		(0.030)		(0.028)		(0.025)		(0.036)		(0.034)		(0.028)
Tangibility		0.012		0.017		−0.005		0.009		0.022		0.010
		(0.020)		(0.021)		(0.018)		(0.022)		(0.022)		(0.020)
Market-to-book		−0.011***		−0.013***		−0.013***		−0.036***		−0.031***		−0.032***
		(0.002)		(0.002)		(0.001)		(0.002)		(0.002)		(0.002)
R&D		0.053		−0.042*		0.018		−0.022		−0.118***		−0.044*
		(0.033)		(0.025)		(0.025)		(0.032)		(0.037)		(0.026)
Dividend payer		−0.056***		−0.047***		−0.042***		−0.061***		−0.057***		−0.048***
		(0.009)		(0.010)		(0.008)		(0.010)		(0.010)		(0.009)
Constant	0.010	−0.010	0.030***	0.019	0.026***	−0.031**	0.027***	0.113***	0.041***	0.111***	0.035***	0.043***
	(0.006)	(0.015)	(0.006)	(0.015)	(0.005)	(0.012)	(0.007)	(0.017)	(0.007)	(0.017)	(0.006)	(0.013)
Year FE	X	X	X	X	X	X	X	X	X	X	X	X
Nobs	8,432	8,432	8,432	8,432	8,432	8,432	8,432	8,432	8,432	8,432	8,432	8,432
Adjusted R^2	0.02	0.07	0.03	0.06	0.02	0.07	0.03	0.15	0.03	0.13	0.03	0.13

Panel B. Regressions of Book and Market Leverage

	Total Book Leverage		Net Book Leverage		Long-Term Book Leverage		Total Market Leverage		Net Market Leverage		Long-Term Market Leverage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Change-firm × Post-SFAS	0.040***	0.037***	0.047***	0.042***	0.033***	0.030***	0.050***	0.042***	0.052***	0.044***	0.036***	0.032***
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.008)	(0.012)	(0.011)	(0.012)	(0.011)	(0.011)	(0.010)
Change-firm	0.038***	0.033***	0.042***	0.034***	0.038***	0.027***	0.044***	0.032***	0.046***	0.034***	0.044***	0.027***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.012)	(0.011)	(0.013)	(0.012)	(0.011)	(0.010)
Post-SFAS	−0.001	−0.004	−0.003	−0.006	−0.003	−0.006	0.000	0.006	0.000	0.004	−0.000	0.001
	(0.012)	(0.011)	(0.012)	(0.012)	(0.011)	(0.010)	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)	(0.012)
Imputed Leverage	0.603***	0.375***	0.593***	0.351***	0.651***	0.377***	0.669***	0.381***	0.671***	0.406***	0.750***	0.434***
	(0.032)	(0.039)	(0.032)	(0.038)	(0.034)	(0.042)	(0.033)	(0.038)	(0.036)	(0.039)	(0.038)	(0.044)
Firm size		0.020***		0.017***		0.026***		0.011***		0.010***		0.020***
		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)		(0.002)
Profitability		−0.192***		−0.167***		−0.095***		−0.300***		−0.259***		−0.156***
		(0.029)		(0.028)		(0.023)		(0.035)		(0.035)		(0.027)
Tangibility		0.134***		0.142***		0.131***		0.125***		0.127***		0.121***
		(0.021)		(0.021)		(0.021)		(0.022)		(0.023)		(0.022)
Market-to-book		−0.019***		−0.021***		−0.017***		−0.047***		−0.040***		−0.038***
		(0.002)		(0.002)		(0.001)		(0.002)		(0.002)		(0.002)
R&D		−0.162***		−0.241***		−0.124***		−0.246***		−0.291***		−0.169***
		(0.047)		(0.055)		(0.035)		(0.067)		(0.071)		(0.044)
Dividend payer		−0.056***		−0.047***		−0.045***		−0.064***		−0.059***		−0.051***
		(0.008)		(0.008)		(0.007)		(0.009)		(0.009)		(0.008)
Constant	0.081***	0.065***	0.081***	0.061***	0.068***	−0.007	0.080***	0.182***	0.080***	0.152***	0.062***	0.065***
	(0.007)	(0.014)	(0.006)	(0.015)	(0.005)	(0.011)	(0.007)	(0.017)	(0.007)	(0.017)	(0.006)	(0.013)
Year FE	X	X	X	X	X	X	X	X	X	X	X	X
Nobs	8,432	8,432	8,432	8,432	8,432	8,432	8,432	8,432	8,432	8,432	8,432	8,432
Adjusted R^2	0.18	0.27	0.18	0.28	0.19	0.29	0.20	0.36	0.19	0.32	0.20	0.33

