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Chapter 1

Introduction

This thesis comprises of three essays on mutual fund and corporate governance. It focuses on (1) the impact of manager duality on managerial decisions and performance, (2) the relationship between managerial ownership and performance, and (3) the role of physical fitness as an important managerial characteristic relevant for hiring decisions of the board of directors.[1]

The need for governance in corporations as well as mutual funds rests on the idea that managers may act in opportunistic ways that are detrimental to shareholders when ownership and control are separated and contracts are incomplete (see, e.g., Jensen and Meckling (1976), Fama and Jensen (1983), and Hart (1995)). Put differently, managers seek to maximize their personal utility, which does not necessarily mean they maximize shareholder wealth. For instance, Yermack (2006) shows that firms in which chief financial officers (CEOs) are permitted to use their companies' aircrafts for personal travel (a sign of weak corporate governance) underperform the market benchmark by about 4% per year. In the context of mutual funds, managers may engage in opportunistic risk-taking behavior, which may ultimately hurt investors' performance (see, e.g., Brown, Harlow, and Starks (1996), Kempf and Ruenzi (2008), Kempf, Ruenzi, and Thiele (2009), and Huang, Sialm, and Zhang (2011)).

Overall, the importance of governance mechanisms to mitigate agency conflicts between managers and shareholders has been highlighted by a series of corporate collapses, including

[1] Mutual funds are often seen as being similar to regular corporations as both are separate legal entities, having their board of directors and shareholders. However, there are significant differences between mutual funds and regular corporations with respect to governance mechanisms (see, e.g., Roiter (2015) and footnote 3 of the present thesis for an example). Thus, the terms mutual fund governance and corporate governance are not used interchangeably in this thesis.

the cases of Enron and WorldCom, or several fund scandals involving market timing and late trading in 2003 (see Zitzewitz (2006)). As a consequence, a sound understanding of the mechanisms that improve or hamper mutual fund and corporate governance appears highly relevant.

The academic literature on mutual fund and corporate governance can broadly be separated into two strands. One strand of this literature is concerned with external governance mechanisms such as the market for corporate control and the impact of blockholders and institutional shareholders on corporate governance.[2] As mutual fund shareholders are able to redeem their fund shares at the net asset value, fund researchers mainly focus on investor flow sensitivity as an external mutual fund governance mechanism.[3] The other strand of the governance literature examines mechanisms of internal governance, primarily the board of directors, the relationship between managerial ownership and performance, and, more generally, the role of managerial incentives.[4] The essays in this thesis complement the latter strand of the governance literature.

The first essay (Kempf, Puetz, and Sonnenburg (2013)) analyzes the consequences of manager duality in the U.S. mutual fund industry, i.e., a sole leadership structure where the manager also acts as the chairman of the board. While previous studies show that manager duality is often associated with poor company performance (see, e.g., Rechner and Dalton (1991)) and a lower performance-turnover sensitivity (see, e.g., Goyal and Park (2002)), comprehensive evidence on the behavior of duality managers is scarce. An analysis of manager duality in the fund industry is attractive as the decisions of fund managers are

[2] Some examples of studies that analyze the external market for corporate takeovers are Holmstrom and Kaplan (2001), Denis and McConnell (2003), Kini, Kracaw, and Mian (2004), Masulis, Wang, and Xie (2007), Netter, Poulsen, and Stegemoller (2009), and Servaes and Tamayo (2014). Examples of papers that examine the role of blockholders and institutional investors in corporate governance are Barclay and Holderness (1991), Brav, et al. (2008), Cronqvist and Fahlenbrach (2009), Burns, Kedia, and Lipson (2010), Becker, Cronqvist, and Fahlenbrach (2011), Clifford and Lindsey (2015), and Edmans (2014) for an overview on the relationship between blockholders and corporate governance.

[3] The idea that fund investors can discipline fund managers by redeeming their shares at the net asset value is based on Fama and Jensen (1983). In regular corporations, shareholders do not have this disciplining mechanism, as they sell their shares at a stock price which is likely to incorporate the problem with the CEO. Some examples of studies that investigate external fund governance are Sirri and Tufano (1998), Johnson (2010), and Evans and Fahlenbrach (2012).

[4] Among others, Hermalin and Weisbach (2003), Boone, et al. (2007), Coles, Daniel, and Naveen (2008), and Linck, Netter, and Yang (2008) examine board structure and its impact on corporate outcomes. For an overview on the role of the board of directors in corporate governance, see Adams, Hermalin, and Weisbach (2010). Some examples of studies that analyze the relation between managerial ownership and corporate performance are Himmelberg, Hubbard, and Palia (1999), Zhou (2001), Fahlenbrach and Stulz (2009), and Lilienfeld-Toal and Ruenzi (2014). Examples of papers that investigate board effectiveness in the mutual fund industry are Tufano and Sevick (1997), Khorana, Tufano, and Wedge (2007), Ferris and Yan (2007), Adams, Mansi, and Nishikawa (2010), and Ding and Wermers (2012). Khorana, Servaes, and Wedge (2007) and Evans (2008) study the relation between fund manager ownership and performance. Some examples of studies that examine board directors' or fund managers' incentives are Chen, Goldstein, and Jiang (2008), Cremers, et al. (2009), and Ma, Tang, and Gómez (2015).

directly reflected in fund returns. In our analyses, we focus on single managed U.S. equity funds since the link between a fund manager's role as chairman of the board and her task to manage the portfolio are most clearly connected if the fund is single-managed. In this case, the fund manager has higher managerial discretion: She decides on the investments of the fund and, at the same time, sets the agenda for the board meetings and potentially replacing her.

Consistent with the aforementioned argumentation, we expect that duality managers are aware of the lower risk of replacement and follow more risky investment strategies than non-duality managers. This strategy is highly sensible since their compensation scheme tends to be more option-based as that of non-duality managers. They benefit from good investment decisions in the same way as non-duality managers without bearing a high replacement risk in case their investment decisions are not successful. We conjecture that it is unfavorable to let the manager of the fund also serve as the board of directors' chairman from an investor's point of view. In particular, duality managers may use their higher discretion in their own interest and spend less effort on their work translating into worse performance compared to non-duality managers. Finally, we expect that the effects of manager duality on investment behavior and performance can be mitigated by a more independent board, i.e., if the manager is only an ordinary board member but not the chairman of the board or if there are many independent directors on the board and if they have invested own money in the fund.

Our main results confirm our expectations about the behavior of duality managers. They make more risky investment decisions than non-duality managers. In particular, duality managers take risk that they could easily avoid, deviate more from their benchmarks, make more extreme decisions, and, consequently, deliver more extreme performance outcomes. Consistently, we document that duality managers significantly underperform non-duality managers by up to 2.5 percent per year. We rule out several alternative explanations and show that our results are not driven by an endogeneity problem, by fewer investment restrictions for duality managers, by the financial crisis, or by a family size effect. Finally, our results support the idea that the effect on investment behavior and performance depends on the extent to which the manager dominates the board. The effect on investment behavior and performance is much weaker if the manager is only an ordinary member of the board and if there are many independent members on the board who invest their own money in the fund.

The findings from the first essay suggest that it is detrimental for shareholders if the manager also serves as the chairman of the board. The most important consequence from the investor's point of view is that duality managers make more risky investment decisions.

A more powerful board consisting of more independent directors seems to be crucial to moderate this agency problem. Another way to better align the manager's interests with those of shareholders can be managerial ownership, given that managers share the downside risk of their own actions with shareholders when they invest their personal wealth in their funds. In this spirit, several well-known mutual fund companies, such as Franklin Templeton Investments, have started requiring their managers to invest in the funds they manage.[5]

Therefore, the second essay (Martin and Sonnenburg (2015)) is concerned with the relation between managerial ownership and fund performance. In particular, we analyze the impact of changes in managerial ownership on changes in future performance. Earlier studies show that the level of ownership predicts future performance in the cross-section (see, e.g, Khorana, Servaes, and Wedge (2007)). Looking at changes in ownership to predict changes in performance has two advantages. First, ownership levels might be correlated with unobserved fund characteristics that also affect performance such as restrictions on fund managers' actions like short-selling constraints. As a consequence, the observed relationship between managerial ownership and performance might be spurious. Second and more important, previous studies cannot investigate the economic mechanism through which managerial ownership may be related to future performance. This relation could be driven by two distinct economic mechanisms. On the one hand, managers may have superior information on future fund performance. If so, managers would very likely invest in those funds they expect to perform well. On the other hand, the incentive alignment hypotheses states that managerial ownership aligns manager's interests with those of fund shareholders leading to better (i.e., more shareholder-oriented) investment decisions or more effort. This is expected to translate into better fund performance.

To disentangle both hypotheses, we use the adoption of fund family policies requiring managers to hold some ownership in all funds they manage. The idea is that these changes are unlikely to reflect the manager's information. If the superior information hypothesis holds, we do not expect that ownership changes which are mandated by the fund family increase fund performance. If the incentive alignment hypothesis holds, ownership leads to aligned incentives regardless if the change in ownership is mandatory or voluntary. Therefore, we expect that mandatory and voluntary ownership changes to be positively related to future changes in performance. Our analyses yield the following results. Ownership changes positively predict changes in future risk-adjusted fund performance. A one-standard-deviation increase in ownership predicts a 1.6 percent increase in alpha in the following year. This

[5] See "Another Way to Assess a Mutual Fund" in *The Wall Street Journal MarketWatch* (26/07/2006) and "Fund Managers: Betting their own money" in *Bloomberg BusinessWeek* (14/01/2010).

result stands several robustness tests. Furthermore, fund managers who are required to increase their ownership by fund family policy show the strongest increase in alpha. In additional analysis, we find that managers who increase ownership simultaneously to the adoption of a family wide ownership requirement increase their active share, turnover, unobserved actions and their equity holdings and decrease their cash holdings. This implies that higher ownership aligns managers' interests with shareholders and induces higher managerial effort.

The first two essays illustrate that board independence and managerial ownership can help to improve fund governance. Besides providing managers with optimal compensation contracts and monitoring them, one of the most important tasks of the board of directors is to hire and fire managers (see, e.g., Adams, Hermalin, and Weisbach (2010)).[6] Thus, directors play a crucial role in selecting managers. In this context, the question arises which personal characteristics matter for performance. More recently, a growing literature deals with this question.[7]

The third essay (Limbach and Sonnenburg (2015)) contributes to this literature. It is related to the first two essays as it investigates the impact of managers' characteristics on performance. In particular, we use hand-collected data on U.S. marathons to study the impact of CEO's fitness on firm value. We classify CEOs as fit if they finish a marathon in a given year.[8] Previous studies from the fields of biology, medicine, psychology and sports document that physical activity and fitness have moderating effects on stress (see, e.g., Gal and Lazarus (1975)) and positive effects on cognitive functions and executive-control processes (see, e.g., Colcombe and Kramer (2003)), and on academic and job performance (see, e.g., Coe, et al. (2006), and Rhea, Alvar, and Gray (2004)). Therefore, fitness should play an important role for CEOs as their jobs are characterized by frequently changing tasks and demands, far-reaching decisions, and high stress. We expect that fit CEOs can better cope with the high

[6] In this context, the literature mainly focuses on the effects of management turnover on performance. Among them are Hotchkiss (1995), Denis and Denis (1995), Khorana (2001), and Jenter and Kanaan (2015).

[7] Examples of studies that analyze the relation between manager characteristics and firm outcomes are Bertrand and Schoar (2003), Malmendier, Tate, and Yan (2011), Schoar and Zuo (2015), Kaplan, Klebanov, and Sorensen (2012), Custódio, Ferreira, and Matos (2013), Custódio and Metzger (2013), Benmelech and Frydman (2015), and Custódio and Metzger (2014). Examples of studies that look at the relationship between fund manager characteristics and fund performance are Golec (1996), Chevalier and Ellison (1999a), Gottesman and Morey (2006), and Fang, Kempf, and Trapp (2014).

[8] We focus on regular corporations to examine the impact of managers` fitness on performance because mutual fund manager ages are not reported in commonly used mutual fund databases. However, managers` age is necessary for an accurately match with our data on marathon finishers. In contrast, the Corporate Library's *Board Analyst* database provides detailed information about CEOs` names and age. Nevertheless, we believe that our results are transferable to other top executives such as fund managers.

stress of their jobs and should be associated with better performance. [9] We test this hypothesis using a panel of S&P 1500 companies.

Consistent with our hypothesis, we find a positive impact of CEO fitness on firm value. Tobin's Q is found to be almost 5% larger for firms managed by a fit CEO. To gain a better understanding how fitness translates into firm value, we study firm profitability. We find that fit CEOs are associated with higher return on assets and higher free cash flow to total assets. We further document that fit CEOs are associated with higher abnormal announcements returns of merger & acquisitions (M&A), especially if these M&As involve large and public targets. We interpret this result as further support for our hypothesis as these M&As are typically very stressful and work-intensive for the CEO due to considerable media scrutiny and pressure to perform. Furthermore, we find the strongest effects on firm value in subsamples where fitness is most important, i.e., for CEOs with high workload, above median age, and above median tenure. This is consistent with the literature and the view that fitness moderates stress and positively affects cognitive functions and performance. Our results are robust to various tests for endogeneity, including CEO-firm fixed effects, time-varying firm and industry effects, permutation tests, reverse causality and sudden deaths. Overall, the results from the third essay provide an explanation for the growing importance of fitness in the managerial labor market.

Taken together, the three essays provide new insights into mutual fund and corporate governance. First, duality managers tend to make more risky investment decisions than non-duality managers. These effects are stronger if managers have more power in the board of directors. Second, managerial ownership is found to positively affect performance. This positive relationship is likely to be the result of better alignment between managers' and shareholders' interests. Finally, managers' physical fitness is associated with better firm performance and seems to be an important attribute which boards should take into account when selecting a new CEO.

[9] In line with this argumentation, there is a growing trend among CEOs to run marathons, see „Executive endurance" in *The Wall Street Journal MarketWatch* (04/10/2007). Examples of running CEOs include Robert Iger (Walt Disney), Klaus Kleinfeld (Alcoa), John Legere (T-Mobile), or Steven Reinemund (PepsiCo).

Chapter 2

The Impact of Duality on Managerial Decisions and Performance: Evidence from the Mutual Fund Industry*

2.1 Introduction

Agency problems are imminent when the decision makers do not bear the wealth effects of their decisions. Therefore, companies typically separate decision making from decision control. The board of directors' role is to control the decisions of the managers and – as the last resort – to fire poor performing managers (see, e.g., Fama and Jensen (1983)). A natural conflict of interest arises if a manager is also member of the board of directors and, thus, controlling herself. This problem is particularly severe if the manager of a company is also chairing the board. Although advocates of such a duality structure emphasize the advantage of ensuring clear responsibilities for the success of the company, empirical evidence suggests that manager duality often leads to poor company performance (see, e.g., Rechner and Dalton

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* This chapter is based on Kempf, Puetz, and Sonnenburg (2013). A previous version of this paper was titled "Fund Manager Duality: Impact on Performance and Investment Behavior". We thank Vikas Agarwal, Nihat Aktas, Erik de Bodt, Gjergji Cici, Rüdiger Fahlenbrach, Richard Fu, Dieter Hess, Olaf Korn, Peter Limbach, Ernst Maug, Daniel Metzger, Alexandra Niessen-Ruenzi, Alexander Wagner, Russ Wermers, and our discussants and other participants at our presentations at the 2013 EFMA Annual Meeting in Reading, 2013 FMA Annual Meeting in Chicago, 2013 Annual Meeting of the German Finance Association (DGF) in Wuppertal, and SKEMA Business School for their helpful comments.

(1991)) and makes it difficult for the board to remove poorly performing duality managers (see, e.g., Goyal and Park (2002)).

This paper is the first to analyze the consequences of manager duality on the decisions they take. We use the fund industry as our laboratory to explore this issue since managerial decisions in the fund industry are more prescribed and more precisely observed than in other industries. This makes the fund industry attractive for exploring issues of general interest in corporate finance (see, e.g., Almazan, et al. (2004)).[10]

We hypothesize that the reduced level of control and replacement risk of duality managers has two main consequences. First, duality managers take more risky decisions since their compensation scheme is more option-like as compared to non-duality managers. Like all managers, they benefit from good outcomes (e.g., by receiving bonus packages) but they bear a lower risk of being fired if the outcomes are bad. Second, duality managers use their flexibility in their own interest, spend less effort on their work, and eventually deliver a worse performance than non-duality managers. Furthermore, we hypothesize that the consequences for managerial decisions and performance are stronger, the more the duality manager dominates the board. Our empirical results strongly support all three hypotheses.

In our first set of tests we find strong support for the hypothesis that duality managers take more risky decisions than non-duality managers. They hold less diversified portfolios, deviate more from their benchmarks, take more unsystematic risk, and follow more extreme investment styles. For example, less than 20% of the non-duality managers take as extreme market bets as the average duality manager.

In our second set of tests, we look at the performance consequences of manager duality. With respect to the average performance consequences, we find that funds run by duality managers (duality funds) significantly underperform funds run by non-duality managers (non-duality funds). This result holds no matter how we measure performance. In a standard multivariate regression approach we find an underperformance of up to 2.5 percent per year and in a matched-sample analysis the underperformance goes up to 3.4 percent per year. All these numbers are based on gross returns, i.e., they do not reflect the funds' expense ratios. Looking at net returns makes the underperformance of duality funds even stronger since they charge significantly higher total expense ratios (1.7 percent versus 1.3 percent).

[10] Besides that, looking at the consequences of manager duality in the fund management industry is important in itself since the decisions in the mutual fund industry are highly relevant for millions of investors using mutual funds to save for retirement. According to ICI (2013) more than 2.1 trillion USD are held in mutual funds just through 401(k) plans at the year-end 2012. The huge amount of money being in danger makes it important to understand the consequences of manager duality in the fund industry.

Furthermore, consistent with their risky decisions, we find that duality managers achieve more extreme performance outcomes than non-duality managers.

We rule out various alternative explanations for our findings. We adopt an instrumental variable approach to rule out endogeneity issues. We show that the more risky decisions of duality managers do not arise because duality managers face fewer investment restrictions. In contrast, they take more risk even though they are less frequently allowed to use leverage, options, or illiquid assets in their portfolios. We also rule out the possibility that the poor performance of the duality managers is caused by the recent financial crisis, which overlaps with our sample period. One might suspect that their high risk taking might have led to poor performance only during the financial crisis, but this is not true. Our results are the same for the period before and during the financial crisis. Finally, we rule out the possibility that the performance effect is driven by a family size effect (duality funds might be more prevalent in small fund families and, as suggested by Chen, et al. (2004), small fund families might have disadvantages associated with trading commissions and lending fees leading to worse average performance in small families).

In our third set of tests, we analyze whether the strength of the duality effect on managerial decisions and performance depends on the extent the manager dominates the board. We show that the consequences are much weaker if the manager is only an ordinary member of the board but not chairing it; the effect almost disappears. Furthermore, the effect of duality on managerial decision taking and performance is smaller when independent board members gain importance. This is the case when there are more independent directors on the board and when they have a stronger incentive to monitor the fund (proxied by the amount of their own money they have invested in the fund). These findings suggest that the consequences of duality on managerial decisions and performance can be mitigated by reducing the manager’s power on the board.

Our paper contributes to three strands of the literature. First, it is related to the corporate finance literature that examines the impact of manager duality on firm performance (see, e.g., Brickley, Coles, and Jarrell (1997), and Rechner and Dalton (1991)). The main contribution to this literature is that our paper is, to our knowledge, the first to look at the consequences of duality on the managerial decisions, not just the average performance outcome.

Second, our paper contributes to the growing literature on the impact of managerial power on managerial behavior and firm performance. Adams, Almeida, and Ferreira (2005) show that firms whose CEOs have more decision-making power experience more variability in performance. In a similar vein, Tang, Crossan, and Rowe (2011) show that dominant CEOs tend to have a strategy that deviates from the industry central tendency and thus extreme performance outcomes. Bebchuk, Cremers, and Peyer (2011) show that firms run by dominant CEOs deliver worse performance. We add to this literature by first showing that duality managers (which obviously have more power than non-duality managers) tend to take more risky decisions and deliver worse and more extreme performance outcomes. Furthermore, we show that these effects are the more pronounced, the more power the duality manager has relative to other board members.

Finally, our paper contributes to the literature on mutual fund governance which highlights the importance of independent board members for fund performance and manager replacement (see, e.g., Tufano and Sevick (1997), Khorana, Tufano, and Wedge (2007), Ferris and Yan (2007), Fu and Wedge (2011), and Ding and Wermers (2012)). We add to this literature in two ways: To begin with, we are the first to study the consequences of poor governance due to manager duality in the fund industry. Besides that, we are the first who look at the consequences of fund governance on the investment decisions of fund managers.

The remainder of this paper is organized as follows. In Section 2.2, we describe the data and provide fund and manager characteristics for duality and non-duality funds. In Section 2.3, we test our first main hypothesis by analyzing differences in the decisions taken by duality and non-duality managers. Section 2.4 is dedicated to tests of our second main hypothesis. Here we study performance differences between both groups. In Section 2.5 we show that our tests are not flawed by an endogeneity problem and rule out various alternative explanations for our findings. In Section 2.6 we test our third hypothesis by analyzing how the consequences of duality for managerial decisions and performance depend on the extent the manager dominates the board. Section 2.7 concludes.

2.2 Data

For our empirical analysis we use various data sources. From the CRSP Survivor-Bias Free Mutual Fund Database we gather information on mutual funds' monthly returns, total net assets, and other fund characteristics.[11] We focus on actively managed, U.S. domestic equity funds and exclude bond funds as well as index funds. We use the Lipper objective code to define a fund's investment objective. We aggregate the Lipper segments into seven broad categories: Aggressive Growth, Growth and Income, Income, Growth, Sector Funds, Utility Funds, and Mid-Cap Funds. If a fund offers multiple share classes, we aggregate them at the

[11] Source: CRSP, Center for Research in Security Prices. Graduate School of Business, The University of Chicago. Used with permission. All rights reserved.

fund level to avoid multiple counting. We concentrate on single managed funds since we conjecture that the duality effect is most pronounced if the manager has the full power to make the investment decisions. We exclude fund-year observations for which less than 12 months of return data are available. To calculate the characteristic selectivity performance measure of Daniel, et al. (1997) we link the CRSP funds to the Thomson Financial Mutual Fund Holdings Database and match the stock returns from the CRSP Monthly Stock Database to the holdings data.

Furthermore, we match the CRSP funds to the funds in the Morningstar Principia Database using fund ticker, fund name, and manager name. The Morningstar database provides detailed information on a manager’s biography that includes data on the manager’s educational background, e.g., whether she holds an MBA, a PhD, or a Chartered Financial Analysts (CFA) designation, and the date that a manager was first assigned to a fund. We calculate a manager’s industry tenure as the number of years since the year that Morningstar reports to be her first year managing a fund in the Morningstar database. We determine the manager's gender by comparing the manager's first name to a list published by the United States Social Security Administration (SSA) that contains the most popular first names by gender.