Robust standard errors in parentheses

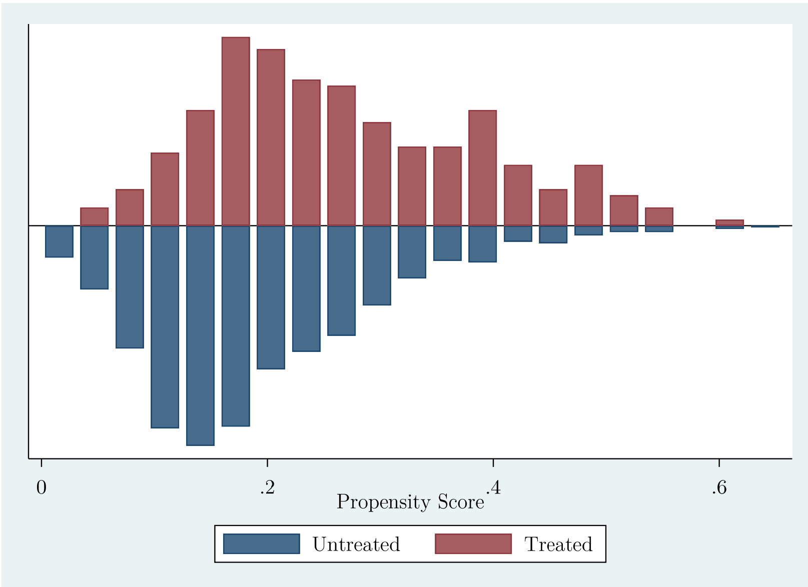
*** p<0.01, ** p<0.05, * p<0.1

Appendix 2.F. Propensity Score Distribution and Common Support

This figure plots the distribution of propensity scores for treated and untreated (control) firms (Section 2.5.3.2) across twenty equal-length partitions of the propensity score distribution. We estimate a probit model of the following form:

$$\textit{Change-firm}_i = \alpha + X_i' \times \beta_i \; + \epsilon_{i,t}$$

, where $\textit{Change-firm}_i$ is the treatment indicator and X_i' is a vector that contains the pre-treatment averages for each matching variable (four periods before the adoption of SFAS 131). Matching variables are *firm size,* profitability, tangibility, market-to-book ratio, R&D activity, dividend payer status, industry competitiveness, speed of profit adjustment, the GIM index, and total share of institutional ownership. The propensity scores of all firms of the full sample (except for three control firms that we discard) lie in the common support region of estimated propensity scores. Detailed variable descriptions are provided in Appendix 2.A.



Appendix 2.G. Assessment of Covariate Balance – Treatment and Control Firms

This table presents difference-in-means tests for all matching variables after performing one-to-one propensity score matching with replacement. The matching variables are firm size, profitability, tangibility, market-to-book ratio, R&D, and dividend payments (the control variables from our baseline leverage regression) as well as industry competitiveness, speed of profit adjustment, percentage of shares held by institutional investors, and the GIM index. Column (7) tests the null hypothesis that the means across the two groups are equal and column (8) provides p-values. We cannot reject the null for any of the ten matching variables. Detailed variable descriptions are provided in Appendix 2.A.

	All Firms		(1) Treated Firms		(2) Control Firms		(1)-(2)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Difference	P-Value
Firm size	5.279	1.546	5.318	1.626	5.231	1.444	0.087	0.56
Profitability	0.137	0.127	0.142	0.098	0.132	0.121	0.010	0.35
Tangibility	0.295	0.198	0.289	0.180	0.302	0.218	−0.013	0.49
Market-to-book	1.639	1.072	1.606	1.021	1.680	1.133	−0.074	0.47
R&D	0.023	0.048	0.022	0.048	0.023	0.048	−0.001	0.88
Dividend payer	0.416	0.469	0.430	0.471	0.400	0.468	0.030	0.51
Industry competitiveness	0.952	0.046	0.954	0.048	0.950	0.043	0.004	0.37
Speed of profit adjustment	0.792	0.079	0.793	0.070	0.790	0.091	0.003	0.73
Institutional Ownership	0.380	0.184	0.380	0.190	0.380	0.177	0.000	0.99
Gompers, Ishii, Metrick Index	8.920	1.294	8.959	1.445	8.874	1.080	0.085	0.49

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

Appendix 3.A. Variable Definitions

Variable	Definition
Segment investment	Annual capital expenditure of the segment (capxs) scaled by the segment's total book assets at the beginning of the year.
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-firm-adjusted segment investment	The difference between the industry-adjusted segment investment and the asset-weighted average industry-adjusted investment of the firm.
Firm size	The natural logarithm of the firm's book value of assets (at).
Segment size	The natural logarithm of the segment's book value of assets (ias).
Segment opex	Segment sales (sales) – segment profit (ops) – segment depreciation and amortization (dps).
Tobin's q	Market value of assets (at + prcc_f × csho – ceq – txdb) scaled by (0.9 × book value of assets (at) + 0.1 × market value of assets).
Industry q	The asset-weighted average 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.
Firm cash flow	Operating income before depreciation (oibdp) scaled by total book assets (at) at the beginning of the year.
Segment cash flow	The segment's operating income before depreciation (ops + dps) scaled by the segment's book value of assets (ias) at the beginning of the year.
Profitability	Operating Income after depreciation (oiadp) scaled by firm sales (sale).
Book leverage	Ratio of total debt (dlc + dltt) scaled by total book assets (at).
Free cash flow	Indicator variable that equals one if the segment's cash flow is positive in a given period and zero otherwise.
Number of segments	Number of business segments reported by the firm.
Core segment	Indicator variable that equals one if the segment's four-digit SIC code equals the firm's four-digit SIC code and zero otherwise.
Business segment concentration	Segment sales (sales) scaled by the aggregated sales of the segments reported by the firm in the same year.