The final data source is the Statement of Additional Information (SAI), which is Part B of the mutual fund’s prospectus. It includes detailed information on each board member. The SAI is contained in the SEC filings 485APOS and 485BPOS which can be downloaded as text files from SEC EDGAR. We match these files with the CRSP funds using the fund’s name. For each fund we manually collect the following information for each board member from the SEC files: Name; whether she is interested or independent as defined by the Investment Company Act (ICA); board member’s ownership in the fund. The ownership is reported in five ranges: None; \$1–\$10,000; \$10,001–\$50,000; \$50,001–\$100,000; over \$100,000.

Our final sample consists of 1,901 fund-year observations covering the period 2005 - 2009. Table 2.1 reports summary statistics for the number of funds in the sample, their size (measured as total net assets), their expense ratio, age, and turnover ratio. Overall, our sample covers a total of 634 distinct funds. The average fund size is around 1.7 billion USD. Its evolution over time clearly reflects the effect of the subprime crisis. The average expense ratio in our sample decreases from 1.45 percent in 2005 to 1.24 percent in 2009.

Table 2.1: Descriptive statistics

Year	Number	Fund Size	Expense ratio	Fund age	Turnover
2005	392	1,784	1.45	16.35	85.27
2006	423	1,814	1.36	15.60	94.62
2007	431	1,995	1.29	16.19	85.69
2008	346	1,164	1.22	17.67	100.20
2009	309	1,534	1.24	18.49	101.51
Total sample	634	1,685	1.32	16.74	92.80

Notes: This table reports summary statistics for our sample of actively single-managed U.S. equity mutual funds between 2005 and 2009. The funds belong to the market segments Aggressive Growth, Growth and Income, Income, Growth, Sector Funds, Utility Funds, and Mid-Cap Funds. For each sample year as well as the total sample, we report the number of funds in the sample, the average funds' size measured as total net assets (TNA) in million US Dollar, the average funds' expense ratio (in %), the average funds' age in years, and the average funds' turnover ratio (in %).

The average fund in our sample is about 17 years old and turns over about 93 percent of its portfolio per year. Over the sample period, the turnover ratio increases from 85 percent to 102 percent.

In Table 2.2 we report characteristics for duality and non-duality funds and managers. As shown in Panel A, for about 14 percent of all fund-year observations (covering 84 distinct funds), the manager also acts as chair of the fund's board. Duality funds are much smaller than non-duality funds. The mean duality fund is only about half the size of the mean non-duality fund. Furthermore, duality funds charge significantly higher expense ratios. Regarding a fund's age and turnover, we do not find a significant difference between duality and non-duality funds.

Panel B reports the distribution of funds across market segments, separately for duality and non-duality funds. Duality funds are observed in all market segments. They are overrepresented in the growth segment and underrepresented among the sector funds.

In Panel C we look at the characteristics of the managers in our sample. The numbers in this panel are calculated at the manager level and refer to a total of 559 managers from which 54 managers also chair their fund's boards. We find that almost none of these duality managers are female. The percentage is lower than the percentage of female managers in non-duality funds. Furthermore, duality managers differ from non-duality managers with respect to their education and experience: Duality managers hold a PhD more often and have more industry experience.

Table 2.2: Descriptive statistics for duality and non-duality funds

Panel A: Fund characteristics

	Duality	Non-duality	Difference
Funds managed	13.73	86.27	
Fund size	894	1,811	-917 ***
Expense ratio	1.70	1.26	0.44 ***
Fund age	16.41	16.79	-0.38
Turnover	92.07	92.92	-0.85

Panel B: Market segments

	Duality	Non-duality	Difference
Aggressive Growth	24.52	22.68	1.84
Growth and Income	16.86	13.29	3.57
Income	6.51	3.54	2.97 **
Growth	42.15	32.87	9.28 ***
Sector	4.60	16.28	-11.68 ***
Utility	0.77	2.13	-1.36
Mid Cap	4.60	9.21	-4.62 **
Total	100.00	100.00	

Panel C: Manager characteristics

	Duality	Non-duality	Difference
Female	1.85	8.71	-6.86 *
MBA	40.74	34.26	6.48
CFA	38.89	50.50	-11.61
PhD	3.70	1.00	2.70 *
Industry tenure	17.85	10.54	7.31 ***

Notes: This table reports summary statistics for funds whose managers also serve as the chair of the board of directors (duality) and for funds whose managers do not (Non-duality). In Panel A, we report the fraction of funds managed (in %), the average fund size as measured by the total net assets in million USD, the average expense ratio (in %), the average fund age in years, and the average fund turnover (in %). Panel B reports the percentage of duality and non-duality funds in the various market segments. Panel C reports the fraction of female managers (in %), the fraction of managers with an MBA (in %), the fraction of managers with a CFA (in %), and the fraction of managers with a PhD (in %). The manager's gender is determined by comparing the manager's first name to a list published by the United States Social Security Administration (SSA) that contains the most popular first names by gender for the last 10 decades. Additionally, we identify the gender of managers with ambiguous first names from several internet sources like the fund prospectus, press releases, or photographs that reveal their gender. We also report the average managers' industry tenure measured in years. To come up with an average industry tenure we first calculate the tenure for each manager. As her starting date in the industry, we take the first year the manager appears in the Morningstar database and as her ending date the last year the manager is in our sample. Thus, we have a single tenure number per manager which we then average to come up with the average value provided in the table. The last column of the table reports the difference in fund and manager characteristics between duality and non-duality funds. ***, **, and * denote statistical significance for the difference in means between both groups at the 1%-, 5%-, and 10%-level, respectively.

2.3 Impact of duality on managerial decisions

In this section, we test our first main hypothesis: Duality managers take more risky decisions than non-duality managers. We use several measures to capture different ways duality managers can take risk: First, we use unsystematic risk as a general measure of risk that could be avoided by diversification. Second, we adopt two measures (stock concentration, industry concentration) to capture the risk coming from taking large bets on specific stocks or industries. The next two measures (active share, tracking error) capture to what degree managers deviate from their benchmark. Finally, we examine whether managers take large bets on specific investment styles.

We calculate the unsystematic risk based on Carhart (1997)'s four-factor model. In each calendar year we regress a fund's excess return on the four factor-mimicking portfolio returns using the twelve monthly return observations of the respective year.[12] The annualized standard deviation of the residual is our measure of unsystematic risk.

We compute the stock concentration as the sum of the squared portfolio weights for all stocks. We do so for each quarter and then average the quarterly stock concentrations to come up with a yearly measure. To calculate the industry concentration we use the same approach but now based on the industry weights. We first sort all stocks into ten industries, as in Kacperczyk, Sialm, and Zheng (2005), and then calculate the weight for a specific industry in a portfolio by summing up the portfolio weights of all stocks belonging to that industry. The sum of the squared industry weights (averaged across the quarters of a year) is our measure of industry concentration.

To measure how a manager deviates from her benchmark, we use the active share and tracking error measures of Cremers and Petajisto (2009) and Petajisto (2013).[13] The active share is calculated as the absolute difference between the portfolio weight of a stock and the stock's weight in the respective benchmark, summed over all positions of the stock universe and divided by two. The tracking error is defined as the residual standard deviation from a regression of excess fund returns on excess benchmark returns.

To measure the extremity of a fund manager's investment style, we again estimate the Carhart (1997) four-factor model for each fund *i* in each year *t* as we did for the unsystematic risk. From this model, we use the sensitivities (beta exposures) regarding the four factors (market factor (MKT), size factor (SMB), value factor (HML), momentum factor (MOM)) to

[12] We downloaded the factor-mimicking portfolio returns for the four-factor model and the risk-free rate from Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[13] We downloaded the active share and tracking error data from Antti Petajisto's website at http://www.petajisto.net/data.html.

capture the fund's investment style. We follow Bär, Kempf, and Ruenzi (2011) and construct extremity measures for a manager's factor sensitivities as:

$$EM_{i,t}^{S} = \frac{|\beta_{i,t}^{S} - \overline{\beta}_{k,t}^{S}|}{\frac{1}{N^{k}} \cdot \sum_{j=1}^{N^{k}} |\beta_{j,t}^{S} - \overline{\beta}_{k,t}^{S}|}. \qquad (2.1)$$

S represents the investment style analyzed (MKT, SMB, HML, and MOM, respectively) and N^{k} gives the number of funds in a specific market segment *k* in a given year *t*. $EM_{i,t}^{S}$ shows high values for funds that strongly deviate in their exposure to a specific style ($\beta_{i,t}^{S}$) from the average exposure of their market segment ($\overline{\beta}_{k,t}^{S}$) in absolute terms. We divide the absolute deviation by the average absolute deviation in the corresponding market segment and respective year to make our style extremity measure comparable across styles, segments, and time. It equals one for the average fund.

We run pooled OLS-regressions and use the respective risk measure as dependent variable:

$$\begin{aligned} Risk_{i,t} = \alpha + \beta D_{i,t}^{Duality} + \gamma_{1} \ln(Size_{i,t-1}) + \gamma_{2} TO_{i,t} + \gamma_{3} FA_{i,t} \\ + \phi_{1} D_{i,t}^{Female} + \phi_{2} D_{i,t}^{MBA} + \phi_{3} D_{i,t}^{CFA} + \phi_{4} D_{i,t}^{PhD} + \phi_{5} Tenure_{i,t} + \varepsilon_{i,t}. \end{aligned} \qquad (2.2)$$

Our main independent variable is the duality dummy which equals one if the manager of a fund also serves as the chair of the board of directors of that fund in the respective year and zero otherwise. We add further variables to control for fund and manager characteristics. At the fund level, we use the logarithm of the fund's lagged size, the fund's yearly turnover ratio (TO), and the fund's age (FA) as control variables in the regression. At the manager level, we use dummies to control for the manager's gender and her educational degrees (MBA, CFA, and PhD). In addition, we use the manager's industry tenure (measured in years) as a control variable. To control for any unobservable time or segment effects that could equally affect all funds in a given year or a particular market segment, respectively, we also include time and segment fixed effects in the regressions. Standard errors are clustered at the fund level. Results are reported in Table 2.3.

Our results clearly support our first main hypothesis: Duality managers take much more risk than non-duality managers. The unsystematic risk of their portfolios is significantly (at 1%-level) higher. The difference of more than 1.3 percentage points is huge given that the total unsystematic risk of non-duality funds is only 3.9 percent (calculated in unreported analysis).

Table 2.3: Managerial decisions

	Unsystematic risk	Stock concentration	Industry concentration	Active share	Tracking error	Style extremity			
						MKT	SMB	HML	MOM
Duality	0.0131 ***	0.0116 ***	0.0249 *	0.1044 ***	0.0310 ***	0.6034 ***	0.3194 ***	0.2955 **	0.3383 ***
	(<0.001)	(0.002)	(0.082)	(<0.001)	(<0.001)	(<0.001)	(0.003)	(0.012)	(<0.001)
Fund characteristics:									
Ln(size)	-0.0011 **	-0.0016 ***	-0.0042 **	-0.0112 ***	-0.0009	-0.0365 **	-0.0462 **	-0.0227	-0.0369 ***
	(0.016)	(<0.001)	(0.019)	(<0.001)	(0.194)	(0.046)	(0.019)	(0.101)	(0.008)
Turnover	0.0055 ***	0.0042 **	0.0117 **	0.0059	0.0068 ***	0.1444 ***	0.1197 ***	0.1670 ***	0.1512 ***
	(<0.001)	(0.033)	(0.013)	(0.332)	(<0.001)	(0.002)	(<0.001)	(0.001)	(<0.001)
Fund age	0.0001	0.0000	0.0000	-0.0003	-0.0000	-0.0005	0.0022	0.0010	0.0004
	(0.216)	(0.318)	(0.795)	(0.489)	(0.748)	(0.817)	(0.292)	(0.576)	(0.807)
Manager characteristics:									
Female	-0.0036	-0.0003	-0.0030	-0.0001	-0.0065 **	-0.0365	0.0567	-0.1587 **	-0.0829
	(0.105)	(0.913)	(0.839)	(0.998)	(0.028)	(0.676)	(0.536)	(0.018)	(0.301)
MBA	0.0012	-0.0031 *	0.0011	-0.0103	0.0026	-0.0455	0.1239 **	0.0247	-0.0174
	(0.387)	(0.055)	(0.888)	(0.405)	(0.333)	(0.402)	(0.027)	(0.646)	(0.727)
CFA	0.0015	-0.0009	-0.0037	0.0405 ***	0.0031	0.0648	0.0161	0.1151 **	0.0335
	(0.238)	(0.563)	(0.601)	(0.002)	(0.224)	(0.215)	(0.753)	(0.027)	(0.506)
PhD	-0.0037	-0.0070	0.0085	-0.0518 *	0.0076	0.6185	-0.0273	0.1103	0.2333
	(0.338)	(0.122)	(0.781)	(0.053)	(0.250)	(0.417)	(0.898)	(0.666)	(0.624)
Industry tenure	-0.0001	0.0001	0.0006	0.0006	0.0001	0.0038	-0.0056	-0.0009	-0.0004
	(0.275)	(0.681)	(0.449)	(0.485)	(0.647)	(0.520)	(0.245)	(0.878)	(0.930)
Observations	1,888	1,782	1,782	1,223	1,223	1,888	1,888	1,888	1,888
Adj. R^2	0.427	0.226	0.786	0.383	0.473	0.092	0.045	0.047	0.060

(Continued)

Table 2.3: Continued

Notes: This table presents results from pooled OLS regressions based on model (2). In the various columns we use unsystematic risk, stock concentration, industry concentration, active share, tracking error, and style extremity as the dependent variable: (1) To measure the fund's unsystematic risk, we first estimate for each fund in each year the Carhart (1997) four-factor model. We then compute the unsystematic risk as the standard deviation of the residuals from the regressions. (2) The stock concentration is measured as the sum of the squared portfolio weights for all stocks in each quarter. We then average the quarterly stock concentrations to come up with a yearly measure. (3) To measure the industry concentration, we follow Kacperczyk, Sialm, and Zheng (2005) and sort all stocks into ten industries and calculate the weight for a specific industry in a portfolio by summing up the portfolio weights of all stocks belonging to that industry. The sum of the squared industry weights (averaged across the quarters of a year) is our measure of industry concentration. (4) We use the active share und tracking error measures of Cremers and Petajisto (2009) and Petajisto (2013). (5) To quantify the style extremity we use the sensitivities (beta exposures) from the Carhart (1997) model regarding the four factors (market factor (MKT), size factor (SMB), value factor (HML), momentum factor (MOM)) to capture the fund's investment style. We then follow the approach of Bär, Kempf, and Ruenzi (2011) and calculate an extremity measure in each year:

$$EM_{i,t}^{S} = \frac{|\beta_{i,t}^{S} - \bar{\beta}_{k,t}^{S}|}{\frac{1}{N^k} \cdot \sum_{j=1}^{N^k} |\beta_{j,t}^{S} - \bar{\beta}_{k,t}^{S}|}$$

where S represents the investment style analyzed (MKT, SMB, HML, and MOM, respectively) and N^k gives the number of funds in a specific market segment k in a given year t. To normalize the extremity measure, we divide it by the average style deviation in the corresponding market segment and respective year. Our main independent variable is the duality dummy which equals one if the fund's manager also serves as the chair of the fund's board of directors and zero otherwise. As fund control variables we use the logarithm of the fund's lagged size (measured in millions USD), the fund's yearly turnover ratio, and the fund's age (measured in years). As manager control variables we use dummies to control for the manager's gender and her educational degrees (MBA, CFA, and PhD) as well as the manager's industry tenure (measured in years). In all regressions we include time fixed effects and segment fixed effects. Robust p-values of the regression coefficients in parentheses are based on standard errors clustered by fund. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Duality managers take this risk by holding more concentrated portfolios, i.e., they take more bets on specific stocks and industries. The difference in stock (industry) concentration is significant at the 1% (10%)-level. Comparing the coefficient of the duality dummy (0.0116) with the average stock concentration measure for non-duality funds (0.0250) shows that the stock concentration of duality funds is almost 50 percent larger than the stock concentration of non-duality funds. The economic dimension can be illustrated with the following example: A non-duality manager would achieve a stock concentration measure of 0.025 if she holds an equally weighted portfolio of 40 stocks. In contrast, the duality manager would have to hold only 27 stocks in her equally weighted portfolio to achieve the concentration measure of 0.037 ($\approx 0.025 + 0.0116$). The difference in industry concentration is less pronounced, but still economically significant. The average value for non-duality funds is 0.2790, meaning that the industry concentration of duality funds is about 10 percent larger than the industry concentration of non-duality funds.

Duality managers also deviate more from their benchmarks than non-duality managers. They take higher active shares and tracking errors. Both differences are statistically significant at the 1%-level, but they are also very significant from an economic point of view. Given the average level of active share (78.55%) and tracking error (5.84%) for non-duality funds, the coefficients for the duality dummy mean that the active share of duality funds is about 13% and the tracking error about 50% larger.

Finally, the results confirm that duality managers follow much more extreme investment styles than non-duality managers. The duality dummy is positive and significant at the 1%-level for three out of four styles (and at the 5%-level for HML). The size of the coefficient is also economically significant. This becomes clear when comparing the coefficients for the duality dummies with the average extremity measures for the non-duality group. The respective numbers are 0.91 for MKT, 0.95 for SMB, 0.96 for HML, and 0.95 for MOM. Thus, the extremity measure is more than 60 percent larger for duality funds than for non-duality funds when looking at the market factor MKT. Putting it differently, only 17% percent of the non-duality managers take as extreme market risk as the average duality manager (calculated in an unreported analysis). The differences are smaller for the other style factors, but still remarkably high: The extremity measures are more than 30 percent larger for duality funds than for non-duality funds when looking at the SMB, HML, and MOM factor, respectively. Since the average style exposure hardly differs between duality and non-duality funds (calculated in an unreported analysis), our results imply that duality managers take extreme style bets in both directions. This means, for example, that some duality managers take a huge amount of market risk while others avoid taking market risk. Some duality managers follow a pure momentum strategy by buying past winners while others do exactly the opposite and follow a contrarian strategy.[14]

Regarding the control variables, we find that a fund's turnover ratio is positively related to a fund's risk and fund size is negatively related to it, consistent with Chevalier and Ellison (1999b) and Bär, Kempf, and Ruenzi (2011). The other fund characteristics and all manager characteristics usually have no significant impact on the risk taking of fund managers.

Overall, the results of our analysis clearly support our first main hypothesis: Duality managers follow much more risky strategies than non-duality managers. They diversify to a lesser degree, are more willing to deviate from their benchmark, and follow more extreme strategies. Such a behavior is highly sensible since it allows duality managers to benefit from good outcomes by receiving bonus packages without bearing a high risk of being fired if the outcomes are bad.

2.4 Impact of duality on manager performance

In this section, we analyze the effect of duality on the performance of managers. In Section 2.4.1 we test the second main hypothesis of our paper: Duality managers deliver worse performance than non-duality managers. Furthermore, we study an implication arising from our results in Table 2.3: Since duality managers follow more extreme investment styles, we expect them to deliver more extreme performance outcomes. We test this hypothesis in Section 2.4.2.

2.4.1 Level of performance

In this section we test our second main hypothesis: Duality funds perform worse than non-duality funds. We use three performance measures: (i) fund return, (ii) Carhart (1997) four-factor alpha, and (iii) the characteristic selectivity measure of Daniel, et al. (1997) which measures performance using holdings data of the fund.[15]

We compute the performance measures (i) and (ii) based on gross fund returns since gross returns measure better the quality of the investment decisions of the fund manager. To calculate a fund's gross returns, we divide a fund's yearly expense ratio by twelve and add it back to the fund's monthly net return observations. By construction, the characteristic

[14] Only the exposure to the size factor is significantly (at the 10%-level) larger for duality funds.

[15] The data on the characteristic benchmarks are taken from Russ Wermer's website, http://www.rhsmith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

selectivity measure (iii) is not influenced by a fund's expense ratio and, thus, also measures the quality of the investment decisions of the manager.

The three performance measures differ with respect to their risk adjustment. The return measure is not adjusted for fund risk at all. The Carhart (1997) four-factor model is adjusted for risk using a linear factor structure, and the characteristic selectivity (CS) measure captures risk by benchmarking the fund with a characteristic-matched portfolio of stocks.

The Carhart (1997) alpha is the constant from the four-factor model, estimated as in Section 2.3. In our regressions, we use the annualized alpha. The CS measure for a fund in month τ is calculated as:

$$CS_{\tau} = \sum_{j=1}^{N} w_{j,\tau-1}\left(r_{j,\tau} - r_{j,\tau}^{b}\right). \tag{2.3}$$

$w_{j,\tau-1}$ is the portfolio weight of stock j at the end of month $\tau - 1$, $r_{j,\tau}$ is the return of stock j in month τ and $r_{j,\tau}^{b}$ is the return of the characteristic benchmark matching stock j. Since portfolio holdings are available only quarterly, we have no monthly updates of the fund holdings and, thus, use the most recent portfolio holdings to calculate $w_{j,\tau-1}$. We then compound the monthly CS observations to get a yearly measure.

We conduct multivariate regressions as in the previous section, but now use the annualized performance measures as dependent variables in the regressions. Our main independent variable is again the duality dummy which equals one if the fund's manager also serves as the chair on the fund's board of directors in the respective year and zero otherwise. The control variables are the same as in Section 2.3. We again control for time and segment fixed effects in the regressions. Standard errors are clustered at the fund level. Results are provided in Table 2.4.

The results of the multivariate regressions (Panel A of Table 2.4) support our second main hypothesis: Duality funds achieve significantly worse performance than non-duality funds. The returns differ by 1.2 percent per year after controlling for fund and manager characteristics. This is a huge number given that the average gross return of non-duality funds is only 6.3 percent per year (calculated in unreported analysis).