Segment market share	Segment sales (sales) scaled by the aggregated sales of firms and segments operating in the same Fama-French 48 industry.
Excess value	The natural log of the ratio of the firm's 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 $\times$ 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 (or sales) multiplied by the asset-weighted average of the market-to-book (or market-to-sales) 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.
Information asymmetry index	A composite index combining three measures of IIA: (1) the number of reported segments, (2) the inverted Herfindahl index of the fraction of segment sales in a firm's total sales, and (3) the percentage of intangible assets in the firm's total assets. The composite governance index is created in the same way as the governance index.

Appendix 3.B. Summary Statistics on Division Efficiency by Industry

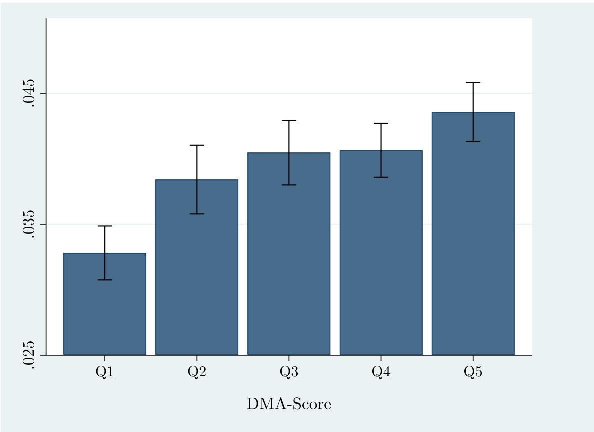
This table presents descriptive statistics on division efficiency sorted by industry, based on Fama and French (1997). The sample period ranges from 1999 to 2018. The sample consists of 74,348 segment-year observations. Division efficiency is measured using DEA based on the vectors described in Section 3.3.4.

	Nobs	Mean	SD	25%	Median	75%
Panel A. Division Efficiency						
Division Efficiency	74,348	0.446	0.205	0.294	0.438	0.584
Panel B. Division Efficiency by Industry						
Food products	2,322	0.540	0.199	0.398	0.542	0.676
Beer & liquor	224	0.397	0.213	0.213	0.387	0.536
Smoking	47	0.435	0.273	0.153	0.442	0.603
Recreation	1,939	0.409	0.171	0.283	0.404	0.522
Printing and publishing	1,220	0.426	0.165	0.310	0.425	0.529
Consumer goods	1,514	0.493	0.176	0.362	0.486	0.611
Apparel	1,216	0.509	0.150	0.407	0.513	0.616
Healthcare	6,531	0.362	0.193	0.218	0.342	0.488
Chemicals	3,023	0.451	0.163	0.335	0.449	0.564
Textiles	502	0.438	0.152	0.333	0.428	0.516
Construction	3,827	0.475	0.185	0.344	0.471	0.602
Steel works	1,660	0.472	0.164	0.354	0.466	0.583
Fabricated products	4,402	0.430	0.158	0.317	0.424	0.535
Electrical equipment	1,188	0.414	0.149	0.316	0.417	0.518
Automobiles and trucks	1,639	0.520	0.162	0.407	0.519	0.638
Aircraft, ships, and railroad	967	0.482	0.192	0.343	0.465	0.608
Metal mining	734	0.373	0.227	0.202	0.346	0.490
Coal	286	0.359	0.185	0.223	0.357	0.489
Petroleum and natural gas	3,093	0.359	0.249	0.153	0.304	0.506
Communication	2,258	0.323	0.207	0.154	0.286	0.460
Personal and business services	10,122	0.402	0.202	0.244	0.384	0.534
Business equipment	8,691	0.386	0.170	0.260	0.369	0.495
Business supplies	1,695	0.496	0.157	0.389	0.498	0.605
Transportation	2,676	0.466	0.249	0.245	0.466	0.659
Wholesale	3,871	0.596	0.208	0.464	0.609	0.743
Retail	4,877	0.634	0.186	0.515	0.649	0.769
Restaraunts, hotels, motels	1,605	0.491	0.182	0.378	0.489	0.603
Other	2,219	0.420	0.162	0.307	0.420	0.525