Table 2.4: Performance

Panel A: Multivariate regressions

	Return	Carhart alpha	CS
Duality	-0.0119 *	-0.0226 ***	-0.0253 ***
	(0.072)	(0.003)	(<0.001)
Fund characteristics:			
Ln(size)	-0.0009	-0.0024 **	-0.0026 **
	(0.410)	(0.033)	(0.012)
Turnover	-0.0040	-0.0179 ***	-0.0057 **
	(0.175)	(<0.001)	(0.033)
Fund age	0.0003 **	0.0000	0.0001
	(0.015)	(0.736)	(0.209)
Manager characteristics:			
Female	-0.0085	-0.0042	-0.0034
	(0.277)	(0.548)	(0.608)
MBA	0.0103 **	-0.0029	0.0032
	(0.021)	(0.540)	(0.442)
CFA	0.0082 *	0.0022	0.0073 **
	(0.056)	(0.609)	(0.046)
PhD	0.0137	0.0231	0.0490 **
	(0.437)	(0.248)	(0.030)
Industry tenure	-0.0004	-0.0001	0.0004
	(0.355)	(0.862)	(0.458)
Observations	1,888	1,888	1,716
Adj. R^2	0.841	0.068	0.149

Panel B: Matched sample

Matching characteristics	Observations	Return	Carhart alpha	CS
Year, segment, and size	254	-0.0168 **	-0.0210 ***	-0.0175 ***
		(0.019)	(0.007)	(0.002)
Year, segment, size, and turnover	186	-0.0215 **	-0.0337 ***	-0.0259 ***
		(0.035)	(0.002)	(0.001)
Year, segment, size, and tenure	185	-0.0190 **	-0.0253 **	-0.0220 ***
		(0.040)	(0.013)	(0.001)
Year, segment, size, and MBA	226	-0.0290 ***	-0.0256 ***	-0.0215 ***
		(0.001)	(0.005)	(0.001)
Year, segment, size, and CFA	233	-0.0187 **	-0.0210 **	-0.0179 ***
		(0.022)	(0.015)	(0.004)

Notes: This table reports performance differences between duality funds and non-duality funds using three different performance measures: (1) Return, (2) Carhart (1997) four-factor alpha, and the (3) characteristic selectivity measure (CS) of Daniel, et al. (1997). Performance measures are calculated using gross-of-fee returns. Panel A shows results from pooled OLS regressions like equation (2.2) with yearly performance measures being the dependent variables now. The main independent variable is again the duality dummy which is defined as in Table 2.3. The control variables are also the same as in Table 2.3. All regression specifications include time fixed effects and segment fixed effects. Robust p-values of the regression coefficients in parentheses are based on standard errors clustered by fund. Panel B presents results from a matched sample analysis where we match each duality fund with an equally weighted portfolio of non-duality funds using the following matching characteristics: Year, segment, fund size, turnover, tenure, and fund managers' education (MBA or CFA). In our base case, shown in the first row, we link a duality fund to all non-duality funds belonging to the same market segment and the same fund-size decile in a specific year. In the second and third row we use a fund's turnover-quintile and a manager's tenure-quintile in a specific year as additional matching criteria. In the last two rows, we use the information of whether the manager holds an MBA or a CFA as additional matching criteria. We then test whether the performance difference between duality funds and their respective matching non-duality fund portfolio is different from zero. The corresponding p-values are in parentheses. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Using the risk-adjusted performance measures, the difference between duality and non-duality funds becomes even bigger. It is about 2.3 percent per year based on the Carhart (1997) four-factor alpha and about 2.5 percent per year based on the characteristic selectivity measure of Daniel, et al. (1997). The performance levels show that non-duality funds deliver a positive risk-adjusted performance before costs (alpha= 1.61%, CS= 0.56%) whereas duality funds deliver a negative performance – even before costs.

Regarding the control variables, we find a negative influence of fund size and turnover on performance in most specifications and CFA managers seem to deliver a slightly better performance. The other control variables are significant only sporadically.

To check the robustness of our results, we conduct a matched-sample comparison between duality and non-duality funds. We match each duality fund with an equally weighted portfolio of non-duality funds that match the duality fund with respect to various matching criteria. In our base case we match funds based on fund segment, year, and fund size. We use fund size as a basic sorting criterion since size has been shown to have an impact on fund performance (see, e.g., Berk and Green (2004), Chen, et al. (2004), and our results in Panel A). Thus, we link a duality fund to all non-duality funds belonging to the same market segment and the same fund-size decile in a specific year. In the base case, we find a matching portfolio for almost all duality funds. The number of fund-year observations goes down only from 261 to 254 when applying the year-segment-size matching criterion.

We also use additional matching criteria to further account for factors that have been shown to influence fund performance in the literature. We add fund turnover, as Carhart (1997) and Chen, et al. (2004) have shown that turnover has a negative impact on fund performance (see also our results in Panel A). Given the empirical evidence of Golec (1996), we also use industry tenure as an additional matching criterion. Thus, we link a duality fund to all non-duality funds belonging to the same market segment and the same fund-size decile and the same turnover-quintile (tenure-quintile) in a specific year. We use quintiles for these additional sorting criteria since the number of matches goes down by another one third if we use deciles instead. As additional matching criteria we use the information whether the manager holds either an MBA or a CFA. We apply these additional sorting criteria since various studies (see, e.g., Golec (1996), Gottesman and Morey (2006), Fang, Kempf, and Trapp (2014)) have documented that manager education has an impact on fund performance.

For each duality fund and its matching non-duality fund portfolio we calculate the same performance measures as above. The average performance differential between duality funds and their respective matching non-duality fund portfolio are provided in Panel B of Table 2.4 for the various matching criteria. The results are remarkably strong. In all 15 cases the performance differential is significantly negative, i.e., duality funds deliver worse performance than comparable non-duality funds. The level of the underperformance is similar to the level reported in Panel A.

Overall, our results clearly support our second main hypothesis: Duality managers deliver a worse performance than non-duality managers. Thus, our findings with respect to average performance in the fund industry are similar to findings in other industries as documented by, e.g., Rechner and Dalton (1991), Brickley, Coles, and Jarrell (1997).

2.4.2 Performance extremity

After having tested for the impact of manager duality on the level of performance, we now turn to the impact on the extremity of performance. Since duality managers take more extreme decisions (see Section 2.3) and these decisions determine the performance outcome, we hypothesize that duality managers also deliver more extreme performance outcomes.

We follow Bär, Kempf, and Ruenzi (2011) and calculate the extremity measure EM^P in each year as:

$$EM_{i,t}^{P} = \frac{|P_{i,t} - \overline{P}_{k,t}|}{\frac{1}{N^k} \cdot \sum_{j=1}^{N^k} |P_{j,t} - \overline{P}_{k,t}|}. \tag{2.4}$$

P stands for the respective performance measure and $\overline{P}$ for the average performance of all funds in the same market segment. We measure the performance extremity EM^P as the absolute deviation of a fund’s performance from the average performance of all funds in the same market segment and divide it by the average absolute deviation of all funds in the segment. Thus, the average fund has an extremity measure of one, by definition.

To analyze whether the performance extremity measures differ for duality and non-duality funds, we run regressions where the performance extremity measures are the dependent variables. The most important independent variable in the regressions is again the duality dummy and the control variables are the same as before. Table 2.5 clearly shows that duality managers deliver much more extreme performance outcomes than non-duality managers.

Table 2.5: Performance extremity

	Return extremity	Carhart alpha extremity	CS extremity
Duality	0.3630 ***	0.4757 ***	0.3954 ***
	(<0.001)	(<0.001)	(<0.001)
Fund characteristics:			
Ln(size)	-0.0335 ***	-0.0427 ***	-0.0428 ***
	(0.009)	(0.001)	(0.006)
Turnover	0.1958 ***	0.2473 ***	0.0850 **
	(<0.001)	(0.002)	(0.036)
Fund age	-0.0008	0.0012	-0.0003
	(0.638)	(0.481)	(0.885)
Manager characteristics:			
Female	-0.1406 **	-0.0181	-0.1040
	(0.023)	(0.832)	(0.148)
MBA	-0.0193	0.0617	0.0357
	(0.668)	(0.216)	(0.531)
CFA	0.1207 ***	0.0299	0.1377 ***
	(0.006)	(0.545)	(0.009)
PhD	0.1358	-0.1971	0.0931
	(0.558)	(0.352)	(0.719)
Industry tenure	0.0026	-0.0035	-0.0048
	(0.488)	(0.466)	(0.477)
Observations	1,888	1,888	1,716
Adj. R^2	0.089	0.105	0.039

Notes: This table reports results from pooled OLS regressions like equation (2.2) with yearly performance extremity measures now the dependent variables. To quantify performance extremity we follow the approach of Bär, Kempf, and Ruenzi (2011) and calculate an extremity measure EM^P in each year. We measure the performance extremity EM^P as the absolute deviation of a fund's performance from the average performance of all funds in the same market segment and divided by the average absolute deviation of all funds in the segment:

$$EM_{i,t}^{P} = \frac{|P_{i,t} - \bar{P}_{k,t}|}{\frac{1}{N^k} \cdot \sum_{j=1}^{N^k} |P_{j,t} - \bar{P}_{k,t}|}$$

where P denotes the respective performance measure. The main independent variable is again the duality dummy which is defined as in Table 2.3. The control variables are also the same as in Table 2.3. All regression specifications include time fixed effects and segment fixed effects. Robust p-values of the regression coefficients in parentheses are based on standard errors clustered by fund. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

The difference is highly significant in both a statistical and economic sense. The coefficient for the duality dummy is different from zero at the 1%-level in all cases, and the size of the coefficient is huge given that the performance extremity of non-duality funds is about 0.94 for all performance measures, on average (calculated in unreported analysis). These extreme performance outcomes might make duality funds attractive for investors who otherwise gamble in the stock market and invest in lottery-stocks (see, e.g., Kumar (2009)). The control variables have an impact similar to that in Table 2.3 where we look at the impact of duality on managerial decisions. A high fund's turnover ratio is related to risky behavior and extreme performance outcomes. In contrast, fund size is negatively related to risky behavior and performance extremity. Both findings are consistent with Bär, Kempf, and Ruenzi (2011).

2.5 Alternative explanations

In this section, we test alternative explanations for our main results. We start by checking whether our analysis is plagued by an endogeneity problem. For example, one might imagine that a fund company wants to offer a fund with a risky investment style for some exogenous reason and, therefore, wants to leave the fund manager flexibility in decision making by appointing her as fund manager and chair of the fund's board. Then, we would have a causality issue in our analysis. We rule out this possibility by adopting an instrumental variable approach using two-stage least squares regressions in Section 2.5.1.

Our first main result (duality fund managers take more risky decisions) might just reflect the fact that duality funds are less constrained for some reason. Although this would not be consistent with the equilibrium argument of Almazan, et al. (2004), it is certainly possible. To rule out this possibility, we control for investment constraints of funds in Section 2.5.2.

For our second main result (duality fund managers deliver worse performance) we test two alternative explanations. First, the result might occur only because our sample period covers the recent financial crisis. Since duality managers take more risk and markets went down in the financial crisis, the high-risk strategy might have destroyed the performance of the duality managers. To control for the impact of the financial crisis, we look at the pre-crisis period and the crisis period separately in Section 2.5.3. Second, we test whether our performance result is caused by a family size effect. If duality managers are more prevalent among smaller fund families and if smaller fund families underperform, as suggested by Chen, et al. (2004), the underperformance of duality funds might be a simple family size effect. To rule out this possibility, we control for family size in Section 2.5.4.

The following sections clearly show that our main results are not caused by these alternative explanations. All our findings remain robust.

2.5.1 Causality

To address the causality problem, we adopt an instrumental variable approach using two-stage least squares regressions (2SLS) as in Ferris and Yan (2007) and Adams, Mansi, and

Nishikawa (2010). We use a firm's complexity as our instrumental variable since the governance structure is known to be related to a firm's complexity (see, e.g., Linck, Netter, and Yang (2008)) and since we do not expect the firm's complexity to have an impact on the performance and investment decisions of the managers of individual funds except through its impact on the governance structure. To measure complexity we follow the idea of Boone, et al. (2007) that the complexity of a firm increases with the number of market segments in which the firm is active and with its age. Therefore, we use the number of investment objectives for each fund family and the age of the fund family as our instrumental variables.[16]

In the first stage of the 2SLS procedure we relate the duality dummy to our instrument variables as well as fund characteristics (log of lagged fund size, turnover, fund age) and manager characteristics (female dummy, MBA dummy, CFA dummy, PhD dummy, industry tenure). We also allow for segment and time fixed effects. The first-stage results (not reported in detail for sake of brevity) confirm that our instrumental variables are well suited. The F-statistic takes a value of at least 30, suggesting that the instrumental variables are highly relevant. Looking at the instrumental variables separately shows that the number of investment objectives has a significantly negative impact on duality (at the 1%-level) whereas family age is not significant at conventional levels.[17] Thus, our results of the first stage suggest that fund families with low complexity tend to choose the duality structure.

In the second stage we re-run our analyses using the fitted value of the first stage instead of the duality dummy. The second stage results are presented in Table 2.6. For sake of brevity we only report the results for the duality dummy but not for the controls. The Hansen J-statistics suggest that the instruments used are appropriately uncorrelated with the disturbance terms. The results of the two-stage regressions all confirm the main conclusions drawn earlier: Duality managers take more risky decisions (Panel A), deliver worse performance (Panel B) and achieve more extreme performance outcomes (Panel C). The Duality dummy has the hypothesized sign and is significant at the 1% level in all cases. This suggests that our main results are not flawed by an endogeneity problem.

[16] Ferris and Yan (2007) and Adams, Mansi, and Nishikawa (2010) use the same variables but use fund turnover and manager tenure as additional instrumental variables. We leave the latter out since we expect them to be directly linked to managerial decisions and performance. See our results in the previous sections and the empirical evidence provided by Carhart (1997), Chen, et al. (2004), Chevalier and Ellison (1999b), and Golec (1996).

[17] Therefore, we run a second specification leaving out family age as instrumental variable. The first and second stage results remain qualitatively the same.

Table 2.6: Second stage regressions

Panel A: Managerial decisions

	Unsystematic risk	Stock concentration	Industry concentration	Active share	Tracking error	Style extremity MKT	Style extremity SMB	Style extremity HML	Style extremity MOM
Duality	0.0227 ***	0.0282 ***	0.1156 ***	0.3181 ***	0.072 ***	1.2948 ***	0.7848 ***	0.9007 ***	0.7208 ***
	(<0.001)	(<0.001)	(0.002)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
J-statistic	0.006	3.476 *	1.721	0.848	1.399	2.436	0.212	0.171	0.060
	(0.939)	(0.062)	(0.189)	(0.357)	(0.237)	(0.119)	(0.646)	(0.679)	(0.807)
Observations	1,888	1,782	1,782	1,223	1,223	1,888	1,888	1,888	1,888
Adj. R^2	0.415	0.179	0.769	0.192	0.362	0.043	0.020	0.006	0.042

Panel B: Performance

	Return	Carhart alpha	CS
Duality	-0.0419 ***	-0.0520 ***	-0.0577 ***
	(0.007)	(0.002)	(<0.001)
J-statistic	0.623	0.072	2.013
	(0.430)	(0.789)	(0.156)
Observations	1,888	1,888	1,716
Adj. R^2	0.840	0.059	0.136

Panel C: Performance extremity

	Return extremity	Carhart Alpha extremity	CS extremity
Duality	0.9023 ***	0.9038 ***	1.1972 ***
	(<0.001)	(<0.001)	(<0.001)
J-statistic	0.022	0.063	0.002
	(0.882)	(0.802)	(0.969)
Observations	1,888	1,888	1,716
Adj. R^2	0.053	0.087	-0.035

Notes: This table reports results of the second stage from two-stage least squared (2SLS) regressions. In the first stage, we relate the duality dummy to our instrumental variables and the same control variables as in Table 2.3. As instrumental variables we use the number of investment objectives for each fund family and the family's age. In the second stage, we relate several dependent variables to the fitted value of the first stage (instead of the duality dummy) and to the control variables of Table 2.3. In Panel A the dependent variables are the managerial decision measures defined as in Table 2.3. In Panel B the dependent variables are the performance measures defined as in Table 2.4. In Panel C the dependent variables are the performance extremity measures defined as in Table 2.5. All regression specifications include time fixed effects and segment fixed effects. For sake of brevity, we only report the coefficients for the fitted value and the corresponding J-Statistic. Robust p-values in parentheses are based on standard errors clustered by fund. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

2.5.2 Impact of constraints

To test whether the higher risk taking of duality managers results from facing fewer constraints, we hand-collected constraint information from the N-SAR reports of the funds and matched them to CRSP as in Christoffersen, Evans, and Musto (2013). In the N-SAR reports the fund managers have to answer (yes/no) whether the investment policy allows pre-specified investment practices. We collect this information for the same investment practices as Almazan, et al. (2004): borrowing of money, margin purchases, short selling, writing or investing in options on equities, writing or investing in stock index futures, and investments in restricted securities. The first three restrictions affect the funds' ability to use leverage, the next two the use of derivatives, and the final one their ability to invest in illiquid assets. Based on this information we calculate the aggregate constraint score for each fund in each year as in Almazan, et al. (2004).[18]

In Table 2.7 we provide information about the restrictedness of funds. We report the percentage of restricted funds for each investment practice and the average aggregate constraint score. We do so separately for duality funds and non-duality funds.

Table 2.7: Restrictedness of funds

	Percentage of restricted funds		
Investment practice	Duality	Non-duality	Difference
Borrow	0.294	0.109	0.186 ***
Margin	0.892	0.832	0.060 **
Short	0.537	0.357	0.179 ***
Options	0.229	0.040	0.190 ***
Futures	0.494	0.094	0.400 ***
Restricted	0.255	0.041	0.215 ***
Score	0.397	0.180	0.217 ***

Notes: This table reports the percentage of restricted duality and non-duality funds with respect to the following investment practices: borrowing of money, margin purchases, short selling, writing or investing in options on equities, writing or investing in stock index futures, and investments in restricted securities. The aggregate constraint score presented in the last row is calculated as in Almazan, et al. (2004). The last column of the table reports the difference in the restrictedness for each investment practice between duality and non-duality funds. ***, **, and * denote statistical significance for the difference in means at the 1%-, 5%-, and 10%-level, respectively.

Although Table 2.7 rules out the possibility that duality managers are able to take more risk due to lower constraints, we check the general impact of constraints on our results by adding

[18] The score is calculated in the following way: Within each category of restrictions (use of leverage, use of derivatives, investing in illiquid assets), we first calculate the within-category score as the proportion of restricted activities in that category. The overall restriction score is obtained by equally weighting the three within-category scores.

the overall constraint score as an additional control variable in our multivariate regressions. The results are provided in Table 2.8. For sake of brevity we report only the results for the duality dummy and the constraint score, but not for the remaining control variables. They have the same qualitative impact as in the earlier tables.

Table 2.8 shows that our main results do not change when controlling for the restrictedness of funds. The constraint score has hardly ever a significant impact in the regressions. The conclusions of our analysis remain unchanged: Duality managers take more risky decisions (Panel A) and deliver worse (Panel B) and more extreme (Panel C) performance outcomes.

2.5.3 Impact of financial crisis

To rule out the possibility that duality funds deliver worse performance only because our sample period covers the financial crisis, we divide our sample in two sub-samples. The first sub-sample covers the pre-crisis years 2005 and 2006 and the second sub-sample covers the crisis years 2008 and 2009.[19] Results are presented in Table 2.9.

We first look at Panel B of Table 2.9, which shows the impact of duality on performance separately for the pre-crisis and the crisis period. The duality variable has a negative sign for all performance measures in the pre-crisis period as well as in the crisis period. In each period, the coefficient is significant in two (out of three) cases. This suggests that our finding that duality fund managers deliver a worse performance than non-duality fund managers is not driven by the financial crisis.

The other panels of Table 2.9 show that our results with respect to the investment behavior of managers hold for the pre-crisis period as well as for the crisis period: Duality managers take more risk (Panel A), and consequently deliver more extreme performance outcomes (Panel C).

Overall, the results of this section clearly show that our main findings in Section 2.3 and 2.4 are not driven by the financial crisis.

[19] We leave out year 2007 since the financial crisis started in this year and it is not clear whether to classify year 2007 as a pre-crisis or a crisis year. As a robustness check we run the analysis also counting year 2007 as a pre-crisis year or as a crisis year; the results remain qualitatively unchanged.

Table 2.8: Impact of constraints

Panel A: Managerial decisions

	Unsystematic risk	Stock concentration	Industry concentration	Active share	Tracking error	Style extremity MKT	Style extremity SMB	Style extremity HML	Style extremity MOM
Duality	0.0128 ***	0.0129 ***	0.0268 *	0.0933 ***	0.0282 ***	0.5528 ***	0.2996 **	0.3395 ***	0.3180 ***
	(<0.001)	(0.001)	(0.064)	(<0.001)	(<0.001)	(<0.001)	(0.012)	(0.001)	(0.002)
Constraint score	0.0063	0.0047	0.0251	0.0615 **	0.023 ***	0.2618	0.2290	0.1941	0.1421
	(0.165)	(0.374)	(0.353)	(0.047)	(0.003)	(0.148)	(0.142)	(0.424)	(0.387)
Observations	1,632	1,544	1,544	1,087	1,087	1,632	1,632	1,632	1,632
Adj. R^2	0.423	0.212	0.774	0.404	0.494	0.089	0.048	0.048	0.063

Panel B: Performance

	Return	Carhart alpha	CS
Duality	-0.0086	-0.0242 ***	-0.0243 ***
	(0.204)	(0.005)	(0.001)
Constraint score	0.0059	0.0005	0.0128
	(0.606)	(0.965)	(0.242)
Observations	1,632	1,632	1,488
Adj. R^2	0.844	0.073	0.139

Panel C: Performance extremity

	Return extremity	Carhart Alpha extremity	CS extremity
Duality	0.3465 ***	0.5325 ***	0.4428 ***
	(<0.001)	(<0.001)	(<0.001)
Constraint score	0.2231	0.0323	0.1035
	(0.104)	(0.846)	(0.497)
Observations	1,632	1,632	1,488
Adj. R^2	0.081	0.116	0.042

Notes: This table presents results from pooled OLS regressions using various dependent variables: In Panel A the dependent variables are the managerial decision measures defined as in Table 2.3. In Panel B the dependent variables are the performance measures defined as in Table 2.4. In Panel C the dependent variables are the performance extremity measures defined as in Table 2.5. The main independent variable is again the duality dummy which is defined as in Table 2.3. Furthermore, we use the constraint score and the control variables of Table 2.3 as independent variables. The constraint score for each fund in each year is calculated as in Almazan, et al. (2004). All regression specifications include time fixed effects and segment fixed effects. For sake of brevity, we only report the coefficients for the duality dummy and the constraint score. Robust p-values of the regression coefficients in parentheses are based on standard errors clustered by fund. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

Table 2.9: Impact of financial crisis

Panel A: Managerial decisions

	Unsystematic risk	Stock concentration	Industry concentration	Active share	Tracking error	Style extremity			
						MKT	SMB	HML	MOM
Duality in pre-crisis period	0.0150 ***	0.0099 **	0.0261	0.1026 ***	0.0237 ***	0.5733 ***	0.3902 **	0.3506 **	0.3034 **
	(<0.001)	(0.012)	(0.126)	(<0.001)	(<0.001)	(<0.001)	(0.017)	(0.017)	(0.029)
Observations	810	780	780	520	520	810	810	810	810
Adj. R^2	0.417	0.245	0.765	0.413	0.351	0.143	0.045	0.051	0.028
Duality in crisis period	0.0128 ***	0.0136 **	0.0237	0.0950 ***	0.0434 ***	0.6745 ***	0.1919	0.0870	0.2884 **
	(0.001)	(0.020)	(0.149)	(<0.001)	(<0.001)	(0.002)	(0.141)	(0.626)	(0.024)
Observations	650	595	595	440	440	650	650	650	650
Adj. R^2	0.394	0.195	0.814	0.353	0.236	0.101	0.036	0.053	0.126

Panel B: Performance

	Return	Carhart alpha	CS
Duality in pre-crisis period	-0.0214 ***	-0.0186	-0.0179 **
	(0.005)	(0.117)	(0.046)
Observations	810	810	772
Adj. R^2	0.136	0.037	0.106
Duality in crisis period	-0.0045	-0.0425 ***	-0.0372 ***
	(0.668)	(0.001)	(<0.001)
Observations	650	650	568
Adj. R^2	0.924	0.108	0.157

Panel C: Performance extremity

	Return extremity	Carhart alpha extremity	CS extremity
Duality in pre-crisis period	0.3835 ***	0.5180 ***	0.5100 ***
	(0.001)	(<0.001)	(0.002)
Observations	810	810	772
Adj. R^2	0.091	0.086	0.063
Duality in crisis period	0.4101 ***	0.3964 ***	0.2361 *
	(0.003)	(0.005)	(0.074)
Observations	650	650	568
Adj. R^2	0.163	0.158	0.038

Notes: This table presents results from pooled OLS regressions for two sub-samples and various dependent variables. The first sub-sample covers the pre-crisis years 2005 and 2006 and the second sub-sample covers the crisis years 2008 and 2009. In Panel A the dependent variables are the managerial decision measures defined as in Table 2.3. In Panel B the dependent variables are the performance measures defined as in Table 2.4. In Panel C the dependent variables are the performance extremity measures defined as in Table 2.5. The main independent variable is again the duality dummy which is defined as in Table 2.3. The control variables are the same as in Table 2.3. All regression specifications include time fixed effects and segment fixed effects. For sake of brevity, we only report the coefficients for the duality dummy. Robust p-values of the regression coefficients in parentheses are based on standard errors clustered by fund. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

2.5.4 Impact of family size

We now test whether our second main result (duality funds deliver worse performance) is caused by a family size effect. If duality managers are more prevalent among smaller fund families and if smaller fund families underperform as suggested by Chen, et al. (2004), the underperformance of duality funds might just be a family size effect.