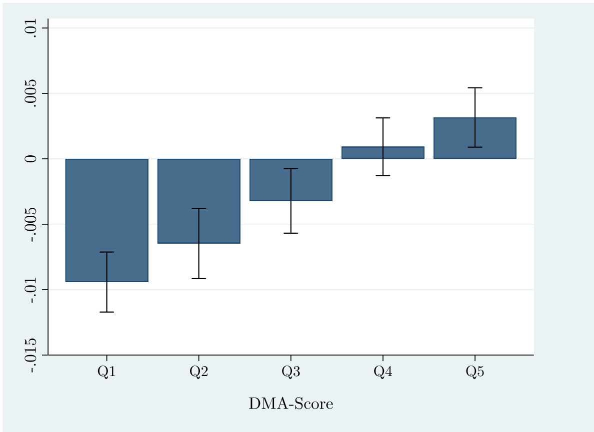
Appendix 3.C. Univariate Results

This figure plots different measures of capital allocation and division manager cash compensation for quintile groups of increasing managerial ability. Panel A shows average segment investment (capital expenditures divided by book assets). Panels B and Panel C show industry-adjusted segment investment and industry-firm-adjusted segment investment, respectively. Panel D shows average salary and average salary plus bonus. *DMA-Score* is the division-manager ability score described in Section 3.3.4. For each bin, the graphs report 95% confidence intervals around the mean. See Appendix 3.A for all variable definitions.

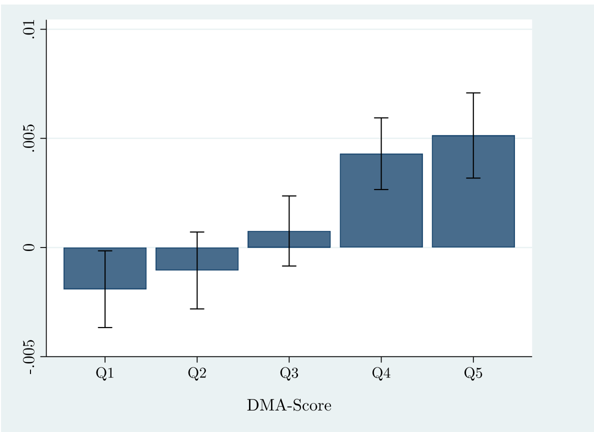
A Segment Investment



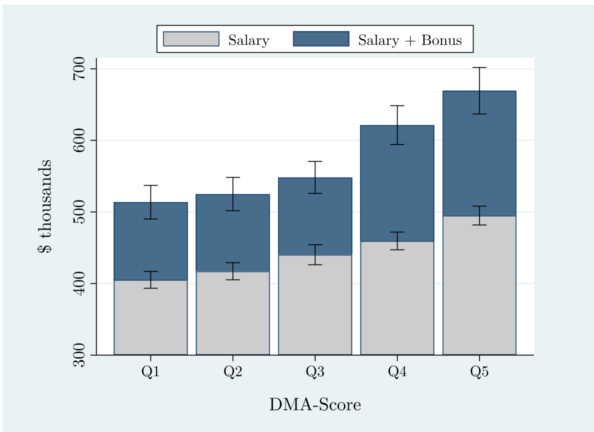
B Industry-Adjusted Segment Investment



C Industry-Firm-Adjusted Segment Investment



D Cash Compensation



Appendix 3.D. Validation Tests: Alternative Measures of Capital Allocation

This table presents fixed effects regressions on the relation between internal capital allocation and division-manager ability. The sample period ranges from 2000 to 2018. In Panel A, the dependent variable is segment investment. In Panel B, the dependent variable is industry-firm-adjusted segment investment. *DMA-Score* is the measure of division-manager ability described in Section 3.3.4. Control variables include the same characteristics of the division, firm, and manager used in Table 3.4. Explanatory variables are lagged one year, and continuous variables are winsorized at the extreme 1%. All regressions include year fixed effects. Standard errors (in brackets) are clustered at the firm level. See Appendix 3.A for all variable definitions.

Dep. Var.:	A. Segment Investment						B. Industry-Firm-Adjusted Segment Investment					
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DMA-Score	0.015**	0.023***	0.021***	0.021***	0.022***	0.020***	0.017***	0.024***	0.022***	0.024***	0.022***	0.023***
	(0.006)	(0.008)	(0.007)	(0.008)	(0.007)	(0.006)	(0.005)	(0.007)	(0.008)	(0.007)	(0.006)	(0.006)
Constant	0.043	0.013	0.033	0.077	0.063	0.074*	0.019	−0.021	−0.000	0.022	0.020	−0.013
	(0.022)	(0.083)	(0.023)	(0.048)	(0.039)	(0.039)	(0.016)	(0.037)	(0.017)	(0.040)	(0.035)	(0.031)
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						
Division FE	X			X			X			X		
Manager FE		X		X				X		X		
CEO FE			X	X					X	X		
Division * Manager FE					X						X	
CEO * Manager FE						X						X
Nobs	5,101	5,101	5,101	5,101	5,101	5,101	5,101	5,101	5,101	5,101	5,101	5,101
Adjusted R^2	0.61	0.63	0.52	0.51	0.64	0.64	0.43	0.42	0.09	0.32	0.49	0.46

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

Appendix 3.E. Measure of Investment Efficiency: *RVA-ABILITY*

This section provides additional information about the measure of investment efficiency with respect to division-manager ability employed in Section 3.6. In essence, we use a variant of the *relative value added* (RVA), defined by Rajan et al. (2000). The RVA measure as defined by Rajan et al. (2000) operates by gauging the sensitivity of cross-divisional investment to *industry q* (the asset-weighted Tobin's q of standalone firms operating in the industry to which a segment belongs).

In the following, we first provide some remarks about the RVA measure to lay the foundation for designing a human capital-based variant of this metric. It is very important to understand that RVA, as defined by Rajan et al. (2000), captures the effect of capital allocation (or more precisely, the reweighting of segment assets through capital allocation) on the asset-weighted average of all the segment *industry q*'s. We first discuss this aspect in detail. Then, we explain the construction of the novel human capital-based variant, *RVA-ABILITY*, which measures the corresponding effect of capital allocation on the asset-weighted average of all the division-manager ability scores (*DMA-Scores*).

Equation (A.1) shows the RVA measure (with respect to *industry q*) as defined by Rajan et al. (2000):[92]

$$RVA = \sum_{i=1}^{N} w_i \times (q_i - \bar{q}) \times \left(\frac{C_i}{A_i} - \frac{C_{SA}}{A_{SA}} - \sum_{i=1}^{N} w_i \times \left(\frac{C_i}{A_i} - \frac{C_{SA}}{A_{SA}}\right)\right) \tag{A.1}$$

, where w_i is the asset weight of segment i, q_i is the *industry q* of segment i, $\bar{q}$ is the asset-weighted average of all of the segment *industry q*'s, $\frac{C_i}{A_i}$ is the capital expenditure-to-assets ratio of segment i, and the term $\left(\frac{C_i}{A_i} - \frac{C_{SA}}{A_{SA}} - \sum_{i=1}^{N} w_i \times \left(\frac{C_i}{A_i} - \frac{C_{SA}}{A_{SA}}\right)\right)$ is the industry-firm-adjusted investment rate of segment i.[93]

[92] *Industry q* is the asset-weighted average Tobin's q ratio of standalone firms operating in the segment's industry.

[93] The industry adjustment is derived from the standalone firms (denoted by the index "SA") operating in the same industry as segment i.

In a more compact notation, equation (A.1) can be written as follows:

$$RVA = \sum_{i=1}^{N} w_i \times (q_i - \bar{q}) \times \left(IC_i - \overline{IC_\iota}\right) \tag{A.2}$$

, where $IC_i = \frac{C_i}{A_i} - \frac{C_{SA}}{A_{SA}}$ is the industry-adjusted segment investment of segment i. Note that $\bar{q}$ can be removed from equations (A.1) and (A.2):

$$\begin{aligned}
RVA &= \sum_{i=1}^{N} w_i \times (q_i - \bar{q}) \times \left(IC_i - \overline{IC}\right) \\
&= \sum_{i=1}^{N} w_i \times q_i \times \left(IC_i - \overline{IC}\right) - \bar{q} \times \sum_{i=1}^{N} w_i \times \left(IC_i - \overline{IC}\right) \\
&= \sum_{i=1}^{N} w_i \times q_i \times \left(IC_i - \overline{IC}\right) - \bar{q} \times \left(\sum_{i=1}^{N} w_i \times IC_i - \overline{IC} \times \sum_{i=1}^{N} w_i\right) \\
&= \sum_{i=1}^{N} w_i \times q_i \times \left(IC_i - \overline{IC}\right)
\end{aligned}$$

We next examine how the firm's capital allocation decision $\left(IC_i - \overline{IC}\right)$ affects the asset distribution across the segments of the firm.[94] Equation (A.3) shows segment *i's* assets after capital allocation:

$$A_i^{post} = A_i^{pre} \times \left(1 + IC_i - \overline{IC}\right) \tag{A.3}$$

The simultaneous change of segment assets triggers a reweighting of segment assets. The new asset weights can be calculated as follows:

$$w_i^{post} = \frac{A_i^{post}}{\sum_{i=1}^{N} A_i^{post}} = \frac{A_i^{pre} \times \left(1 + IC_i - \overline{IC}\right)}{\sum_{i=1}^{N} A_i^{pre} \times \left(1 + IC_i - \overline{IC}\right)} \tag{A.4}$$

[94] To facilitate calculations, we abstract here from depreciation.