When comparing the size of fund families that do not offer duality funds among their single-managed funds (non-duality families) with those which do (duality families), we indeed find remarkable differences. Non-duality families are far larger than duality families. The average total net assets of a non-duality family (calculated as the total net assets of all team- and single-managed mutual funds in the family) is 114,088 Mio. USD whereas the respective number for a duality family is only 3,505 Mio. USD. The difference is significant at the 1%-level. To check whether these differences in family characteristics explain our results, we re-run our multivariate regressions but now use family size (measured as total net assets of a family) as an additional control variable.

The results for the main variables are presented in Table 2.10. Panel B of Table 2.10 shows that the duality effect on performance is not a family size effect in disguise. Even after controlling for family size, duality funds deliver a worse performance than non-duality funds. The coefficient for the duality dummy is negative in all cases and significant based on risk-adjusted performance measures. Furthermore, Panel B provides no convincing evidence that fund performance is positively related to family size as in Chen, et al. (2004). Although the respective coefficients are positive in all models of Panel B, only one of them is marginally significant.[20]

Looking at the relation between family size and managerial decision taking (Panel A) we find that managers behave more carefully in large fund families, which is consistent with Chevalier and Ellison (1999b) who show that the risk of being laid off is higher in large families. Nevertheless, our results with respect to the decisions of duality managers remain unchanged: Duality funds take more risky decisions (Panel A) and deliver more extreme performance outcomes (Panel C).

[20] When using the number of funds in a family as an alternative proxy for family size, our results remain qualitatively the same.

Table 2.10: Impact of family size

Panel A: Managerial decisions

	Unsystematic risk	Stock concentration	Industry concentration	Active share	Tracking error	Style extremity MKT	Style extremity SMB	Style extremity HML	Style extremity MOM
Duality	0.0110 ***	0.0091 **	0.0143	0.0721 ***	0.0252 ***	0.5003 ***	0.2009 *	0.1882 *	0.2822 ***
	(<0.001)	(0.013)	(0.339)	(<0.001)	(<0.001)	(<0.001)	(0.051)	(0.099)	(0.003)
Ln(family size)	-0.0009 **	-0.0011 ***	-0.0045 **	-0.0146 ***	-0.0026 ***	-0.0431 ***	-0.0496 ***	-0.0449 ***	-0.0235 **
	(0.010)	(0.004)	(0.044)	(<0.001)	(<0.001)	(0.001)	(<0.001)	(<0.001)	(0.029)
Observations	1,888	1,782	1,782	1,223	1,223	1,888	1,888	1,888	1,888
Adj. R^2	0.432	0.234	0.788	0.419	0.492	0.100	0.057	0.056	0.063

Panel B: Performance

	Return	Carhart alpha	CS
Duality	-0.0086	-0.0179 **	-0.0220 ***
	(0.214)	(0.021)	(0.002)
Ln(family size)	0.0014	0.0019 *	0.0014
	(0.161)	(0.067)	(0.163)
Observations	1,888	1,888	1,716
Adj. R^2	0.841	0.069	0.150

Panel C: Performance extremity

	Return extremity	Carhart Alpha extremity	CS extremity
Duality	0.2720 ***	0.3933 ***	0.2613 **
	(0.001)	(<0.001)	(0.018)
Ln(family size)	-0.0381 ***	-0.0345 ***	-0.0587 ***
	(<0.001)	(0.002)	(<0.001)
Observations	1,888	1,888	1,716
Adj. R^2	0.097	0.110	0.055

Notes: This table presents results from pooled OLS regressions using various dependent variables: In Panel A the dependent variables are the managerial decision measures defined as in Table 2.3. In Panel B the dependent variables are the performance measures defined as in Table 2.4. In Panel C the dependent variables are the performance extremity measures defined as in Table 2.5. The main independent variable is again the duality dummy which is defined as in Table 2.3. Furthermore, we use the natural logarithm of a fund's family lagged total net assets and the control variables of Table 2.3 as independent variables. All regression specifications include time fixed effects and segment fixed effects. For sake of brevity, we only report the coefficients for the duality dummy and the family size. Robust p-values of the regression coefficients in parentheses are based on standard errors clustered by fund. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

2.6 Impact of the power of the manager

In this section we test whether the strength of the behavior and performance effects depends on the power the fund manager has in the board. In particular, we test two hypotheses: (i) The effect is weaker if the manager is an ordinary member of the board, but not chairing the board. (ii) The effect is weaker if the influence of independent directors in the board is stronger. The first hypothesis is tested in Section 2.6.1, the second in Section 2.6.2.

2.6.1 Fund manager as ordinary member of the board

The chair takes the most prominent position in the board since she leads the questioning of the management's decisions, evaluates the manager, reports the findings to the board, and influences how issues are presented (see, e.g., Barclift (2011)). Therefore, the manager's impact on the board is stronger if she acts as chair (what we define as duality) compared to being only an ordinary member of the board.

We now define two dummy variables to differentiate between fund managers who are chair of the board (duality dummy) and fund managers who are ordinary members of the board (board member dummy). The base group consists of the funds in which the manager is not a member of the board. We thus extend our multivariate regression models by adding the board member dummy. The results are provided in Table 2.11.The bottom line of Table 2.11 is that it makes a difference whether the fund manager is an ordinary member of the board or its chair.

Looking at the managerial decisions (Panel A), we find that both duality managers and board member managers tend to take more risky decisions than managers who are not members of the board. However, the effect is much stronger for duality members. All coefficients are significant at the 1%- or 5%-level for duality managers, but only five (out of nine) coefficients are significant for ordinary board member managers.

Looking at the performance consequences shows even more pronounced differences: We again find a strong negative impact of manager duality on fund performance in all cases, but there is no significantly negative impact on performance if the manager is only an ordinary member of the board (Panel B). With respect to performance extremity (Panel C), we find results consistent with the behavioral results in Panel A: Both groups tend to deliver more extreme performance outcomes, but the effect is much stronger for duality managers than for board member managers.

Table 2.11: Managerial power: board chair versus ordinary board member

Panel A: Managerial decisions

	Unsystematic risk	Stock concentration	Industry concentration	Active share	Tracking error	Style extremity			
						MKT	SMB	HML	MOM
Duality	0.0132 ***	0.0124 ***	0.0303 **	0.1103 ***	0.0328 ***	0.6553 ***	0.3317 ***	0.3319 ***	0.3646 ***
	(<0.001)	(0.001)	(0.030)	(<0.001)	(<0.001)	(<0.001)	(0.002)	(0.004)	(<0.001)
Board member	0.0015	0.0076 ***	0.0532 *	0.0666 ***	0.0203 ***	0.5462 ***	0.1289	0.3829	0.2766
	(0.681)	(0.006)	(0.087)	(0.003)	(0.005)	(0.001)	(0.397)	(0.111)	(0.116)
Observations	1,888	1,782	1,782	1,223	1,223	1,888	1,888	1,888	1,888
Adj. R^2	0.427	0.228	0.788	0.388	0.481	0.101	0.045	0.051	0.063

Panel B: Performance

	Return	Carhart alpha	CS
Duality	-0.0158 **	-0.0271 ***	-0.0240 ***
	(0.024)	(0.001)	(<0.001)
Board member	-0.0140	-0.0171	0.0127
	(0.211)	(0.156)	(0.457)
Observations	1,888	1,888	1,716
Adj. R^2	0.839	0.072	0.149

Panel C: Performance extremity

	Return extremity	Carhart alpha extremity	CS extremity
Duality	0.3836 ***	0.4958 ***	0.4214 ***
	(<0.001)	(<0.001)	(<0.001)
Board member	0.2165 *	0.2111	0.2574
	(0.074)	(0.222)	(0.225)
Observations	1,888	1,888	1,716
Adj. R^2	0.091	0.106	0.040

Notes: This table presents results from pooled OLS regressions using various dependent variables: In Panel A the dependent variables are the managerial decision measures defined as in Table 2.3. In Panel B the dependent variables are the performance measures defined as in Table 2.4. In Panel C the dependent variables are the performance extremity measures defined as in Table 2.5. The main independent variable is again the duality dummy which is defined as in Table 2.3. In addition, we use a board member dummy that equals one if the fund's manager is a board member but the chair of the board and zero otherwise and the control variables of Table 2.3 as independent variables. All regression specifications include time fixed effects and segment fixed effects. For sake of brevity, we only report the coefficients for the duality dummy and the board member dummy. Robust p-values of the regression coefficients in parentheses are based on standard errors clustered by fund. ***, **, and * denote statistical significance at the 1%-, 5%- and 10%-level, respectively.

Overall, our findings suggest that managers who are members of the board behave differently from managers who are not board members. They tend to take more risky decisions and deliver lower and more extreme performance outcomes. However, all effects are much stronger when the manager is not just an ordinary member of board, but its chair. This suggests that it matters how much power the manager has in the board.

2.6.2 Independent members of the board

Several studies suggest that board independence goes along with good governance (see, e.g., Weisbach (1988), Byrd and Hickman (1992), Cotter, Shivdasani, and Zenner (1997), Tufano and Sevick (1997), Khorana, Tufano, and Wedge (2007), and Ding and Wermers (2012)). However, Cremers, et al. (2009) point out that a lack of ownership could lead independent directors to be less active monitors. Therefore, we hypothesize that the governance is particularly strong if there are many independent directors on the board and if they have invested their own money in the fund. In that case we expect that they act as a stronger counterbalance to the duality manager in the board and leave her less power. Therefore, we hypothesize that the effect of duality on managerial decisions and performance is weaker in that case.

To test this hypothesis we regress the dependent variables used in the multivariate regressions of Sections 2.3 and 2.4 on the duality dummy and the usual control variables but now additionally include interaction terms between the duality dummy and the governance factors (number of independent directors, ownership of the independent directors) as independent variables. The coefficients of these interactions can be interpreted as the impact of the respective governance factor on the duality consequences. We measure independent directors' ownership as the average ownership of the independent directors in a specific fund. As ownership information is only disclosed using specified dollar ranges, we use the ranges' respective mean to proxy for a director's ownership in a fund and divide it by 1,000 USD to make the coefficients' magnitude more feasible. For the highest range, which has no upper limit, we assume that a director's ownership equals the range's lower limit as in Khorana, Servaes, and Wedge (2007). Results are presented in Table 2.12. Panel A of Table 2.12 shows that independent directors have some impact on the decisions of duality managers. The interaction terms have the expected (negative) sign in 15 (out of 18) cases, but they are significant at the conventional levels only in seven cases.

Table 2.12: Managerial power: impact of independent board members

Panel A: Managerial decisions

	Unsystematic risk	Stock concentration	Industry concentration	Active share	Tracking error	Style extremity			
						MKT	SMB	HML	MOM
Duality	0.0319 ***	0.0231 **	0.0004	0.0739 *	0.0298 **	1.0715 ***	1.0263 **	0.7181 **	0.5367 **
	(<0.001)	(0.029)	(0.991)	(0.082)	(0.020)	(0.001)	(0.015)	(0.012)	(0.038)
Interaction:									
Duality* # IND	-0.0040 **	-0.0028	0.0033	0.0023	-0.0001	-0.1700 **	-0.1483 *	-0.1154 **	-0.0028
	(0.015)	(0.133)	(0.700)	(0.816)	(0.986)	(0.011)	(0.072)	(0.038)	(0.958)
Duality*Ownership IND	-0.0018 **	-0.0009	-0.0007	-0.0050	-0.0015	0.0163	-0.0626 **	-0.0149	-0.0588 **
	(0.019)	(0.336)	(0.832)	(0.273)	(0.238)	(0.700)	(0.026)	(0.520)	(0.015)
Governance factors:									
# IND	-0.0004	-0.0004	-0.0047 **	-0.0071 ***	-0.0016 ***	-0.0129	-0.0110	-0.0228 *	-0.0012
	(0.281)	(0.228)	(0.016)	(0.009)	(0.009)	(0.366)	(0.301)	(0.051)	(0.910)
Ownership IND	0.0009 **	0.0007 **	0.0011	0.0102 ***	0.0016 **	0.0247 *	0.0245 *	0.0013	0.0170
	(0.021)	(0.032)	(0.599)	(<0.001)	(0.019)	(0.050)	(0.094)	(0.932)	(0.133)
Observations	1,888	1,782	1,782	1,223	1,223	1,888	1,888	1,888	1,888
Adj. R^2	0.442	0.235	0.787	0.408	0.486	0.106	0.060	0.055	0.062

(Continued)

Table 2.12: Continued

Panel B: Performance

	Return	Carhart alpha	CS
Duality	-0.0448 *	-0.0759 ***	-0.0271
	(0.063)	(0.001)	(0.161)
Interaction:			
Duality* # IND	0.0084 **	0.0084 *	0.0018
	(0.044)	(0.075)	(0.666)
Duality*Ownership IND	0.0007	0.0064 **	-0.0004
	(0.750)	(0.026)	(0.840)
Governance factors:			
# IND	0.0028 **	0.0015	0.0028 **
	(0.012)	(0.164)	(0.013)
Ownership IND	0.0015	-0.0008	0.0015
	(0.202)	(0.531)	(0.159)
Observations	1,888	1,888	1,716
Adj. R^2	0.840	0.079	0.152

Panel C: Performance extremity

	Return extremity	Carhart alpha extremity	CS extremity
Duality	0.6867 ***	0.6689 **	0.4750
	(0.007)	(0.030)	(0.114)
Interaction:			
Duality* # IND	-0.0734	-0.0087	0.0003
	(0.141)	(0.881)	(0.997)
Duality*Ownership IND	-0.0273	-0.0638 **	-0.0484 *
	(0.260)	(0.032)	(0.096)
Governance factors:			
# IND	-0.0201 *	-0.0123	-0.0042
	(0.059)	(0.267)	(0.755)
Ownership IND	0.0012	0.0240	0.0413 ***
	(0.913)	(0.111)	(0.005)
Observations	1,888	1,888	1,716
Adj. R^2	0.095	0.108	0.042

Notes: This table presents results from pooled OLS regressions using various dependent variables: In Panel A the dependent variables are the managerial decision measures defined as in Table 2.3. In Panel B the dependent variables are the performance measures defined as in Table 2.4. In Panel C the dependent variables are the performance extremity measures defined as in Table 2.5. The main independent variable is again the duality dummy which is defined as in Table 2.3. In addition, we use interaction terms between the duality dummy and governance factors (# IND, Ownership IND) and the control variables of Table 2.3 as independent variables. # IND is defined as the number of independent board directors for each fund in each year. Ownership IND is specified as the fund ownership of the fund's average independent director in a given year, divided by 1,000 USD. All regression specifications include time fixed effects and segment fixed effects. For sake of brevity, we only report the coefficients for the duality dummy, the governance factors, and the interaction between the duality dummy and the governance factors. Other independent variables are defined as in Tables 2.2 and 2.3. All regression specifications include time fixed effects and segment fixed effects (Robust p-values of the regression coefficients in parentheses are based on standard errors clustered by fund. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

We get a similar conclusion when looking at the performance effects (Panels B and C). The interaction coefficients typically have the opposite sign of the basic effect, i.e., independent directors tend to reduce the negative effect of duality on fund performance. However, the effect is not very strong in a statistical sense; the interaction coefficients are insignificant in most cases. Overall, our results suggest that independent directors do form a counterpart to duality managers, but they are not able to fully prevent duality managers from making risky decisions and delivering poor and extreme performance outcomes.

Taking all results of Section 2.6 together, we interpret them as supporting our hypothesis: The more power the manager has in the board, the more risky the decisions she takes and the poorer and more extreme her performance is.

2.7 Conclusion

Separation of decision making and decision control is the common approach to avoid agency problems when the decision makers do not bear the wealth effects of their decisions. The main task of the board of directors is to oversee the management and, if necessary, replace the manager. Thus, a natural conflict of interests arises when the manager herself is also serving as the chair of the board. In our laboratory for exploring the consequences of this conflict, the mutual fund industry, this happens in 14 percent of all cases.

In this paper we document several novel findings on the consequences of this conflict: Most importantly, we find that managers who also chair the board (duality managers) tend to make more risky decisions than other managers. They take risk which could be avoided by diversifying their assets, they hold highly concentrated portfolios, deviate from their benchmarks, take extreme style bets, and, consequently, achieve extreme performance outcomes. Such a risky behavior is highly sensible since duality managers have option-like incentive schemes: They get a bonus when their bets work well but do not bear the risk of being laid off when their bets go wrong.

Furthermore, we find that duality managers underperform non-duality managers on average. They make worse investment decisions leading to an underperformance before fees between 1.2 and 2.5 percent per year and, in addition, charge fees that are higher by 0.4 percentage points per year.

Finally, we document that the effects of duality on the manager's decisions and performance depends on the extent to which the manager dominates the board. If the manager is only ordinary member of the board but not chairing it, the effect is much weaker.

Independent board members are able to reduce the effect of duality, but the position of the duality manager seems to be so strong that the duality effect does not disappear.

Chapter 3

Managerial Ownership Changes and Mutual Fund Performance[†]

3.1 Introduction

Since March 2005, mutual funds have to report fund managers' ownership within the Statement of Additional Information (SAI) using broad ownership ranges. By using one year of ownership data, Khorana, Servaes, and Wedge (2007) and Evans (2008) show that the *level* of ownership predicts future risk-adjusted performance. Since then, more and more fund investors are paying attention to manager ownership (see, e.g., Ma and Tang (2014)) and some mutual fund families adopted policies which require their managers to hold ownership in the funds they manage.[21] This raises the question if the increased attention to managerial ownership and the implementation of ownership requirements by fund families is warranted. Does managerial ownership provide valuable information about future fund performance or is the observed cross-sectional correlation driven by unobserved fund characteristics?

[†]This chapter is based on Martin and Sonnenburg (2015). We thank Laurent Calvet, Jean Eduoard Colliard, Thierry Foucault, Johan Hombert, Stefan Jaspersen, Alexander Kempf, Hugues Langlois, Peter Limbach, Stefano Lovo, Alina Rosu, Clemens Otto, Jacques Olivier, Alexei Ovtchinnikov, Daniel Schmidt, Paul Tetlock, David Thesmar and participants at the CFR seminar, University of Cologne for comments on an earlier draft of this paper.

[21] See ”Another Way to Assess a Mutual Fund” in *The Wall Street Journal MarketWatch* (26/07/2006) and “Fund Managers: Betting their own money” in the *Bloomberg BusinessWeek* (14/01/2010). Both articles report that some mutual fund companies have started requiring their managers to invest in the funds they manage including Franklin Templeton Investments, Janus Capital Group, and T. Rowe Price.

Does ownership align incentives and can ownership requirements therefore be used to increase performance? Or do managers have superior information about future fund performance and choose to invest in funds which they know will perform better in the future? Given the nature of their cross-sectional data, these early studies are unable to answer these questions.

We fill this gap in the literature by examining the relationship between ownership *changes* and *changes* in future risk-adjusted fund performance using a hand-collected panel data set on mutual fund manager ownership. Examining ownership changes has two advantages in our setting. First, we are able to eliminate any heterogeneity bias stemming from time-invariant unobserved fund characteristics. For instance, funds differ in the degree of managerial discretion in making investment decisions. This managerial discretion may lead to higher fund returns on average, but exposes the fund investor to greater risk of moral hazard (see, e.g., Chen, Goldstein, and Jiang (2008)) and thus increases the optimal level of ownership.[22] Therefore, unobservable differences in managerial discretion may bias the ownership coefficient upwards. If managerial discretion is relatively stable within funds over time, we are able to eliminate this bias by using a first-difference approach. Moreover, we control for changes in a host of fund, board and family characteristics as well as predictors of fund performance which have been recently proposed by the literature.

Second, the cross-sectional studies are unable to examine whether the positive relationship between ownership levels and performance reflects fund managers' superior information about future fund performance or better alignment of fund managers' and shareholders' interests. We use changes in ownership mandated by family policy to disentangle the superior information and the incentive alignment hypotheses. The idea is that family mandated changes unlikely reflect a fund manager's information about future fund performance. If the positive relationship between manager ownership and fund performance reflects fund manager's superior information about future fund performance, we do not expect that ownership changes which are mandated by the fund family increase fund performance. If on the other hand manager ownership aligns the fund manager's interests with those of shareholders, we expect ownership changes to have a causal effect on performance even if the change is required by the fund family.

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[22] For example, Chen, Desai, and Krishnamurthy (2013) show that short-selling mutual funds outperform benchmarks by 1.5% per year. Consider a fund manager running two identical funds, but one is short-selling restricted and the other is not. From an optimal contracting perspective the manager should own more in the unrestricted fund as his ability to take actions against the interests of shareholders is greater. If this is the case, this creates a positive correlation between ownership and performance in the cross-section if short-selling restrictions are not controlled for.

Using a hand-collected dataset on managerial ownership for a sample of single managed U.S. domestic equity mutual funds over the period from 2005 to 2011, we find that ownership changes are positively related to changes in future risk-adjusted fund performance no matter whether we measure performance as Fama and French (1993) three-factor alpha, Carhart (1997) four-factor alpha, or Pástor and Stambaugh (2003) five-factor alpha. The relation between increases in ownership and increases in future risk-adjusted fund performance is also economically significant: a one-standard-deviation increase in ownership leads to an increase in alpha between 1.1 percentage points for the Carhart (1997) four-factor alpha and 1.6 percentage points for the Pástor and Stambaugh (2003) five-factor alpha. This result stands several robustness tests regarding the construction of our ownership measure.

Next, we control for other predictors of fund performance. Recent studies show that the level of ownership (Khorana, Servaes, and Wedge (2007) and Evans (2008)), the industry concentration (Kacperczyk, Sialm, and Zheng (2005)), return gap (Kacperczyk, Sialm, and Zheng (2008)), active share (Cremers and Petajisto (2009), and Petajisto (2013)) and a fund's R^2 with respect to its benchmark (Amihud and Goyenko (2013)) predict future fund performance. We find that ownership changes are highly significant predictors of changes in future risk-adjusted fund performance even after controlling for the lagged level of ownership as well as changes in industry concentration, active share, return gap and R^2. A one-standard-deviation increase in ownership predicts an increase in risk-adjusted performance of up to 1.6 percentage points.

We then analyze whether the documented positive relation between ownership changes and changes in risk-adjusted performance is due to *incentive alignment* or due to *superior information*. To disentangle these two hypotheses, we use the adoption of fund family policies requiring managers to hold some ownership in all funds they manage. We proxy for such a policy by using the ownership information we observe. If in a given year and fund family at least one fund has zero ownership, we define that the fund family has no strict ownership requirement in place. Contrary, if all funds within a given fund family have ownership greater than zero in a given year, we define that the family has a strict ownership requirement in place.

We find that future risk-adjusted performance increases even stronger with ownership when managers increase their ownership simultaneously to the adoption of a new family policy which requires managers to hold some ownership in their funds. A one-standard-deviation ownership increase simultaneous to the adoption of an ownership requirement by the family increases alpha between 0.4 and 0.5 percentage points more than other ownership increases. As these changes are most likely not driven by fund managers' superior information about future fund performance, these results support the view that ownership aligns interests of fund manager's and shareholders and causally affects fund performance. One possibility is that mandatory ownership increases induce the manager to exert more effort to seek out profitable investment opportunities. In line with this view, we find that mandatory ownership changes strongly predict future changes in trading activity. Managers who increase ownership simultaneously to the adoption of a family wide ownership requirement increase their active share, turnover, unobserved actions and their equity holdings and decrease their cash holdings.

The paper contributes to three main strands of the literature. First, our paper relates to the growing literature on mutual fund governance. Several studies suggest that a fund's governance is significantly improved if more independent directors are on the board or if independent directors have a higher ownership in the fund and thus a higher motivation to effectively monitor the fund (see, e.g., Tufano and Sevick (1997), Ferris and Yan (2007), Khorana, Tufano, and Wedge (2007), Cremers, et al. (2009), and Ding and Wermers (2012). More related to our study, Khorana, Servaes, and Wedge (2007) and Evans (2008) show in their cross-sectional analysis that managers with higher levels of ownership have better future fund performance. Our study contributes to this literature in two ways. To begin with, we are the first who use panel data on managerial ownership. Therefore we are able to rule out that any unobservable fund, manager or family fixed effects lead to a spurious correlation between ownership and performance. Our second contribution to this literature is that we are able to disentangle the *superior information* and *incentive alignment hypotheses* and we find support for the latter.

Second, our paper is related to a growing body of literature that analyzes managerial incentives in the mutual fund industry. Several studies look at the relationship between fund managers' incentives and their risk-taking behavior arising from the convex flow-performance relation (see, e.g., Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), Koski and Pontiff (1999), Kempf and Ruenzi (2008) , Kempf, Ruenzi, and Thiele (2009), and Schwarz (2011)). Another strand of this literature analyzes the link between advisory fee contracts and performance (see, e.g., Elton, Gruber, and Blake (2003), Dass, Massa, and Patgiri (2008), and Massa and Patgiri (2009)). In a recent paper, Ma, Tang, and Gómez (2015) show that fund managers with explicit performance-based incentives perform better. We complement this literature by showing that fund manager ownership can act as an explicit incentive tool to align managers' and shareholders' interests.

Third, our paper relates to the vast literature of managerial ownership in corporations. We find that ownership changes which are mandated by the fund family increase fund performance and therefore contribute to the controversy if manager ownership can be used to change firm value (see, e.g. Himmelberg, Hubbard, and Palia (1999), Zhou (2001), and Fahlenbrach and Stulz (2009)).

The rest of the paper proceeds as follows. Section 3.2 describes the data and compares our sample to the CRSP universe of mutual funds. In Section 3.3, we analyze the relation between ownership changes and changes in future risk-adjusted performance. In section 3.4, we examine if the results are robust to controlling for changes in other predictors of fund performance. In section 3.5 we explore how ownership changes due to fund family policy rather than personal portfolio decisions affect performance and Section 3.6 concludes.

3.2 Data and summary statistics

For our empirical analysis, we use data from three sources: (1) the Center for Research in Security Prices (CSRP) Survivor-Bias Free U.S. Mutual Fund Database[23], (2) Thomson Financial Mutual Fund Holdings Database and (3) mutual funds' Statement of Additional Information (SAI) filed with the SEC.

From the CRSP Survivor-Bias Free Mutual Fund Database we gather information on mutual funds' monthly returns, total net assets, and other fund characteristics. We focus on single actively managed, domestic equity funds with no manager replacements during our sample period and exclude bond funds and international funds as well as index funds. We use the Lipper objective code to define a fund's investment objective. We aggregate the Lipper segments into seven broad categories: Aggressive Growth, Growth and Income, Income, Growth, Sector Funds, Utility Funds, and Mid-Cap Funds. Many funds offer multiple share classes which are listed as separate entries in the CRSP database. As these share classes are backed up by the same portfolio, we aggregate all share classes at the fund level to avoid multiple counting.

We match the CRSP funds to the Thomson Financial Mutual Fund Holdings Database using MFLINKS tables. Our last data source is the mutual funds' SAI (in SEC filings 485APOS and 485BPOS), which are Part B of the mutual fund's prospectus. The data from the SEC filings 485APOS and 485BPOS can be downloaded in text files from SEC EDGAR. We match these files with the CRSP data using the fund's name, also accounting for the fact

[23] Source: CRSP, Center for Research in Security Prices. Graduate School of Business, The University of Chicago. Used with permission. All rights reserved.

that the fund name often differs from the filer name under which a mutual fund discloses its filings with the SEC or that the filings 485APOS and 485BPOS may contain SAI from multiple funds. The SAI reports detailed information on each portfolio manager's ownership in the fund. The ownership is reported in seven ranges: None; \$1–\$10,000; \$10,001–\$50,000; \$50,001–\$100,000, \$100,001–\$500,000, \$500,001–\$1,000,000, or over \$1,000,000. We convert these ownership ranges into dollar amounts using the bottom of each range.

We build two ownership measures: (1) We construct a yearly percentage ownership measure by dividing the converted dollar amount by a fund's year–end total net assets (TNA) as suggested by the existing literature studying the impact of ownership on firm value going back to Jensen and Meckling (1976). (2) We define ownership changes as the difference between fund managers' current and lagged percentage ownership. To control for commonly used board characteristics, we further collect the following board information from the SEC files: Name of director, and whether the director is interested or independent as defined in the Investment Company Act (ICA). Our data cover 2,196 fund-year observations over the period 2005-2011.

Table 3.1 compares the summary statistics of our sample to the CRSP mutual fund universe with respect to the funds' total net assets (TNA), fund families' total net assets (Family TNA), funds' flows, the turnover ratio of the fund, and the Pástor and Stambaugh (2003) five-factor alpha. Table 3.1 also provides summary statistics on the board and ownership measures for our sample of funds, namely the funds' board size, the fraction of independent directors on the board, the level of ownership and the change in ownership.

The sample comparison shows that our sample funds are larger and belong to larger families. They also have slightly higher turnover and attract more flows. These differences are likely due to our sample selection criteria as we exclude team-managed funds as well as funds with manager changes to prevent that group dynamics or manager replacements drive the results. Further, as we are interested in manager ownership changes, we exclude funds without at least two consecutive years in the sample. The average fund in our sample has managerial ownership of 0.52 percent of the fund's TNA and changes it on average by 0.05 percent per year.

Table 3.1: Descriptive statistics

	Mean			Median		
	Sample	CRSP Universe	Difference	Sample	CRSP Universe	Difference
Fund and family characteristics:						
Fund size	1,758.04	1,005.42	752.62***	299.05	205.15	93.90***
Turnover (%)	92.97	90.30	2.67	64.00	64.00	0.00
Fund flows (%)	9.62	7.08	2.53*	-5.24	-6.89	1.64***
Family size	88,199.48	32,076.07	56,123.41***	7,070.10	5,280.60	1,789.50***
5 factor alpha (%)	0.64	0.95	-0.31	0.87	1.02	-0.16
Board characteristics:						
Board size	8.00	n/a	n/a	8.00	n/a	n/a
Indep. directors (%)	78.92	n/a	n/a	80.00	n/a	n/a
Ownership measures:						
Ownership level (%)	0.52	n/a	n/a	0.01	n/a	n/a
Ownership change (%)	0.05	n/a	n/a	0.00	n/a	n/a

Notes: This table reports summary statistics for our sample of single-managed U.S. equity mutual funds between 2005 and 2011 compared to the CRSP universe. We report mean and median differences for both samples for the following variables: fund size as measured by the total net assets in million USD, the fund turnover (in %), the fund flows (in %), the fund family size calculated as the total net assets of all team- and single-managed mutual funds in the family, and the Pástor and Stambaugh (2003) five-factor alpha. As the board characteristics and ownership measures are not available for the CRSP universe (denoted as n/a), we only report means and medians for the following variables for our sample: the fund board size, the fraction of independent directors on the board, the fund manager ownership level (in % of TNA), and the fund manager ownership change (in %) defined as the difference between the current percentage ownership and the lagged percentage ownership. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively, for the difference in means and medians between both samples (based on t-tests and Mann-Whitney-Wilcoxon rank-sum tests).

3.3 Ownership changes and changes in future fund performance

In this section, we analyze the relation between ownership changes and changes in future risk-adjusted performance (Section 3.3.1). We check the robustness of our results in Section 3.3.2.

3.3.1 Main results

To examine the relation between ownership changes and changes in future risk-adjusted performance, we use three different performance measures: (1) Fama and French (1993) three-factor alpha, (2) Carhart (1997) four-factor alpha, and (3) Pástor and Stambaugh (2003) five-factor alpha. The alpha measures are determined based on a yearly estimation of the respective factor models. We calculate the performance measures based on gross returns as gross returns better reflect the quality of the investment decisions of the fund manager. To calculate a fund’s gross return, we divide a fund’s yearly expense ratio by twelve and add it to the fund’s monthly net return observations.

We conduct first-difference regressions and use the change in the annualized performance measures from *t-1* to *t* as dependent variable $(\Delta Performance)$ in these regressions:

$$\begin{aligned}\Delta \text{Performance}_{i,t} = \alpha + \beta \Delta \text{Ownership}_{i,t-1} & \\ + \gamma_1 \Delta \ln(\text{FundSize}_{i,t-1}) + \gamma_2 \Delta \text{Turnover}_{i,t-1} + \gamma_3 \Delta \ln(\text{FamilySize}_{i,t-1}) & \\ + \Phi_1 \Delta \text{BoardSize}_{i,t-1} + \Phi_2 \Delta \text{IndepDirectors}_{i,t-1} + \varepsilon_{i,t} &\end{aligned} \tag{3.1}$$

Our main independent variable is the change in managerial ownership form year *t-2* to *t-1* $(\Delta Ownership)$. We add further variables to control for changes in fund, fund family, and governance characteristics. All of these changes are also measured from *t-2* to *t-1*. At the fund level, we add changes in the logarithm of the fund’s size $(\Delta FundSize)$, and the fund’s yearly turnover ratio $(\Delta Turnover)$ as control variables to the regressions. At the fund family level, we control for changes in the logarithm of the fund family’s size $(\Delta FamilySize)$. The governance controls include changes in the fund’s board size $(\Delta BoardSize)$ as well as changes in the fraction of independent directors on the board $(\Delta IndepDirectors)$. To control for any unobservable time or segment effects that could equally affect all funds in a given year or a particular market segment, respectively, we also include time and segment fixed effects in all regressions. We cluster the standard errors at the fund level. Table 3.2 presents the results. The results clearly show that ownership changes are positively related to changes in future risk-adjusted performance. The coefficient of ownership changes is positive and significant at the 1%-level in all specifications. The effect is not only statistically but also economically significant: For example, when Pástor and Stambaugh (2003) five-factor alpha is used as performance measure, an increase in ownership by one-standard-deviation (0.02935) predicts a 1.6 percent higher alpha (= 0.02935 × 0.5311), after taking all control variables into account .The other control variables have no notable consistent impact on future risk-adjusted performance.

Overall, the results from this section provide evidence that the observed cross-sectional correlation between ownership and future fund performance is not stemming from a heterogeneity bias due to unobserved time-invariant fund characteristics.

3.3.2 Robustness

In this section, we conduct additional tests to check that the positive effect of ownership changes on changes in future risk-adjusted performance is robust. The results from these tests are reported in Table 3.3.

Thus far, we have converted the bottom of each reported dollar range into dollar amounts. We now convert the reported dollar ranges into dollar amounts by assuming that the midpoint of the reported interval is always invested, except for ownership levels above $1 million, where we employ the bottom of the range. The results shown in Panel A remain similar: Ownership changes are positively associated with changes in future risk-adjusted performance.

In Panel B, we conduct a test to see whether our documented effect is driven by changes in the denominator of our ownership change measure. We replace our ownership change measure by a placebo ownership change measure. The nominator of this placebo ownership change measure takes on the mean dollar ownership in the sample for all funds and years whereas the denominator remains the fund size. Thus, all variation in this ownership change measure stems from variation in the denominator. We employ this measure in our first-difference regressions and do not find a significant effect on changes in future risk-adjusted performance. This implies that the positive relation between ownership changes and changes in future risk-adjusted performance is not simply driven by changes in the denominator of the ownership change measure.

Table 3.2: Ownership changes and changes in fund performance

Dependent variable:	Change in Alpha $_{t\text{-}1 \text{ to } t}$					
	3F		4F		5F	
	(1)	(2)	(3)	(4)	(5)	(6)
Ownership change $_{t\text{-}2 \text{ to } t\text{-}1}$	**0.4372*** **	**0.4022*** **	**0.4340*** **	**0.3785*** **	**0.5409*** **	**0.5311*** **
	(3.880)	**(3.101)**	**(2.927)**	**(2.954)**	**(3.546)**	**(3.726)**
Fund and family characteristics:						
Change in fund size $_{t\text{-}2 \text{ to } t\text{-}1}$		0.0055		0.0002		-0.0023
		(0.516)		(0.020)		(-0.175)
Change in turnover $_{t\text{-}2 \text{ to } t\text{-}1}$		0.0176		0.0284*		0.0288*
		(1.514)		(1.843)		(1.852)
Change in family size $_{t\text{-}2 \text{ to } t\text{-}1}$		0.0104		0.0156		0.0153
		(0.545)		(0.819)		(0.765)
Board characteristics:						
Change in boards size $_{t\text{-}2 \text{ to } t\text{-}1}$		-0.0009		-0.0020		-0.0055
		(-0.205)		(-0.465)		(-1.255)
Change in indep. directors $_{t\text{-}2 \text{ to } t\text{-}1}$		0.0372		0.0205		0.0569
		(0.388)		(0.246)		(0.586)
Segment fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	864	606	864	606	864	606
Adjusted R-squared	0.112	0.111	0.071	0.093	0.063	0.091

Notes: This table reports results from first-difference regressions of performance on lagged percentage ownership using three different performance measures: (1) Fama and French (1993) three-factor alpha, (2) Carhart (1997) four-factor alpha, and (3) Pástor and Stambaugh (2003) five-factor alpha. The dependent variable is the change from year *t-1* to year *t* of the respective performance measure. As fund control variables we use the logarithm of the fund's lagged size (measured in million USD), the fund's yearly turnover ratio, and the logarithm of fund's lagged family size (calculated as the total net assets of all team- and single-managed mutual funds in the family). As board control variables we use fund's lagged board size as well as the lagged fraction of independent directors on the board. All independent variables are calculated as changes from year *t-2* to year *t-1*. The regression specifications include time fixed effects and segment fixed effects. Robust t-statistics of the regression coefficients in parentheses are based on standard errors clustered by fund. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

In Panel C, we additionally control for changes in fund flows. Although we control for changes in fund size, one might argue that the denominator of our ownership change measure is driven by changes in fund flows. Panel C shows that our main results do not change when controlling for changes in fund flows: Ownership changes are positively related to changes in risk-adjusted performance even after controlling for fund flows.

Finally, we split our sample into small and large funds using the median fund size in the sample as cut-off. As we are using changes in percentage ownership as our main independent variable, the results could be driven by small funds as a given dollar ownership change leads to a larger percentage ownership change for small funds. The results from Panel D show that the observed effect of ownership on performance is not driven by small funds. Ownership changes predict future changes in performance for both small and large funds. The economic magnitude of the effect is even bigger for large funds. Given that the standard deviation of ownership changes for large funds (small funds) is 0.00053 (0.03913), a one-standard-deviation increase in percentage ownership of a large fund leads to an increase in risk-adjusted performance up to 2.0 percentage points (= 0.00053 × 37.156), compared to an increase in risk-adjusted performance up to 1.5 percentage points (= 0.03913 × 0.3867) for small funds.

Taken together, the findings in this section show that the baseline result of a positive impact of ownership changes on changes in risk-adjusted performance is robust to (1) using the midrange of the reported ownership range, (2) is not driven by changes in the denominator of the ownership measure, (3) is not driven by changes in fund flows, and (4) is not solely driven by small funds.

Table 3.3: Robustness

Panel A: Mid range

Dependent variable:	Change in Alpha $_{t-1\ to\ t}$		
	3F	4F	5F
	(1)	(2)	(3)
Ownership change $_{t-2\ to\ t-1}$	**0.4262****	**0.4359***	**0.5780****
	(2.088)	**(1.862)**	**(2.439)**
Change in fund and family characteristics	Yes	Yes	Yes
Change in board characteristics	Yes	Yes	Yes
Segment fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	606	606	606
Adjusted R-squared	0.112	0.095	0.093

Panel B: Placebo ownership change

Dependent variable:	Change in Alpha $_{t-1\ to\ t}$		
	3F	4F	5F
	(1)	(2)	(3)
Ownership change $_{t-2\ to\ t-1}$	**0.9719**	**1.1012**	**1.2241**
	(1.147)	**(1.133)**	**(1.257)**
Change in fund and family characteristics	Yes	Yes	Yes
Change in board characteristics	Yes	Yes	Yes
Segment fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	606	606	606
Adjusted R-squared	0.112	0.097	0.093

Panel C: Impact of fund flows

Dependent variable:	Change in Alpha $_{t-1\ to\ t}$		
	3F	4F	5F
	(1)	(2)	(3)
Ownership change $_{t-2\ to\ t-1}$	**0.2974****	**0.2939****	**0.4338*****
	(2.523)	**(2.354)**	**(3.443)**
Change in fund flows $_{t-2\ to\ t-1}$	-0.0408***	-0.0345**	-0.0387***
	(-3.178)	(-2.520)	(-2.682)
Change in fund and family characteristics	Yes	Yes	Yes
Change in board characteristics	Yes	Yes	Yes
Segment fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	569	569	569
Adjusted R-squared	0.121	0.098	0.100

(Continued)

Table 3.3: Continued

Panel D: Small versus large funds

Dependent variable:	Change in Alpha $_{t-1\ to\ t}$					
	Small funds			Large funds		
	3F	4F	5F	3F	4F	5F
	(1)	(2)	(3)	(4)	(5)	(6)
Ownership change $_{t-2\ to\ t-1}$	**0.2810****	**0.2727****	**0.3867*****	**37.1560*****	**19.9214***	**21.9912****
	(2.211)	**(2.048)**	**(2.896)**	**(3.370)**	**(1.746)**	**(2.297)**
Change in fund and family characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Change in board characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Segment fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	253	253	253	316	316	316
Adjusted R-squared	0.097	0.078	0.094	0.162	0.114	0.111

Notes: This table reports results from first-difference regressions of performance on lagged percentage ownership using three different performance measures: (1) Fama and French (1993) three-factor alpha, (2) Carhart (1997) four-factor alpha, and (3) Pástor and Stambaugh (2003) five-factor alpha. The dependent variable is the change from year *t-1* to year *t* of the respective performance measure. In Panel A, the percentage ownership measure is calculated using the midpoint of the reported ownership range instead of the bottom of each range. In Panel B, we replace our percentage ownership measure by a placebo percentage ownership measure. The nominator of this placebo ownership measure takes on the mean dollar ownership in the sample for all funds and years whereas the denominator remains the fund size. In Panel C, we additionally control for the change in fund flows. Panel D shows results for the subsamples of small and large funds using the sample median of fund size as cutoff. For sake of brevity, we only report the coefficients for the change in ownership. Other independent variables are defined as in Table 3.2. All independent variables are calculated as changes from year *t-2* to year *t-1*. The regression specifications include time fixed effects and segment fixed effects. Robust t-statistics of the regression coefficients in parentheses are based on standard errors clustered by fund. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

3.4 Ownership changes and other predictors of future fund performance

Having identified a robust measure to predict changes in future risk-adjusted performance, we now examine whether our measure survives after controlling for other existing measures to predict future performance.

In this context, Khorana, Servaes, and Wedge (2007) and Evans (2008), both provide evidence that the level of ownership is positively associated with superior future performance. Besides that, a growing body of literature uses holdings data of mutual funds to create performance predictability measures. Kacperczyk, Sialm, and Zheng (2005) develop the industry concentration index (ICI) and show that a high industry concentration is positively associated with future fund performance. Kacperczyk, Sialm, and Zheng (2008) use the return gap (RG) defined as the difference between the reported fund return and the return predicted from the previously disclosed fund holdings to measure unobserved actions by mutual fund managers. They find a positive correlation between the return gap (RG) and future fund performance. Cremers and Petajisto (2009) and Petajisto (2013) measure a fund's active share (AS) as the extent to which a manager deviates from her benchmark and find that active share positively predicts future fund performance. Finally, without using holdings data, Amihud and Goyenko (2013) show that a fund's R^2 with respect to its benchmark positively predicts performance. To test if changes in ownership survive as performance predictability measure, we now additionally control for the lagged level of ownership and changes in industry concentration (ICI), return gap (RG), active share (AS) and R^2 in our regressions.

To compute the industry concentration index (ICI), we first sort all stocks into ten industries following Kacperczyk, Sialm, and Zheng (2005) and then calculate the weight for a specific industry in a portfolio by summing up the portfolio weights of all stocks belonging to that industry. The sum of the squared industry weights (averaged across the quarters of a year) is then used as a measure of industry concentration.

To calculate the return gap, we follow Kacperczyk, Sialm, and Zheng (2008) by comparing the realized fund returns with holding-based fund returns. The latter is a hypothetical portfolio that invests in the previously disclosed fund holdings. We then compound the monthly return gap observations to come up with a yearly measure.

We use the active share database of Cremers and Petajisto (2009) and Petajisto (2013).[24] The active share is calculated as the absolute difference between the portfolio weight of a stock and the stock's weight in the respective benchmark, summed over all positions of the stock universe and divided by two.