Note that $\sum_{i=1}^{N} A_i^{post} = \sum_{i=1}^{N} A_i^{pre}$.[95] Therefore, equation (A.4) can be rewritten as follows:

$$w_i^{post} = \frac{A_i^{pre} \times \left(1 + IC_i - \overline{IC}\right)}{\sum_{i=1}^{N} A_i^{pre}} \tag{A.5}$$

Finally, the reweighting of segment assets leads to a change in the asset-weighted average of all the segment *industry q's*:

$$\bar{q}^{post} = \sum_{i=1}^{N} w_i^{post} \times q_i \tag{A.6}$$

In summary, we have shown that internal capital allocation triggers a reweighting of segment assets that alters the asset-weighted *industry q* of the firm. We next show that RVA, at its core, measures the after-minus-before change in the asset-weighted *industry q* of the firm:

$$\begin{aligned}
\bar{q}^{post} - \bar{q}^{pre} &= \sum_{i=1}^{N} w_i^{post} \times q_i - \sum_{i=1}^{N} w_i^{pre} \times q_i \\
&= \sum_{i=1}^{N} \left(\frac{A_i^{pre} \times \left(1 + IC_i - \overline{IC}\right)}{\sum_{i=1}^{N} A_i^{pre}} - \frac{A_i^{pre}}{\sum_{i=1}^{N} A_i^{pre}}\right) \times q_i \\
&= \sum_{i=1}^{N} \frac{A_i^{pre} \times \left(IC_i - \overline{IC}\right)}{\sum_{i=1}^{N} A_i^{pre}} \times q_i \\
&= \sum_{i=1}^{N} w_i^{pre} \times q_i \times \left(IC_i - \overline{IC}\right) \\
&= \textit{Relative value added} \ \text{(RVA)}
\end{aligned}$$

[95] This must be true as the sum of industry-firm-adjusted segment investment across all segments is zero.

Thus, the RVA measure, as defined by Rajan et al. (2000), captures the effect of capital allocation (or more precisely, the reweighting of segment assets through capital allocation) on the asset-weighted *industry q* across all segments of the firm. We build on this intuition for the construction of a human capital-based variant of the RVA metric that captures the effect of capital allocation on the asset-weighted division-manager ability score (*DMA-Score*) across all division managers of the firm.

Technically, we modify the RVA formula by replacing *industry q* with the (one-period-lagged) *DMA-Scores* of the firm's division managers. This definition requires that one-period-lagged *DMA-Scores* are available for each division manager in a given year.[96] Equation (A.7) presents our human capital-based variant of the RVA measure:

$$RVA\text{–}ABILITY = \sum_{i=1}^{N} w_i \times DMA\text{–}Score_i \times \left(IC_i - \overline{IC}\right) \tag{A.7}$$

In technical terms, *RVA-ABILITY* is the asset-weighted covariance between cross-segment investment and division-manager ability.[97] Positive (negative) values of *RVA-ABILITY* thus indicate that resources (assets) are moved from segments of less (more) able division managers to segments of more (less) able division managers.

[96] This condition implies that *RVA-ABILITY* is not available in firm-years with (1) division manager turnover or (2) changes in the number of reported segments, e.g., due to restructuring or changes in segment reporting.

[97] A benefit of this approach is that we circumvent the empirical concerns about measurement error related to *industry q* mentioned in Çolak and Whited (2007).

Appendix 4.A. Variable Definitions

Variable	Definition
FR	An indicator equal to one if the firm has at least one female division manager in a given year and zero otherwise.
Persistent-FR	An indicator equal to one if the firm has one or more female division managers in any year of the firm and zero otherwise.
Never-FR	An indicator equal to one if the firm never has a female division manager in any year of the firm and zero otherwise.
Tobin's q	Market value of assets (at + prcc_f × csho – ceq – txdb) scaled by (0.9 × book value of assets (at) + 0.1 × market value of assets).
Excess value	The natural log of the ratio of the firm's 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 (ias) 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.
Firm size	The natural log of the book value of assets (at).
Firm age	The natural log of the firm's age in years with firm birth determined by the firm's first year in Compustat.
Profitability	Operating income before depreciation (oibdp) scaled by book value of assets (at).
Tangibility	Property, plant and equipment (ppent) scaled by the book value of assets (at).
Capex intensity	Annual capital expenditure of the firm (capx) scaled by the firm's total book assets at the beginning of the year.
CEO age	The CEO's age in years.
Female CEO	An indicator equal to one if the CEO is female and zero otherwise.
CEO tenure	The number of years the CEO has been serving as the firm's CEO.
CEO equity pay	The fraction of equity-based pay in the CEO's total pay.
Number of female directors	The number of female directors on the board.
Female director dummy	An indicator equal to one if the firm at least one director is female and zero otherwise.

Board size	The number of board members.
Board independence	The percentage of outside directors on the board, where outside directors are directors who do not have an executive position in the firm.
Number of managers	The number of division managers employed by the company as reported in BoardEx.
Tenure (position)	The number of years the manager has held this position.
Age	The manager's age in years.
MBA degree	An indicator equal to one if the manager holds an MBA degree and zero otherwise.
Graduate degree	An indicator equal to one if the manager holds a graduate degree and zero otherwise.
Ivy league degree	An indicator that equals one if the manager holds a degree from an Ivy League university and zero otherwise.