To compute the R^2 measure of Amihud and Goyenko (2013), we first run yearly regressions of fund's monthly excess returns on the Carhart (1997) four factors. We then obtain the fund's R^2 from these regressions.

We add these other performance predictors to our baseline regressions from Section 3.3.1. The control variables are the same as in (3.1). We again control for time and segment fixed effects in the regressions. Standard errors are clustered at the fund level. For the sake of brevity we report only the results for the changes in ownership as well as for the lagged level of ownership and the changes in the other performance predictors. Results are provided in Table 3.4.

[24] We downloaded the active share data from Antti Petajisto's website at http://www.petajisto.net/data.html.

Table 3.4: Ownership changes and alternative predictors of fund performance

Dependent variable:	Change in Alpha $_{t-1 \text{ to } t}$		
	3F	4F	5F
	(1)	(2)	(3)
Ownership change $_{t-2 \text{ to } t-1}$	**0.4362*** **	**0.3055** **	**0.5323*** **
	(2.895)	**(2.311)**	**(4.183)**
Additional controls			
Ownership level $_{t-1}$	0.0038	0.1581	0.0278
	(0.024)	(1.098)	(0.200)
Change in active share $_{t-2 \text{ to } t-1}$	0.3378**	0.2198	0.2080
	(2.277)	(1.444)	(1.320)
Change in industry concentration $_{t-2 \text{ to } t-1}$	-0.3426	-0.3353	-0.3768*
	(-1.592)	(-1.567)	(-1.708)
Change in return gap $_{t-2 \text{ to } t-1}$	-0.4957***	-0.4674***	-0.5725***
	(-2.868)	(-3.042)	(-3.258)
Change in R^2 $_{t-2 \text{ to } t-1}$	0.1344	0.1097	0.1719
	(0.890)	(0.725)	(1.080)
Change in fund and family characteristics	Yes	Yes	Yes
Change in board characteristics	Yes	Yes	Yes
Segment fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	321	321	321
Adjusted R-squared	0.211	0.164	0.204

Notes: This table reports results from first-difference regressions of performance on lagged percentage ownership using three different performance measures: (1) Fama and French (1993) three-factor alpha, (2) Carhart (1997) four-factor alpha, and (3) Pástor and Stambaugh (2003) five-factor alpha. The dependent variable is the change from year *t-1* to year *t* of the respective performance measure. The *ownership level* is calculated as percentage ownership measure by dividing the converted dollar amount by a fund's year–end total net assets (TNA) and lagged by one year. We use the *active share* measure of Cremers and Petajisto (2009) and Petajisto (2013). To measure the *industry concentration*, we follow Kacperczyk, Sialm, and Zheng (2005) and sort all stocks into ten industries and calculate the weight for a specific industry in a portfolio by summing up the portfolio weights of all stocks belonging to that industry. The sum of the squared industry weights (averaged across the quarters of a year) is then used as a measure of industry concentration. To calculate the *return gap*, we follow Kacperczyk, Sialm, and Zheng (2008) by comparing the realized fund returns with holding-based fund returns. The latter is a hypothetical portfolio that invests in the previously disclosed fund holdings. We then compound the monthly return gap observations to come up with a yearly measure. To compute the R^2 measure of Amihud and Goyenko (2013), we first run yearly regressions of fund´s monthly excess returns on the Carhart (1997) four factors. We then obtain the fund´s R^2 from these regressions. For sake of brevity, we only report the coefficients for the change in ownership and the additional control variables. Other independent variables include those defined in Table 3.2 and fund flows. All independent variables are calculated as changes from year *t-2* to year *t-1* (except for the ownership level in *t-1*). The regression specifications include time fixed effects and segment fixed effects. Robust t-statistics of the regression coefficients in parentheses are based on standard errors clustered by fund. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

The ownership change measure is positive and significant at the 1% level for the three-factor and five-factor alpha (and at the 5%-level for the four-factor alpha). The effect is also economically significant: After controlling for the alternative predictors of fund performance, we still find an economically meaningful effect of ownership changes on changes in future risk-adjusted performance. A one-standard-deviation increase in ownership leads to an increase in four-factor alpha of 0.9 percentage points (= 0.02935 × 0.3055) and an increase in five-factor alpha of 1.6 percentage points (= 0.02935 × 0.5323). Of the alternative predictors only changes in return gap are significantly negatively related to changes in future fund performance. The standard deviation of return gap is 0.03906. Thus, the estimated slope of -0.5725 based on five-factor alpha implies that a one-standard-deviation increase in return gap translates to a decrease of 2.2 percentage points (= 0.03906 × -0.5725) in five-factor alpha.

Overall, the results from this section clearly show that ownership changes predict future risk-adjusted performance even after controlling for existing predictors of fund performance.

3.5 Ownership changes induced by family policies

The results so far indicate that the cross-sectional correlation between managerial ownership and fund performance is not merely driven by unobserved time-invariant fund, manager or family characteristics. We now turn to the question whether the positive correlation is driven by incentive alignment or superior information. Under the *superior information hypothesis* managers increase their ownership in funds because they know these funds will perform better in the future. Under the *incentive alignment hypothesis*, managerial ownership aligns the manager's interests with those of fund shareholders leading to better investment decisions resulting in better performance.

We use the adoption of fund family policies requiring managers to hold some ownership in all funds they manage to disentangle the *superior information hypothesis* from the *incentive alignment hypothesis*. The idea is to capture ownership changes which are mandated by the fund family and thus do not reflect the manager's information. Under the *superior information hypothesis*, we expect that these mandatory ownership changes are not related to future changes in fund performance. Under the *incentive alignment hypothesis* however, ownership leads to aligned incentives regardless if the change in ownership is mandatory or voluntary. Therefore we expect mandatory and voluntary ownership changes to be positively related to future changes in fund performance under the incentive alignment hypothesis.

We construct a dummy variable for fund family policy changes which takes on the value one if the fund family did not have an ownership requirement in place in the past year and has such a requirement in place this year, and zero otherwise. As we cannot directly observe if such a family policy is in place, we proxy for it by using the ownership information we observe. If in a given year and fund family at least one fund has zero ownership, we define that in this fund family and year no strict ownership requirement is in place. If on the other hand, in a given year and fund family all funds in the family have ownership greater than zero, we define that in this fund family and year a strict ownership requirement is in place. We then interact the fund family policy change dummy with the ownership change measure and run first-difference regressions using the change in the respective performance measure as dependent variable. Other control variables are the same as in (3.1). We again control for time and segment fixed effects in the regressions and cluster standard errors at the fund level. For the sake of brevity we report only the results for the ownership change measure, the family policy change dummy and the interaction between both. The results are shown in Table 3.5.

Table 3.5: Family policy change: fund performance

Dependent variable:	Change in Alpha $_{t-1\ to\ t}$		
	3F	4F	5F
	(1)	(2)	(3)
Ownership change $_{t-2\ to\ t-1}$	0.2869**	0.2856**	0.4269***
	(2.460)	(2.304)	(3.442)
Ownership change $_{t-2\ to\ t-1}$ * Family policy change $_{t-2\ to\ t-1}$	**11.8349*** **	**9.4690*** **	**7.2716*** **
	(4.654)	**(3.680)**	**(2.680)**
Family policy change $_{t-2\ to\ t-1}$	-0.0261	-0.0231	-0.0106
	(-1.460)	(-1.285)	(-0.581)
Change in fund and family characteristics	Yes	Yes	Yes
Change in board characteristics	Yes	Yes	Yes
Segment fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Observations	569	569	569
Adjusted R-squared	0.123	0.099	0.098

Notes: This table reports results from first-difference regressions of performance on lagged percentage ownership and the interaction between the ownership change measure and a family policy change dummy using three different performance measures: (1) Fama and French (1993) three-factor alpha, (2) Carhart (1997) four-factor alpha, and (3) Pástor and Stambaugh (2003) five-factor alpha. The dependent variable is the change from year *t-1* to year *t* of the respective performance measure. The family policy changes dummy takes on the value one if the fund family did not have an ownership requirement in place in the past year and has such a requirement in place this year, and zero otherwise. For sake of brevity, we only report the coefficients for the change in ownership, the family policy dummy and the interaction between ownership changes and family policy changes. Other independent variables include those defined in Table 3.2 and fund flows. All independent variables are calculated as changes from year *t-2* to year *t-1*. The regression specifications include time fixed effects and segment fixed effects. Robust t-statistics of the regression coefficients in parentheses are based on standard errors clustered by fund. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

We find that both the change in the ownership measure as well as the interaction of this change with the fund family policy change dummy strongly predict future changes in risk-adjusted performance. Given that the standard deviation of ownership changes within the family policy change group is 0.00054, a one-standard-deviation increase of funds where the family adopted an ownership requirement increases future alpha by 0.4 percentage points

(= 0.00054 × 7.2716 (estimated slope for the five-factor alpha)) to 0.6 percentage points ((= 0.00054 × 11.8349 (estimated slope for the three-factor alpha)) more than for all other funds.

This leads to an overall effect of up to 1.6 percentage points based on five-factor alpha (= 0.02935 × 0.4269 + 0.00054 × 7.2716). These results support the *incentive alignment hypothesis*: Ownership has an even stronger effect on performance if the changes are mandated by the fund family.

Next we examine where this performance effect stems from. One possible explanation is that fund managers who are required by their fund family to start holding some ownership in the funds they manage subsequently exert more effort in seeking out profitable investment opportunities. If this is the case, we expect to observe increased activity by these fund managers. In Table 3.6 we employ the same setup as in Table 3.5, using changes in the fund's active share, turnover, return gap, as well as cash and equity holdings as dependent variables.[25]

Table 3.6 shows that the interaction terms have the expected sign: A one standard deviation increase in percentage ownership concurrent to the adoption of an ownership requirement by the fund family increases active share by 0.09 percentage points (= 0.00054 × 1.6869), a fund's turnover by 1.23 percentage points (= 0.00054 × 22.8426), return gap by 0.45 percentage points (= 0.00054 × 8.3254) and equity holdings by 0.48 percentage points (= 0.00054 × 8.8644), whereas cash holdings decrease by 0.63 percentage points (= 0.00054 × -11.3762). The results reinforce the *incentive alignment hypothesis*: Ownership increases by funds when their families adopt ownership requirements significantly predict higher trading activity.

Taking all results of Section 3.5 together, we interpret them as supporting the view that managerial ownership aligns interests of managers with those of shareholders and induces managers to exert more effort.

[25] We measure cash (equity) holdings as reported cash (equity) from CRSP.

Table 3.6: Family policy change: trading activity

Dependent variable:	Change $_{t-1\ to\ t}$ in				
	Active share	Turnover	Return gap	Cash holdings	Equity holdings
	(1)	(2)	(3)	(4)	(5)
Ownership change $_{t-2\ to\ t-1}$	-0.0214	-0.2467	0.0164	0.1439	-0.1572
	(-1.006)	(-0.215)	(0.313)	(0.788)	(-1.033)
Ownership change $_{t-2\ to\ t-1}$ * Family policy change $_{t-2\ to\ t-1}$	**1.6869***	**22.8426*****	**8.3254*****	**-11.3762*****	**8.8644*****
	(1.879)	**(3.655)**	**(7.298)**	**(-7.141)**	**(5.937)**
Family policy change $_{t-2\ to\ t-1}$	0.0026	-0.0440	-0.0050	0.0048	-0.0023
	(0.248)	(-0.857)	(-0.486)	(0.522)	(-0.269)
Change in fund and family characteristics	Yes	Yes	Yes	Yes	Yes
Change in board characteristics	Yes	Yes	Yes	Yes	Yes
Segment fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	243	567	485	570	570
Adjusted R-squared	0.038	0.028	0.075	0.033	0.045

Notes: This table reports results from first-difference regressions of various trading activity measures as dependent variables on lagged percentage ownership and the interaction between the ownership change measure and a family policy change dummy. Active share and return gap are defined as in Table 3.4. To examine changes in cash and equity holdings, we measure cash (equity) holdings as reported cash (equity) from CRSP. The family policy changes dummy takes on the value one if the fund family did not have an ownership requirement in place in the past year and has such a requirement in place this year, and zero otherwise. For sake of brevity, we only report the coefficients for the change in ownership, the family policy dummy and the interaction between ownership changes and family policy changes. Other independent variables include those defined in Table 3.2 and fund flows. All independent variables are calculated as changes from year *t-2* to year *t-1*. The regression specifications include time fixed effects and segment fixed effects. Robust t-statistics of the regression coefficients in parentheses are based on standard errors clustered by fund. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

3.6 Conclusion

In response to a number of scandals in the mutual fund industry, the Securities and Exchange Commission (SEC) adopted new disclosure requirements for mutual funds in 2004. Since March 2005, mutual fund managers are required to report their ownership in the funds they manage.

In contrast to earlier studies, we investigate the relationship between managerial ownership and fund performance dynamically. We find that managerial ownership changes are positively related to future changes in risk-adjusted fund performance. We show that this effect is robust to using the mid range instead of the minimum range of the reported dollar range and the results are not driven by changes in the denominator of our ownership measure or by small funds. We further show that our results hold even after controlling for the lagged level of ownership and changes in holdings-based predictors of future fund performance and a fund's R^2. Thus, the relationship between ownership changes and future risk-adjusted performance is robust to controlling for existing predictability measures.

Using family ownership requirements, we disentangle the *superior information* and *incentive alignment hypotheses*: Contrary to the superior information hypothesis and in line with incentive alignment, we find that ownership changes which are induced by family policies predict changes in future fund performance even better. Funds that are required to increase their ownership are associated with an increase in alpha by up to 1.6 percent per standard deviation of ownership increase. They do so by increasing their active share, turnover, unobserved actions, equity holdings and by decreasing their cash holdings.

Altogether, this study provides evidence that managerial ownership is an important tool to align manager interests with those of shareholders.

Chapter 4

CEO Fitness and Firm Value‡

4.1 Introduction

This study provides evidence for an economically significant, positive impact of chief executive officer (CEO) fitness on firm value. Fitness should be an important attribute of CEOs as they face increasingly high levels of demands and responsibilities (Hambrick, Finkelstein, and Mooney (2005), Lovelace, Manz, and Alves (2007), and Neck, et al. (2000)). Their job is characterized by high work stress due to far-reaching decisions accompanied by frequent media and shareholder scrutiny, changing schedules, and frequent global travel.

It is hence not surprising that the business press has featured several articles about the growing importance of fitness in the managerial labor market.[26] Consistent with an increasing demand for fitness, there has been a significant trend among CEOs to participate in endurance

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[26] The Wall Street Journal (WSJ) article „When Job Fatigue Hits the CEO" (05/07/2013) mentions a study by the Harvard Medical School in which more than 90% of senior leaders report to feel burned out. The WSJ article „Want to Be CEO? What's Your BMI?" (01/16/2013) comments on the importance of fitness for executives. It states: *"Because the demands of leadership can be quite strenuous, the physical aspects are just as important as everything else"* and *"While marathon training and predawn workouts aren't explicitly part of a senior manager's job description, leadership experts and executive recruiters say that staying trim is now virtually required for anyone on the track for the corner office".*

sports, particularly marathons.[27] Examples of running CEOs include Robert Iger (Walt Disney), Klaus Kleinfeld (Alcoa), John Legere (T-Mobile), or Steven Reinemund (PepsiCo).

This trend among CEOs can be explained by the nature of running: it can be done at virtually any place and any time, and without any teammates. This makes it a primary sport for CEOs and other people with high need for flexibility. Further, the most common reason to start running is to improve fitness (Summers, et al. (1982)). Therefore, in this study we use hand-collected data on U.S. marathons to measure CEO fitness. We find that an increasing number of CEOs run (see Figure 4.2).

Studies from the fields of biology, medicine, psychology and sports find that fitness and physical activity have buffering effects on stress (Gal and Lazarus (1975), Brown (1991), and Unger, Johnson, and Marks (1997)) as well as positive effects on cognitive functions and executive-control processes (see, e.g., Colcombe and Kramer (2003), and Kramer, et al. (1999)), work behavior (see, e.g., Folkins and Sime (1981)), and on academic and job performance (see, e.g., Coe, et al. (2006), and Rhea, Alvar, and Gray (2004)). Accordingly, fit CEOs should be better able to stand the high stress of their jobs, should be less exhausted, more efficient and better performing, and should thus ultimately be associated with better firm performance.

Using a panel of more than 9,500 firm-year observations between 2001 and 2011, we find that S&P 1500 CEOs who finish a marathon in a given year – denoted as fit CEOs – are associated with a significantly higher firm value (measured by Tobin’s Q). Results are found both on univariate and multivariate level and are economically significant: on average, firm value is almost 5% larger for firms managed by fit CEOs, taking CEO and governance characteristics, firm characteristics, and firm and year fixed effects into account.

To understand how CEO fitness translates into firm value, we consider two primary channels of firm valuation, profitability and mergers and acquisitions (M&As). We find that fit CEOs are associated with significantly higher return on assets and more free cash flow. When we examine firms’ abnormal stock returns around M&A announcements, we find that the abnormal returns are less likely negative and, on average, at least 1.3 percentage points higher when the bidding firm’s CEO is fit.

M&As are an optimal laboratory to study CEO fitness. They constitute far-reaching decisions, often particularly work-intensive and stressful for the CEO due to intense

[27] See „Executive endurance” in The Wall Street Journal MarketWatch (10/04/2007). The article reports about the increasing number of CEOs and high-ranked managers who run marathons. It states that *“[…] for many CEOs, a motivation to keep running is that it leads to business success by reducing stress, creating a balance in their lives and fostering a mental toughness that can bring rewards in the boardroom.”*

(re)negotiations (Officer (2004)), considerable media and shareholder scrutiny (Liu and McConnell (2013), Lehn and Zhao (2006)), and hence pressure to perform. As a consequence, due to its stress-buffering and performance-enhancing effects, fitness should be highly relevant for CEOs, all the more if bids are made for large and public targets which put the CEO in particular spotlight. This is exactly where we find the strongest effects of CEO fitness on abnormal M&A announcement returns.

The M&A event study is a first attempt to address endogeneity. In the following, we address several endogeneity concerns in detail. The most important appear to be i) the question if we really measure CEOs' fitness, ii) the endogenous CEO-firm matching, iii) reverse causality and iv) unobserved time-varying firm and industry heterogeneity. A variety of robustness tests suggest that our results are robust to all of these concerns.

To address the concern that we might not measure CEO fitness and its consequences, we first consider three different types of CEOs for which fitness is expected to be most important. Specifically, fitness should significantly matter to older managers as cognitive and physical abilities decline with age (Verhaeghen and Salthouse (1997), Rhodes (2004)). It should also matter to CEOs who have been in a top position for many years, and thus get exhausted over time (Knudsen, Ducharme, and Roman (2009), Schaufeli and Bakker (2004)), and for CEOs with high responsibility and workload. Accordingly, we find that the positive relation between CEO fitness and Tobin's Q is particularly pronounced for CEOs with above-median age, CEOs with above-median tenure and for "busy" CEOs, i.e., for CEOs with two or more outside directorships (Fich and Shivdasani (2006), Perry and Peyer (2005)). The effect of CEO fitness on firm value amounts to at least 8%, which is almost twice as much as the average effect found for all CEOs. Results are consistent with the related literature, support the idea that we measure fitness, and further explain its importance for CEOs.

Next, our results could be the outcome of unobserved CEO heterogeneity, i.e., CEO fitness might correlate with other unobserved CEO characteristics (such as innate talent) important for firm value. To address this concern, we exploit CEO-specific variation over our time-varying fitness measure. First, we consider only those CEOs who finish at least one marathon over the sample period. This way, we only examine changes in observable fitness within the group of CEOs who have demonstrated to be able to finish a marathon. When we focus on this group, the difference in Tobin's Q between fit and less fit CEOs does not disappear. Thus, it is very unlikely that some unobserved shared characteristic among fit CEOs causes our results. Second, to address unobserved CEO heterogeneity more generally, we use CEO-firm fixed effects. This approach also takes the endogenous matching between firms and CEOs into account. Our results for firm value, including those for the different types of CEOs, remain economically and statistically significant.

As a last attempt to address the concern that we do not measure CEO fitness and its consequences, we perform permutation tests where each CEO is assigned a random (pseudo) fitness status. Since an insignificant number of permutations yield similar or larger coefficients for our fitness measure, the positive relation between CEO fitness and firm value is further supported by this test.

Next, we address reverse causality which constitutes another important endogeneity concern in this study. One might argue that our results for firm value are simply the outcome of CEOs who can afford the time to get fit (and finish a marathon) when their firm has performed well, while their fitness actually does not matter for firm value. We address this concern in several ways. First, we provide evidence suggesting that CEOs, even those of large companies, can afford the time to run frequently. Second, we find that past performance (Tobin’s Q lagged and operating cash flow lagged) does not explain CEO fitness, i.e., CEOs are not more likely to run a marathon when their firm has performed well. The number of (current or past) board meetings, used to measure the time that has to be spent with the firm, neither explain CEO fitness. Third, our results remain significant when we exclude the fittest CEOs, i.e., those with the fastest marathon finish times, who likely practice the most.

To further address reverse causality and to account for time-varying heterogeneity, we include additional controls. Specifically, we use the lagged value of Tobin’s Q to control for past performance and we use current operating cash flow, industry competition, sales growth and time-varying industry effects. This way, we particularly control for firm- and industry-specific heterogeneity that might allow the CEO to take the time to get fit. For example, CEOs might run if the industry their firm operates in performs very well in a specific year or if the firm’s current operating cash flow or sales growth show a positive trend. If so, CEO fitness and high firm value could both be the outcome of positive firm or industry trends. This does not seem to be the case. Our results for firm value remain significant even after including the forgone controls, independent of whether we use firm fixed or CEO-firm fixed effects.

As a last test whether CEO fitness affects firm value, which again addresses reverse causality, we implement an identification strategy based on sudden deaths. This allows us to draw inferences about causality. Specifically, we define CEOs as being fit when they are characterized as fit (in the related news and obituaries) around the time of their death. Among others, cases of fit CEOs include active mountaineers, skiers and tennis players. The broader definition of fitness, necessary due to the small sample size, allows for a more general test of the validity of our results. We find a significantly negative effect of fit CEOs on the abnormal stock return to the announcement of a sudden death which amounts to about 5 percentage points (consistent with our results for Tobin's Q). This result strongly supports our previous findings as it suggests (using a broader definition of fitness) that a fit CEO's contribution to firm value is significantly higher than a less fit CEO's contribution.

In general, our study contributes to the literature on CEO-specific heterogeneity based on Bertrand and Schoar (2003). It suggests that fitness is an important explanator for the heterogeneity among CEOs so far unaddressed by the literature. Existing studies have identified CEO attributes such as early-life experience and personality traits (see, e.g., Graham, Harvey, and Puri (2013), Malmendier, Tate, and Yan (2011)), military background (Benmelech and Frydman (2015)), industry and financial expertise (Custódio and Metzger (2013), and Custódio and Metzger (2014)) as well as general and interpersonal manager skills or, more broadly, cognitive and non-cognitive abilities (see, e.g., Kaplan, Klebanov, and Sorensen (2012), and Adams, Keloharju, and Knüpfer (2015)).

In particular, our study contributes to an emerging literature about the importance of CEOs' physiology. Apart from evidence on the effects of height on income and the likelihood of becoming a CEO (see, e.g., Lindqvist (2012)), two recent studies are related to our work in the sense that they also consider aspects of CEOs' physiology. Both use data about facial traits to examine how others perceive CEO's outward appearance. In experimental work, Graham, Harvey, and Puri (2015) find that CEOs' "look of competence" positively affect their selection and compensation, while it does not affect firm performance. Regarding firm value, Halford and Hsu (2014) find that S&P 500 CEOs who score high in a facial attractiveness index are associated with higher stock returns around their first day on the job and around announcements of M&As.

In contrast to most of the studies mentioned before, we identify a (physical) CEO attribute - relevant for firm value - that can actively be influenced by (most) CEOs and other executives, basically over their entire career. While attaining or improving on the aforementioned attributes is either impossible or associated with very high costs, it appears feasible that a majority of CEOs can improve their fitness.

The results of our study are important for shareholders as well as for participants in the managerial labor market including CEOs, senior executives, board members, and executive recruiting firms. We provide a rationale for why recruiting firms define physical fitness as a requirement for potential CEO candidates (see footnote 26) and can explain the growing trend among executives to stay fit. We believe that our results can be applied to other corporate executives and people whose jobs resemble that of the CEO.

The remainder of this paper is organized as follows. In Section 4.2, we describe the data and sample. Section 4.3 presents our empirical results for firm value and for firm profitability and M&As. Addressing issues of endogeneity and identification, Section 4.4 deals with the robustness of the positive relation between CEO fitness and firm value. Conclusions follow.

4.2 Data and sample

4.2.1 Data on CEO fitness and sample selection

To construct our sample, we use two main data sources. Our panel of S&P 1500 firms is from The Corporate Library's *Board Analyst* database and covers the sample period 2001 to 2011.[28] The database provides detailed information about CEOs' names, gender and age. This information is necessary to accurately match our firm-CEO panel with CEO-specific data. This CEO-specific information constitutes our second main source of data, information about CEOs who finish at least one marathon in a given year. We classify these CEOs as fit CEOs, i.e., our main variable of interest, *Fit CEO*, is defined on an annual basis.[29]

We hand-collect the fitness (marathon finisher) data from public data sources on the internet. Particularly, in order to keep the costs of hand-collection of data manageable, we collect data about all people who finished one of the fifteen largest U.S. marathons (in terms of the number of finishers) for each year over the sample period 2001 to 2011. Table 4.1 provides an overview of the marathons we consider. For the vast majority of these marathons, information about finishers is available on the respective marathons' websites. For each person who finished one of the marathons in the sample period, we gather the following data: first name, last name, age, gender, country. In case data are not available on the official marathon websites, we gather the data from www.marathonguide.com, a public website providing detailed information about U.S. marathons from 2000 onwards.

[28] *Board Analyst* is a machine-readable database which provides proxy-statement data including detailed information about CEOs and about firms' governance structures. The database includes information about founder CEOs, exact descriptions of chairmen resulting in comprehensible flags for CEO duality, and data about firms' age since foundation, a primary indicator for the stage of a firm's life cycle. Data is available for the year 2001 onwards. The database is used in recent studies on corporate boards (see, e.g., Alam, et al. (2014)).

[29] The use of an annual measure of fitness is not only preferable econometrically (as it allows to exploit CEO-specific variation over the fitness measure), but it is rather necessary to accurately measure (differences in) fitness according to the medicine and sports literature. Specifically, several studies document that fitness levels vary between periods of training and detraining, i.e., fitness levels increase/revert when practice is started/stopped (see, e.g., Coyle, et al. (1984), Mujika and Padilla (2000), Ready and Quinney (1982)).

Table 4.1: Largest 15 U.S. marathons by number of finishers

	Name of marathon	Location	# finishers 2011	Avrg. # finishers 2001-2011
1	ING New York City	New York, NY	47,133	37,665
2	Bank of America Chicago	Chicago, IL	35,755	32,196
3	Boston	Boston, MA	23,913	19,193
4	Marine Corps	Washington, DC	21,042	18,604
5	Honda LA	Los Angeles, CA	19,902	21,121
6	Honolulu	Honolulu, HI	19,102	21,742
7	Walt Disney World	Orlando, FL	13,551	11,072
8	Philadelphia	Philadelphia, PA	10,267	6,927
9	Medtronic Twin Cities	St. Paul, MN	8,534	7,593
10	Portland	Portland, OR	8,461	7,424
11	Rock'n'Roll San Diego	San Diego, CA	8,290	14,467
12	Chevron Houston	Houston, TX	6,919	5,368
13	Grandma's	Duluth, MN	6,337	6,594
14	Nike Women's	San Francisco, CA	6,108	4,193
15	San Francisco	San Francisco, CA	5,989	3,948
∑			243,859	218,107

Notes: This table presents the fifteen largest marathons in the United States ranked by the number of finishers in the year 2011. Data about the number of marathon finishers in the U.S. is provided by www.runningusa.org.

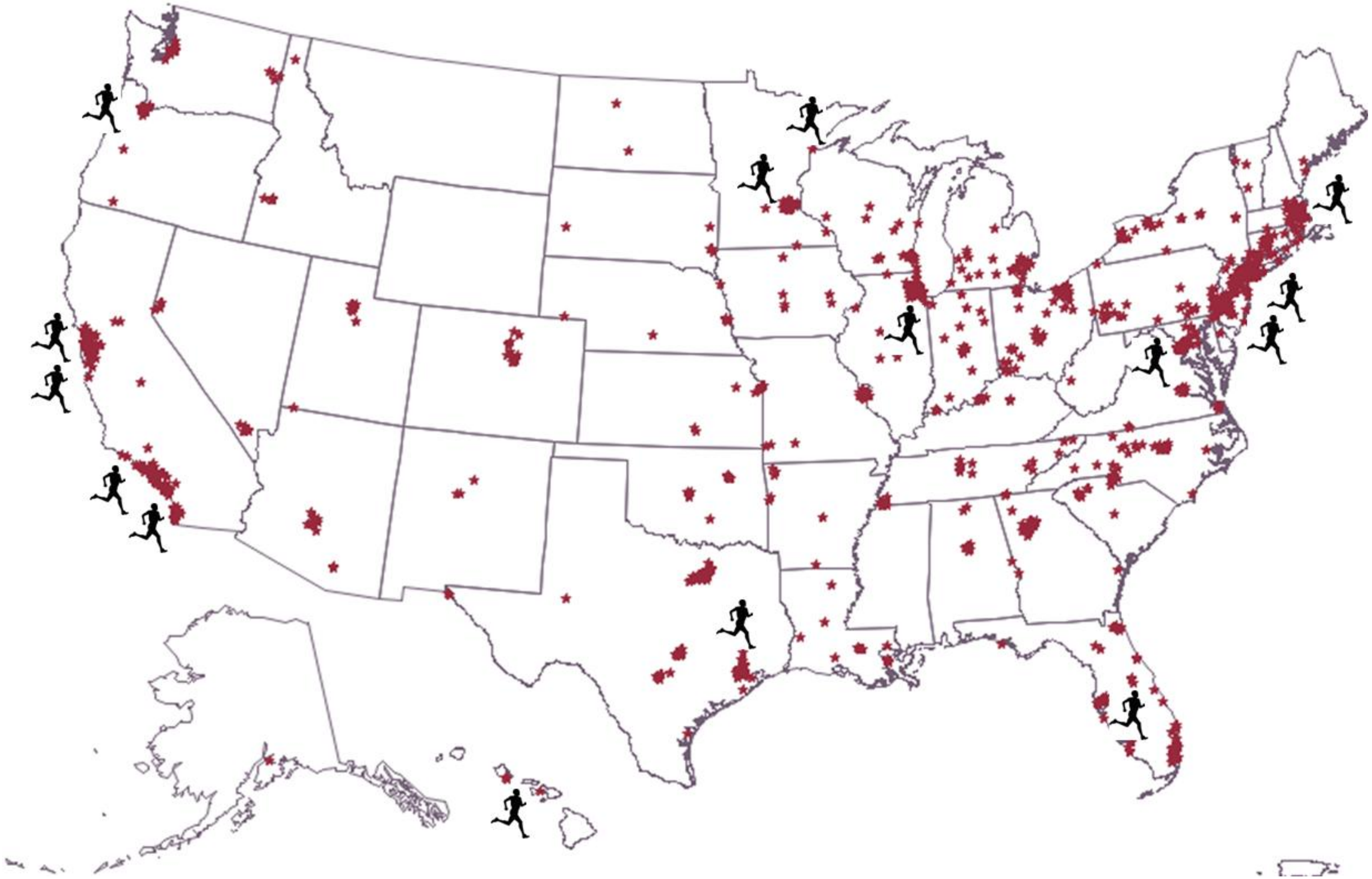
Our data gathering process generates a sample of almost 2.4 million non-distinct and more than 1.5 million distinct marathon finishers. This sample accounts for about 50% of all non-distinct U.S. marathon finishers over the sample period and, given that people run several marathons, for an even larger fraction of distinct marathoners.[30] The fact that we do not cover all U.S. marathons may lead us to exclude some CEOs who are actually fit (i.e., unidentified marathoners) from the group of fit CEOs. Yet, in this case, our reference group also contains some fit CEOs and we thus tend to underestimate the true effects of CEO fitness. The same reasoning applies to other CEOs who remain undetected as they do other sports.

From a geographical viewpoint, our focus on the fifteen largest U.S. marathons does not appear to be a serious limitation for our empirical analysis. In fact, the locations of the marathons we use fit the geographical distribution of the S&P 1500 firms very well as illustrated in Figure 4.1. In the figure we use zip codes to plot the locations of all S&P 1500 companies' headquarters. The runner symbol indicates the locations of the marathons we use. Figure 4.1 indicates that we cover the vast majority of all major U.S. business centers.[31]

[30] The estimated total number of U.S. marathon finishers (provided by www.runningusa.org) in the year 2011 was 518,000. The number of finishers of the fifteen largest marathons in 2011 was 244,000 (see Table 4.1). In the earlier years of our sample period, these marathons even account for a higher fraction of all marathoners.

[31] One might argue that our fitness measure captures regional aspects as CEOs of firms not located in business centers could be less likely to participate in the marathons we examine. This unlikely affects our results as we use firm fixed effects and as headquarter changes are very rare events (see Pirinsky and Wang (2006)).

Figure 4.1: Company clusters and marathon locations



Notes: This figure plots the geographical distribution of the S&P 1500 companies (based on zip codes) and the 15 largest U.S. marathons. Each red star marks a company's headquarter location. The runner symbol indicates the marathon's location. For an overview of the 15 largest U.S. marathons, see Table 4.1.

We match our data on marathon finishers described above with the initial sample of CEOs from the *Board Analyst* database using the information about each CEO's first name, last name, and age. Particularly, if the first name, the last name, and the age of the marathon finisher exactly match the CEO´s first name, last name and age, we define this as a positive (non-final) match. In case the names perfectly match, but the age matching results in an age difference between the CEO and the marathon finisher of one year, we consider this a potential positive (non-final) match. The reason is that it is possible that the CEO´s birthday is before or after the marathon event and thus our matching procedure creates an age difference greater than zero, although the match may be correct. Matches are then manually checked (if possible) by screening the internet using LexisNexis, LinkedIn, and different Google searches, among other sources. Additionally, we gather data on name distributions from the U.S. census to calculate - for each positive match we identify - the probability of a false positive match for a given CEO's first name, last name and age.[32] Whenever the probability is greater than ten percent, we define an initially positive match as a false match.

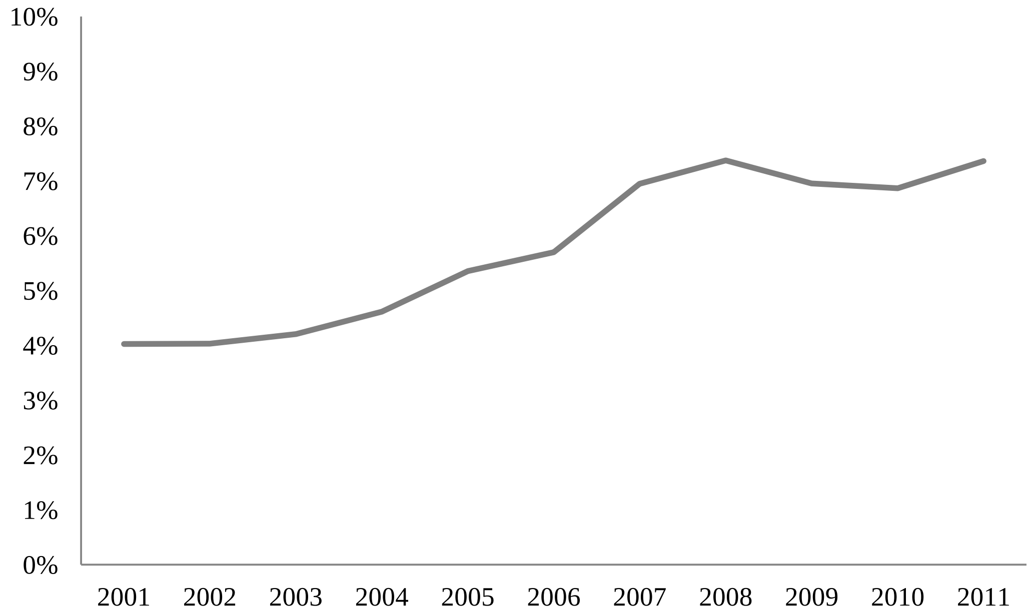
Using the described procedure, we find that about six percent of all CEOs can be classified as fit, i.e., they finish at least one marathon in our sample period. The fraction of CEOs with at least one finished marathon has almost doubled between 2001 and 2011, as can be seen from Figure 4.2 which shows the annual percentage of CEOs identified as marathon finishers over the entire sample period. The figure shows that the fraction of CEOs with at least one finished marathon has increased over the sample period. On average, these CEOs finish two marathons. The 25% percentile is one, the 75% percentile is three, and the maximum is nine.

Our final sample consists of 9,549 firm-year observations (by 2,694 CEOs) with all available data, including CEO, firm and governance characteristics. CEO-specific data include age, duality, whether the CEO is the firm's founder, and tenure. Firm characteristics include the standard controls used in the literature, i.e., book leverage, business segments, capital expenditures (CapEx), firm age and firm size, operating cash flow, and R&D. All accounting data is from Compustat. Governance characteristics include the fraction (%) of independent directors, board size, the E-index (Bebchuk, Cohen, and Ferrell (2009)), and whether the majority of a firm's outstanding shares are held by institutions (i.e., institutional majority). Our measure for firm value is Tobin's Q. Firm profitability is measured by return

[32] Therefore, we assume that the 1.5 million distinct marathon finishers in our marathon dataset are representative for the U.S. population and consequently handle them as random draws from the population. We use the age distribution from this population together with the name distribution from the U.S. census to estimate the probability of a randomly achieved false positive match for a given CEO.

on assets (ROA) and free cash flow to total assets.[33] All variables are defined in the Appendix.

Figure 4.2: Fraction of CEOs identified as marathon runners over the sample period



Notes: This figure shows the annual fraction of S&P 1500 CEOs identified as marathon finishers over the sample period 2001 to 2011.

4.2.2 Summary statistics

The summary statistics for our sample are presented in Table 4.2. In terms of CEO characteristics, we report that the typical CEO in our sample is 55 years old and has been on the company's board for 11 years. 63% of the CEOs in our sample are also the chairman of their board and 8% of the CEOs are the founders of the company they lead. The typical firm in our sample has a book leverage of 21%, three business segments, CapEx (over sales) of 7%, and is 50 years old (measuring firm age since foundation). On average, firm size is $2.54 billion (i.e., ln (total assets lagged) is 7.84), operating cash flow is 11%, and R&D (defined as R&D expenses over sales) is 5%. In terms of firm performance, average Tobin's Q amounts to 1.81, while ROA and free cash flow are 13% and 8%, respectively. Regarding governance characteristics, our sample firms have an average fraction of independent directors of 70%, a board size of 9, and an E-index of 2.67. For 81% of our sample firms the majority of their outstanding shares are held by institutions.

[33] The number of observations is lower for measures of firm profitability because EBITDA and free cash flow are not reported for all firms. Generally, EBITDA is not available for financial firms and, more specifically, working capital (used to calculate free cash flow) is not provided for all firms in the Compustat universe.

Table 4.2: Summary statistics

	Mean	p25	p50	p75	Std Dev	N	Mean: Fit CEO=1	Mean: Fit CEO=0	Mean: Difference		Median: Fit CEO=1	Median: Fit CEO=0	Median: Difference	
CEO characteristics:														
CEO age	55.53	51.00	55.00	60.00	7.22	9,549	53.12	55.56	-2.44	***	53.00	55.00	-2.00	***
CEO duality	0.63				0.48	9,549	0.64	0.63	0.01					
CEO tenure	11.30	5.00	9.00	16.00	9.05	9,549	11.32	9.98	1.34		8.00	9.00	-1.00	
Founder CEO	0.08				0.27	9,549	0.04	0.08	-0.04					
Firm characteristics:														
Book leverage	0.21	0.06	0.20	0.33	0.18	9,549	0.21	0.21	-0.01		0.19	0.20	-0.01	
Business segments	2.90	1.00	3.00	4.00	2.14	9,549	2.82	2.91	-0.08		3.00	3.00	0.00	
CapEx	0.07	0.02	0.03	0.07	0.14	9,549	0.10	0.07	0.03	**	0.03	0.03	0.00	
Firm age	50.1	19.0	36.0	76.0	40.8	9,549	45.7	50.1	-4.48		34.0	36.0	-2.00	
Firm size	7.84	6.63	7.69	8.91	1.66	9,549	7.34	7.85	-0.51	***	7.18	7.70	-0.51	***
Free cash flow	0.08	0.02	0.07	0.13	0.12	8,250	0.08	0.08	0.00		0.07	0.07	0.00	
Operating cash flow	0.11	0.06	0.10	0.16	0.10	9,549	0.13	0.11	0.01		0.10	0.10	0.00	
R&D	0.05	0.00	0.00	0.03	0.30	9,549	0.03	0.05	-0.02		0.00	0.00	0.00	
ROA	0.13	0.08	0.12	0.18	0.10	9,331	0.16	0.13	0.03	***	0.14	0.12	0.02	**
Tobin´s Q	1.81	1.13	1.46	2.07	1.09	9,549	2.14	1.80	0.33	***	1.53	1.46	0.07	*
Governance characteristics:														
% indep. directors	0.70	0.60	0.71	0.82	0.15	9,549	0.69	0.70	-0.01		0.70	0.71	-0.01	
Board size	9.45	8.00	9.00	11.00	2.47	9,549	8.66	9.46	-0.80	***	9.00	9.00	0.00	***
E-Index	2.67	2.00	3.00	3.00	1.32	9,549	2.53	2.68	-0.15		2.00	3.00	-1.00	
Institutional majority	0.81	1.00	1.00	1.00	0.39	9,549	0.77	0.81	-0.03		1.00	1.00	0.00	

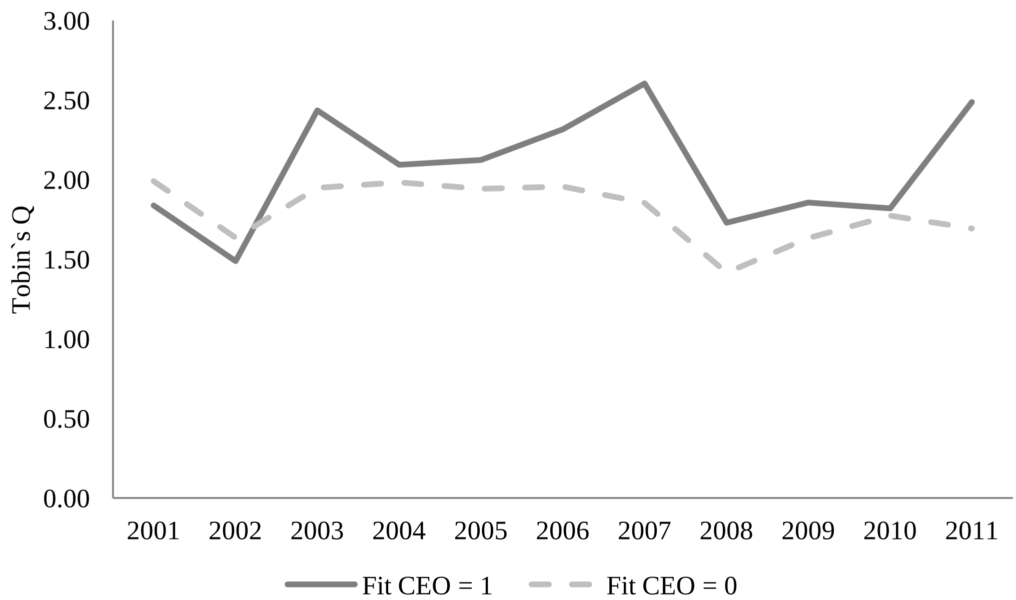
Notes: This table reports summary statistics (on firm-year level) for our full sample of S&P 1500 companies for the sample period 2001 to 2011 as well as for the subsamples as defined by CEO fitness. Mean and median differences for the subsamples of firms with and without a *Fit CEO* are reported. All variables are defined in the Appendix. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively, for the difference in means and medians between both subsamples (based on t-tests and Mann-Whitney-Wilcoxon rank-sum tests).

In terms of CEO, firm and governance characteristics, our sample compares well to the related literature (see, e.g., Adams, Almeida, and Ferreira (2005), Alam, et al. (2014), Benmelech and Frydman (2015), Custódio and Metzger (2014), Fahlenbrach (2009)).[34]

Table 4.2 also presents summary statistics for the subsamples of firms with and without fit CEOs (i.e., the variable *Fit CEO* is used to split the sample). Tests for mean and median differences suggest that the two subsamples show a few significant disparities: fit CEOs are younger (53 vs. 55 years), manage smaller companies (with smaller boards), and are associated with slightly higher CapEx. Most important, ROA and, in particular, Tobin's Q are significantly higher for firms managed by fit CEOs. Figure 4.3 illustrates the annual differences in firm value between firms with and without fit CEOs for our sample period.

As can be seen from Figure 4.3, except for the very beginning of our sample period (years 2001 and 2002), Tobin's Q is always higher for the sample of fit CEOs. Hence, a positive relation between CEO fitness and firm value is directly reflected in the data. In this regard, we note that firms with and without fit CEOs do not belong to significantly different industries based on first-digit SIC codes (not reported for brevity).

Figure 4.3: CEO fitness and firm value



Notes: This figure shows the annual mean *Tobin´s Q* for firms with and without a *Fit CEO* for each year in the sample period 2001 to 2011. Variables are defined in the Appendix.