Appendix 4.B. Job Titles and Roles of Division Managers

This table tabulates the titles and roles of the 17,020 division managers that served at the sample firms. The sample period ranges from 2000 to 2018. Panel A shows the composition of job titles for the full sample and for subsamples of female and male executives. Panel B provides examples of specific roles associated with the job titles from Panel A.

A. Division Manager Job Titles

	Full sample		Women		Men	
Title	Number	Percent	Number	Percent	Number	Percent
Division President	6,734	39.6%	703	28.7%	6,031	41.4%
EVP / SVP	4,281	25.2%	567	23.1%	3,714	25.5%
Division EVP / SVP	2,349	13.8%	435	17.7%	1,914	13.1%
Other	3,656	21.5%	747	30.5%	2,909	20.0%
Total	17,020	100.0%	2,452	100.0%	14,568	100.0%

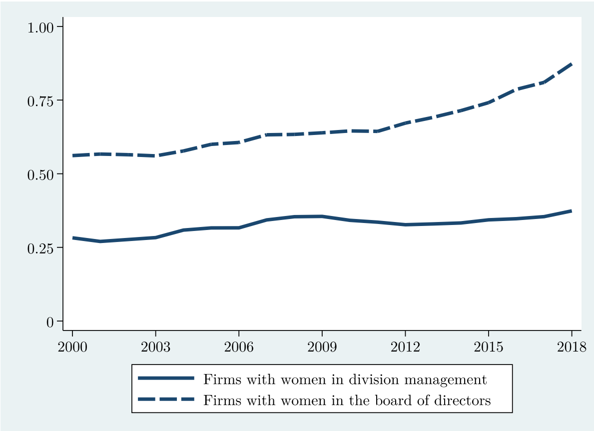
B. Examples of Role Descriptions

Title	Examples
Division President	President of Semiconductor Business, President of Hospitality Division, President of Transport Solutions, Business Unit President of Solution Delivery Print, President of Diagnostics, President Aluminum Products, President of Pulp and Paperboard Division, President of Foodservice Operations, President of Energy Systems, Segment President Electronic Systems, Segment President Aerospace and Defense Electronics
EVP / SVP	Executive VP Steel, Executive VP of Structurals Division, Executive VP Electronic Technologies Group, Executive VP Home Services, Senior VP Water Transmission Group, Senior VP of Precoat Division, Senior VP of Clinical Support Services, Senior VP Beauty, Senior VP Specialty Business Division, Senior VP Wireless Access Products Division
Other	Head of Division Process Analytics, Head of Division Networking Systems, Division CEO Automotive Division, Division Director Electronic Materials Division, Division COO Auto Parts Business, Division Group VP Fresh Meats

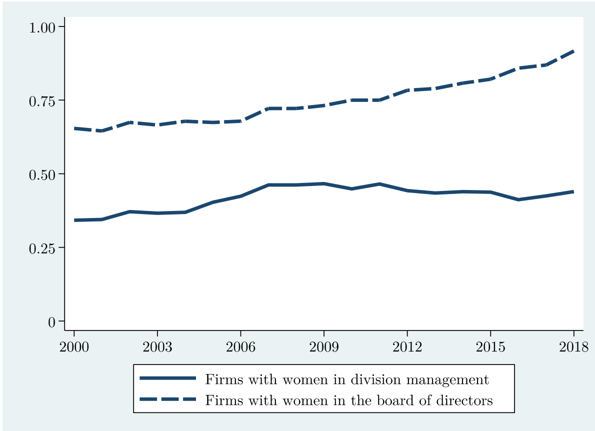
Appendix 4.C. Female Representation in Division Management over Time

This figure plots the fraction of firms with (i) one or more female division managers (solid lines) and (ii) one or more female directors on the board (dashed lines). The sample period ranges from 2000 to 2018. The full sample (Panel A) consists of 14,527 firm-year observations from 1,363 US public firms that operate two or more business segments (with a required minimum of five valid observations per firm). The balanced sample (Panel B) consists of 316 firms (5,334 firm-years) and is defined by the presence of firms in 17 or more years during the sample period.

A Full Sample



B Balanced Sample



Appendix 4.D. Determinants of Female Representation in Division Management

This table reports the results of logit regressions of female representation in division management. The sample period ranges from 2000 to 2018. *FR* is an indicator equal to one if the firm has one or more female division managers in a given year; *Persistent-FR* is an indicator equal to one if a firm has one or more female division managers in any year of the sample period; *Never-FR* is an indicator equal to one if the firm never has women among its division managers during the sample period. Standard errors (in brackets) are clustered at the firm level. Significance levels are indicated as follows: * = 10%, ** = 5%, *** = 1%. Detailed variable definitions appear in Appendix 4.A.

	FR		Persistent-FR		Never-FR	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Size)	0.397***	0.503***	0.532***	0.625***	−0.429***	−0.593***
	(0.037)	(0.039)	(0.082)	(0.094)	(0.044)	(0.054)
Log(Age)	−0.094	0.142*	−0.230	0.064	0.099	−0.175*
	(0.067)	(0.076)	(0.146)	(0.180)	(0.092)	(0.104)
Profitability	0.739	0.007	1.568	0.632	−0.267	0.528
	(0.509)	(0.523)	(1.175)	(1.266)	(0.568)	(0.599)
Capex intensity	1.537	0.839	1.856	−0.662	−0.243	−0.207
	(1.045)	(1.116)	(2.194)	(2.665)	(1.097)	(1.166)
Tangibility	−1.578***	−0.427	−1.951***	0.176	1.242***	0.826
	(0.342)	(0.373)	(0.699)	(0.739)	(0.399)	(0.515)
Female CEO	0.763***	0.469*	1.486***	1.230***	−1.133***	−0.883**
	(0.242)	(0.263)	(0.357)	(0.391)	(0.334)	(0.341)
CEO tenure	0.000	0.003	0.022	0.025	0.009	0.004
	(0.007)	(0.008)	(0.016)	(0.016)	(0.009)	(0.010)
CEO equity pay	2.132**	0.041	2.300	0.073	−3.270**	−1.366
	(1.037)	(1.074)	(2.039)	(2.035)	(1.391)	(1.620)
Board independence	0.150	0.251	−0.446	−0.320	−0.234	−0.318
	(0.146)	(0.155)	(0.283)	(0.297)	(0.172)	(0.197)
Female director dummy	0.432***	0.297***	0.490***	0.326***	−0.547***	−0.407***
	(0.046)	(0.048)	(0.088)	(0.090)	(0.068)	(0.076)
Year FE	X	X	X	X	X	X
Industry FE		X		X		X
Nobs	14,527	14,527	14,527	14,527	14,527	14,527
Adjusted R^2	0.13	0.21	0.18	0.28	0.16	0.26

Appendix 4.E. Female Representation and Firm Value

This table reports the results of firm-level regressions on the relation between female representation in division management and firm value. The sample period ranges from 2000 to 2018. The dependent variable is excess value, defined as the natural log of the ratio of a firm's actual value to its imputed value (Berger and Ofek, 1995). *FR* (*Persistent-FR*) is an indicator equal to one if the firm has one or more female division managers in a given year (any given year of the sample period); *Never-FR* is an indicator equal to one if the firm never has women among its division managers during the sample period. The regressions are estimated separately for the full sample in columns (1)-(3) and for a balanced sample in columns (4)-(6). Standard errors (in brackets) are clustered at the firm level. Significance levels are indicated as follows: * = 10%, ** = 5%, *** = 1%. Detailed variable definitions appear in Appendix 4.A.

	A. Full Sample			B. Balanced Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
FR	0.097***	0.047**	0.023	0.140***	0.091***	0.028
	(0.026)	(0.024)	(0.023)	(0.043)	(0.035)	(0.036)
Persistent-FR			0.129**			0.210**
			(0.053)			(0.095)
Never-FR			0.000			−0.122**
			(0.029)			(0.053)
Log(Size)		−0.001	−0.001		0.025	0.013
		(0.012)	(0.012)		(0.018)	(0.018)
Profitability		2.634***	2.635***		3.596***	3.619***
		(0.167)	(0.167)		(0.297)	(0.292)
Log(Age)		−0.012	−0.011		−0.072	−0.079
		(0.017)	(0.017)		(0.049)	(0.049)
Capex intensity		0.135	0.141		−0.519	−0.461
		(0.229)	(0.229)		(0.446)	(0.454)
Tangibility		−0.186*	−0.193*		−0.191	−0.197
		(0.107)	(0.107)		(0.185)	(0.183)
Female CEO		−0.063	−0.074		−0.240**	−0.237**
		(0.07)	(0.068)		(0.112)	(0.106)
CEO age		−0.004***	−0.005***		−0.004*	−0.005*
		(0.002)	(0.002)		(0.003)	(0.003)
CEO tenure		0.004**	0.004**		−0.001	−0.001
		(0.002)	(0.002)		(0.003)	(0.003)
CEO equity pay		0.135***	0.137***		0.182***	0.183***
		(0.044)	(0.044)		(0.063)	(0.062)
Board size		0.003	0.002		−0.007	−0.006
		(0.007)	(0.007)		(0.010)	(0.009)
Board independence		−0.017	−0.015		−0.062	−0.081
		(0.037)	(0.037)		(0.054)	(0.053)
Female director dummy		0.018	0.020		0.048	0.032
		(0.026)	(0.026)		(0.045)	(0.044)
Year FE	X	X	X	X	X	X
Industry FE	X	X	X	X	X	X
Nobs	14,527	14,527	14,527	5,334	5,334	5,334
Adjusted R^2	0.06	0.18	0.18	0.09	0.27	0.28