[34] For example, Adams, Almeida, and Ferreira (2005) and Fahlenbrach (2009) report fractions of founder CEOs of 9% and 10.6%, respectively, only slightly larger than the 8% we report. These studies also report comparable values with regard to business segments, CapEx, firm age, and leverage. In terms of governance characteristics, Cremers and Romano (2011), for example, report comparable values for institutional ownership (72%), while Bebchuk, Cohen, and Ferrell (2009) report comparable E-index values. A very important statistic for our study is the CEO's age as we use it for our marathon runner-CEO match and to create subsamples. Among other studies, Custódio and Metzger (2014) report the same mean and median CEO age as we do.

4.3 Empirical results

In this section, we examine the relation between CEO fitness and firm value in a multivariate setting (in Section 4.3.1) and analyze important channels for value creation, namely firm profitability and mergers and acquisitions (M&As), to provide evidence for how CEO fitness translates into firm value (in Section 4.3.2).

4.3.1 CEO fitness and firm value

We test the relation between CEO fitness and firm value using our full sample of 9,549 firm-year observations. In Table 4.3, we show results from regressions of the natural logarithm of Tobin´s Q (specification (1)) and Tobin`s Q (specification (2)) on the CEO, firm and governance variables described in Section 4.2. Our main variable of interest is *Fit CEO* which equals one if a CEO finishes a marathon in a given year. The regression specifications include firm- and year-fixed effects to control for unobserved heterogeneity and time trends. All regressions we show use robust t-values of the regression coefficients based on standard errors clustered by firm.

In terms of control variables, we follow recent studies which examine determinants of firm value (see, e.g., Custódio and Metzger (2014), Fahlenbrach (2009), and Nguyen and Meisner Nielsen (2014)). Apart from the standard firm characteristics – book leverage, business segments, CapEx, firm age, firm size, operating cash flow, and R&D – we control for CEO and governance characteristics commonly used in the literature. CEO characteristics are age, CEO-chairman duality, whether the CEO is the firm’s founder, and tenure. Corporate governance characteristics include the fraction (%) of independent directors, board size, the E-index, and a dummy for institutional majority ownership of outstanding shares.

Including firm age since foundation, firm size, and a CEO founder dummy, we are able to account for the stage of a firm’s life cycle. Book leverage, business segments, and R&D control for firm complexity and risk, while CapEx and operating cash flow control for investments and performance. The CEO and corporate governance controls allow us to account for the career concerns, experience and power of CEOs. In this regard, CEO age constitutes a particularly important control as it has been shown to negatively affect firms’ investment activities and risk (see, e.g., Li, Low, and Makhija (2014)), while it also correlates negatively with the likelihood of a CEO being fit.

Table 4.3: CEO fitness and firm value

Dep. variable:	Ln(Tobin´s Q)	Tobin´s Q
	(1)	(2)
Fit CEO	**0.0461****	**0.1440****
	(2.067)	**(2.165)**
CEO characteristics:		
CEO age	0.0009	0.0027
	(0.822)	(0.959)
CEO tenure	-0.0029	-0.0081
	(-0.405)	(-0.442)
CEO duality	0.0092	0.0173
	(0.761)	(0.482)
Founder CEO	-0.0323	-0.0356
	(-1.220)	(-0.438)
Firm characteristics:		
Firm age	0.0275	0.0822
	(0.888)	(1.104)
Firm size	-0.1707***	-0.4278***
	(-12.100)	(-9.445)
Book leverage	-0.1052**	-0.2808*
	(-2.158)	(-1.822)
R&D	0.1148***	0.4763***
	(19.333)	(15.253)
CapEx	-0.0882	-0.4127
	(-1.590)	(-1.169)
Operating cash flow	0.4821***	1.1426***
	(7.495)	(4.860)
Business segments	-0.0011	-0.0087
	(-0.153)	(-0.520)
Governance characteristics:		
Board size	-0.0214	-0.0739
	(-0.783)	(-1.008)
% indep. directors	-0.0033	0.0118
	(-0.132)	(0.177)
E-Index	-0.0151***	-0.0301***
	(-3.233)	(-2.606)
Institutional majority	0.0322***	0.0472**
	(3.442)	(1.993)
Year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
NObs	9,549	9,549
Within R-Squared	0.288	0.223

Notes: This table reports coefficients from firm fixed effects regressions of the natural logarithm of Tobin´s Q and Tobin´s Q on the *Fit CEO* dummy and other control variables. Both regression specifications include year fixed effects and a constant (not reported). All variables are defined in the Appendix. Robust t-values of the regression coefficients (in parentheses) are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

The results in Table 4.3 corroborate our findings from Section 4.2. Fit CEOs are associated with a significantly higher firm value. The coefficient of the variable *Fit CEO* is statistically significant at the 5% level, independent of whether we use the natural logarithm of Tobin's Q (i.e., Ln(Tobin's Q)) or Tobin's Q as dependent variables in specifications (1) and (2), respectively. The former suggests that the effect of fitness is economically significant. The coefficient of *Fit CEO* is 0.0461 in specification (1), which means that Tobin´s Q is almost 5% higher for fit CEOs, taking all control variables into account.

With regard to the employed control variables, we report that firm size, leverage and the E-index have significantly negative effects on Tobin's Q, while operating cash flow, R&D and institutional ownership have significantly positive effects. The results are in line with the studies named above and with recent studies on CEOs, corporate governance and firm value (see, e.g., Bebchuk, Cohen, and Ferrell (2009), Li, Lu, and Phillips (2014)).[35]

To conclude, firms managed by fit CEOs have higher firm values, consistent with the postulated positive effects of fitness on CEO efficiency, performance and stress coping.

4.3.2 Channels

To gain a better understanding where the positive relation between CEO fitness and firm value comes from, we examine profitability and, in particular, mergers and acquisitions as important channels that have an immediate impact on firm value.

4.3.2.1 CEO fitness and firm profitability

We use two measures of firm profitability, return on assets (ROA) and free cash flow to total assets (FCF). The latter is infrequently used in the literature, although it is highly relevant for firm value. We define free cash flow as a firm's EBITDA minus its capital expenditures and changes in working capital, i.e., it takes corporate investments into account. We run regressions of these two measures on our variable *Fit CEO* and the control variables used in Section 4.3.1. Results are shown in Table 4.4. Specification (1) uses ROA as the dependent variable, while specification (2) uses FCF.

[35] With regard to the CEO characteristics age, duality, founder and tenure, the literature finds either insignificant or opposing effects. For example, while Fahlenbrach (2009) finds a positive effect of founder CEOs on firm value, Nguyen and Meisner Nielsen (2014) find no effect, and Li, Lu, and Phillips (2014) find a negative effect. Similar examples can be made for all other CEO characteristics we use.

Table 4.4: CEO fitness and firm profitability

Dep. variable:	ROA (1)	FCF (2)
Fit CEO	**0.0090****	**0.0182****
	(2.298)	**(2.387)**
CEO characteristics:		
CEO age	-0.0002	-0.0001
	(-0.680)	(-0.336)
CEO tenure	-0.0011	-0.0016
	(-0.642)	(-0.515)
CEO duality	0.0060*	0.0009
	(1.872)	(0.185)
Founder CEO	-0.0185**	-0.0189
	(-2.494)	(-1.578)
Firm characteristics:		
Firm age	0.0060	0.0168*
	(0.858)	(1.799)
Firm size	-0.0154***	0.0406***
	(-4.261)	(7.063)
Book leverage	0.0086	0.0499**
	(0.647)	(2.255)
R&D	-0.0342***	-0.0235***
	(-9.047)	(-5.797)
CapEx	-0.0174	-0.0773***
	(-0.824)	(-2.853)
Operating cash flow	0.1582***	0.1086***
	(6.012)	(3.335)
Business segments	-0.0032*	0.0012
	(-1.817)	(0.530)
Governance characteristics:		
Board size	0.0178***	-0.0086
	(2.803)	(-0.780)
% indep. directors	0.0052	-0.0076
	(0.972)	(-0.729)
E-Index	0.0006	0.0026
	(0.465)	(1.337)
Institutional majority	0.0057**	-0.0010
	(2.221)	(-0.234)
Year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
NObs	9,331	8,250
Within R-Squared	0.113	0.046

Notes: This table reports coefficients from firm fixed effects regressions of Return on Assets (ROA) and Free Cash Flow (FCF) on the *Fit CEO* dummy and other control variables. Both regression specifications include year fixed effects and a constant (not reported). All variables are defined in the Appendix. Robust t-values of the regression coefficients (in parentheses) are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

As can be seen from Table 4.4, the regression coefficient of *Fit CEO* is positive and significant at the 5% level in both specifications. That means, fit CEOs are associated with a significantly higher firm profitability. The effect is also economically relevant. For example, when evaluated at the mean, ROA is 6.9% higher for firms managed by a fit CEO. Results for the employed control variables are in line with the literature and economic intuition.

The results for return on assets and free cash flow provide a first explanation for the positive relation between CEO fitness and firm value found in Section 4.3.1. However, these results only reflect multivariate correlations. Therefore, we focus on the M&A event study results, presented in the following, as they are less likely to suffer from endogeneity.

4.3.2.2 CEO fitness and M&A performance

Besides putting the firm's assets to work in the most profitable way, making new investments with positive net present values is another important channel of value creation. Thus, we now turn to M&As which constitute the largest investments that firms undertake. As such they have an immediate impact on firm value (see, e.g., Betton, Eckbo, and Thorburn (2008)). To measure firm value, we examine the abnormal stock returns in the three and seven trading days around announcements of M&As, denoted *CAR [-1,1]* and *CAR [-3,3]*.

M&As are an optimal laboratory for our study because fitness - which enables CEOs to better cope with stress and enhances their performance - should be highly relevant in this context. M&As do not only constitute far-reaching decisions often times including plant closures and layoffs, but they also tend to be particularly stressful and work-intensive for the CEO due to considerable media scrutiny (Liu and McConnell (2013)), lengthy and uncertain (re)negotiations (Officer (2004)), and pressure to perform. Regarding the latter, Lehn and Zhao (2006) find that CEOs who are bad bidders are significantly more likely to get fired. The aforementioned reasoning should particularly apply to M&A bids for large and public targets as they tend to be the most complex transactions, which draw the most attention by the media and by firms' shareholders and thus put CEOs in direct spotlight.

To examine the effect of CEO fitness on abnormal announcement returns, we use a sample of 2,203 M&A transactions announced by our sample firms during the period 2001 to 2011. The respective data is retrieved from the Standard and Poor's Capital IQ database. Our M&A sample includes all deals with a total transaction value of at least five million US dollars. Only bids for a majority stake (i.e., for at least 50%) of the target firm are included. For these deals, we are able to use the same control variables as in the previous analyses. We further include additional M&A-specific controls which follow the extant literature (see, e.g., Custódio and Metzger (2013), Fuller, Netter, and Stegemoller (2002), and Moeller, Schlingemann, and Stulz (2005)). The additional controls are the absolute and the relative size of the transaction, whether the target is a publicly listed firm, dummy variables for cross-border, focusing, and hostile transactions as well as the means of payment. All additional controls are defined in Table 4.5, which shows the results of regressions of *CAR [-1,1]* and *CAR [-3,3]* on the variable *Fit CEO* and all controls. We cluster standard errors at the acquirer level. In specifications (5) and (6) we use *CAR [-1,1]* < 0 and *CAR [-3,3] < 0*, which are dummy variables set to one if the cumulative abnormal return is negative, as dependent variables. This is done for robustness purposes.

As shown in Table 4.5, when we use all 2,203 M&A transactions without any restriction on relative deal size in specifications (1) and (2), we find a significantly positive effect of the variable *Fit CEO* for the dependent variable *CAR [-3,3]* only. In this case, the regression coefficient of *Fit CEO* amounts to about 0.8 percentage points (significant at the 5% level). As frequently done in the M&A literature (see, e.g., Moeller, Schlingemann, and Stulz (2005), Lehn and Zhao (2006)), we restrict relative deal size to at least 1% in specifications (3) to (6) in order to exclude M&As that are unlikely to affect the CEO (and the firm). When we focus on larger deals, *Fit CEO* is statistically significant at the 5% and the 1% level when used to explain *CAR [-1,1]* and *CAR [-3,3]* in specifications (3) and (4) and at the 5% and the 10% level when used to explain *CAR [-1,1]* < 0 and *CAR [-3,3] < 0* in specifications (5) and (6), respectively. The coefficient of *Fit CEO* also increases considerably in terms of magnitude: it ranges from 1.3 to 2.2 percentage points (in specifications (3) and (4)).

Finally, in specifications (7) to (10) we again use all M&A transactions and interact the variable *Fit CEO* with the variables *Relative size* (in specifications (7) and (8)) and *Public target* (in specifications (9) and (10)). Following our reasoning, we expect that the importance of CEO fitness increases with relative size and is particularly pronounced in bids for public targets as they tend to include larger firms and as they are accompanied by most intensive media and shareholder scrutiny. The results strongly support our expectation. For both dependent variables *CAR [-1,1]* and *CAR [-3,3]*, the interaction terms are positive and significant at the 1% level. Importantly, while M&A bids for public targets are generally associated with negative announcement returns (see also Custódio and Metzger (2013), and Moeller, Schlingemann, and Stulz (2005)), we find significantly positive returns if bids for public targets are announced by fit CEOs as indicated by the variable *Fit CEO*Public target*.

Table 4.5: CEO fitness and M&A performance

	All M&A transactions		M&A transactions with relative size >= 1%				All M&A transactions			
					CAR < 0 dummies					
Dep. variable:	CAR [-1,1] (1)	CAR [-3,3] (2)	CAR [-1,1] (3)	CAR [-3,3] (4)	CAR [-1,1] (5)	CAR [-3,3] (6)	CAR [-1,1] (7)	CAR [-3,3] (8)	CAR [-1,1] (9)	CAR [-3,3] (10)
Fit CEO	**0.0047**	**0.0077****	**0.0132****	**0.0221*****	**-0.2528****	**-0.2691***	**-0.0133**	**-0.0126**	**0.0008**	**0.0028**
	(0.845)	**(2.211)**	**(2.448)**	**(3.040)**	**(-2.119)**	**(-1.887)**	**(-1.333)**	**(-1.503)**	**(0.118)**	**(0.579)**
Fit CEO * Relative size							**0.7169*****	**0.8105*****		
							(2.609)	**(2.782)**		
Fit CEO * Public target									**0.0253*****	**0.0318*****
									(3.135)	**(3.214)**
Deal characteristics:										
Public target	-0.0105***	-0.0099**	-0.0122***	-0.0117**	0.1010***	0.0756*	-0.0105***	-0.0100**	-0.0106***	-0.0101**
	(-3.296)	(-2.338)	(-2.967)	(-2.178)	(2.584)	(1.879)	(-3.312)	(-2.349)	(-3.322)	(-2.371)
Relative size	0.0203**	0.0219**	0.0196*	0.0218*	-0.0470	-0.1095*	0.0205**	0.0220**	0.0204**	0.0220**
	(2.081)	(1.985)	(1.811)	(1.736)	(-0.764)	(-1.894)	(2.092)	(1.996)	(2.086)	(1.991)
Transaction value	-0.0004	-0.0020	0.0015	-0.0014	-0.0444	0.0178	-0.0005	-0.0021	-0.0004	-0.0020
	(-0.209)	(-0.721)	(0.347)	(-0.236)	(-1.227)	(0.498)	(-0.246)	(-0.752)	(-0.209)	(-0.720)
Payment includes stock	-0.0031	0.0009	-0.0045	0.0028	0.0564	0.0202	-0.0030	0.0009	-0.0030	0.0010
	(-0.663)	(0.154)	(-0.822)	(0.385)	(1.260)	(0.487)	(-0.662)	(0.156)	(-0.658)	(0.160)
Cross-border	-0.0016	0.0007	-0.0007	0.0049	-0.0355	-0.0504	-0.0017	0.0006	-0.0017	0.0006
	(-0.683)	(0.200)	(-0.189)	(1.113)	(-1.034)	(-1.524)	(-0.707)	(0.179)	(-0.699)	(0.185)
Same industry	0.0023	0.0001	0.0017	-0.0007	-0.0817***	-0.0174	0.0023	0.0001	0.0023	0.0001
	(0.866)	(0.018)	(0.516)	(-0.173)	(-2.625)	(-0.530)	(0.875)	(0.027)	(0.865)	(0.018)
Hostile	-0.0040	0.0123	-0.0021	0.0147	0.0600	-0.0245	-0.0039	0.0124	-0.0039	0.0124
	(-0.166)	(0.559)	(-0.083)	(0.585)	(0.266)	(-0.118)	(-0.163)	(0.562)	(-0.164)	(0.562)
CEO characteristics:										
CEO age	0.0000	0.0002	-0.0000	0.0003	0.0001	-0.0020	0.0001	0.0002	0.0000	0.0002
	(0.258)	(0.812)	(-0.115)	(0.876)	(0.044)	(-0.822)	(0.281)	(0.832)	(0.265)	(0.819)
CEO tenure	-0.0016	-0.0015	-0.0036	-0.0032	0.0391	0.0104	-0.0017	-0.0016	-0.0016	-0.0015
	(-0.906)	(-0.646)	(-1.443)	(-1.022)	(1.642)	(0.423)	(-0.945)	(-0.679)	(-0.924)	(-0.663)
CEO duality	0.0026	0.0020	0.0039	0.0028	-0.0540*	-0.0283	0.0027	0.0021	0.0026	0.0020
	(1.132)	(0.630)	(1.232)	(0.651)	(-1.747)	(-0.872)	(1.161)	(0.654)	(1.139)	(0.637)
Founder CEO	0.0045	0.0032	0.0073	0.0054	-0.0627	-0.0582	0.0045	0.0033	0.0045	0.0032
	(0.932)	(0.501)	(1.114)	(0.632)	(-1.128)	(-0.997)	(0.941)	(0.509)	(0.937)	(0.506)

Firm characteristics:										
Firm age	0.0010	0.0027	0.0017	0.0037	-0.0125	-0.0158	0.0011	0.0027	0.0010	0.0027
	(0.740)	(1.415)	(0.887)	(1.588)	(-0.742)	(-0.869)	(0.761)	(1.434)	(0.733)	(1.408)
Firm size	-0.0019*	-0.0015	-0.0030	-0.0025	0.0337*	0.0159	-0.0018*	-0.0014	-0.0018*	-0.0014
	(-1.902)	(-1.201)	(-1.573)	(-0.968)	(1.956)	(0.897)	(-1.880)	(-1.181)	(-1.875)	(-1.175)
Book leverage	-0.0022	-0.0242**	0.0032	-0.0172	-0.0853	0.0253	-0.0023	-0.0243**	-0.0021	-0.0241**
	(-0.280)	(-2.455)	(0.286)	(-1.274)	(-0.920)	(0.257)	(-0.286)	(-2.458)	(-0.269)	(-2.441)
R&D	0.0294**	0.0014	0.0229	0.0068	0.3660***	0.4995***	0.0295**	0.0015	0.0293**	0.0012
	(1.984)	(0.077)	(1.123)	(0.276)	(3.041)	(3.871)	(1.989)	(0.084)	(1.977)	(0.071)
CapEx	0.0083	0.0262*	0.0041	0.0279	-0.0374	-0.1466	0.0084	0.0263*	0.0082	0.0261*
	(0.755)	(1.809)	(0.285)	(1.478)	(-0.349)	(-1.329)	(0.760)	(1.813)	(0.747)	(1.801)
Operating cash flow	-0.0289***	-0.0571***	-0.0393***	-0.0675***	-0.2665	0.0996	-0.0289***	-0.0571***	-0.0289***	-0.0571***
	(-2.595)	(-4.290)	(-2.636)	(-3.962)	(-1.620)	(0.557)	(-2.588)	(-4.284)	(-2.595)	(-4.290)
MTB	0.0004	0.0006	0.0007	0.0009	-0.0042	-0.0048	0.0004	0.0006	0.0004	0.0006
	(1.525)	(1.633)	(1.115)	(1.197)	(-0.800)	(-0.948)	(1.527)	(1.634)	(1.517)	(1.626)
Business segments	0.0006	0.0000	0.0006	0.0001	-0.0044	-0.0033	0.0006	0.0000	0.0006	0.0000
	(1.425)	(0.033)	(0.973)	(0.107)	(-0.805)	(-0.563)	(1.419)	(0.027)	(1.432)	(0.040)
Governance characteristics:										
Board size	0.0009	0.0004	0.0020	0.0018	0.0587	0.1243	0.0009	0.0004	0.0009	0.0004
	(0.941)	(0.316)	(1.552)	(1.174)	(0.801)	(1.601)	(0.941)	(0.317)	(0.931)	(0.307)
% indep. directors	0.0035	0.0010	0.0039	0.0013	0.1444	0.0474	0.0035	0.0009	0.0034	0.0008
	(0.588)	(0.131)	(0.480)	(0.133)	(1.409)	(0.451)	(0.576)	(0.121)	(0.558)	(0.102)
E-Index	0.0029	0.0053	0.0071*	0.0103*	-0.0295**	-0.0185	0.0029	0.0052	0.0030	0.0053
	(0.928)	(1.275)	(1.704)	(1.958)	(-2.523)	(-1.567)	(0.921)	(1.269)	(0.929)	(1.276)
Institutional majority	-0.0112	0.0003	-0.0201*	-0.0014	-0.0624*	-0.0426	-0.0111	0.0004	-0.0112	0.0003
	(-1.180)	(0.028)	(-1.662)	(-0.097)	(-1.820)	(-1.257)	(-1.173)	(0.033)	(-1.178)	(0.029)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NObs	2,203	2,203	1,425	1,425	1,425	1,425	2,203	2,203	2,203	2,203
Adj. R-Squared	0.036	0.035	0.052	0.052	0.017	0.013	0.036	0.035	0.036	0.035

(Continued)

Table 4.5: Continued

Notes: This table reports coefficients from OLS regressions of cumulative abnormal returns around the announcement of mergers and acquisitions (M&As) on the *Fit CEO* dummy, other control variables and interaction terms between the *Fit CEO* dummy and various deal characteristics. *CAR[-1,1]* (*CAR[-3,3])* is the cumulative abnormal return around the merger announcement over the three (seven)-day event window. CARs are estimated using the market-model event study approach with an estimation window of 200 trading days ending 21 trading days before the announcement of the deal. In specification (5) and (6) the dependent variables are indicator variables set to one if *CAR[-1,1]* or *CAR[-3,3]* are below zero (denoted CAR < 0 dummies). *Cross-border* is a dummy variable that is set to one if the deal is a cross-border deal, zero for domestic deals. *Hostile* is a dummy variable that is set to one for deals defined as hostile deals, zero otherwise. *MTB* is the acquiring firm's market-to-book ratio defined as the acquirer's market capitalization 20 trading days prior to deal announcement divided by the acquirer´s common equity as of the end of the fiscal year prior the announcement of the M&A deal. *Payment includes stock* is a dummy variable (regarding the acquirer´s chosen method of payment) that equals one for deals in which the consideration includes some stock, zero otherwise. *Public target* is dummy variable that equals one if the target firm is a listed company, zero otherwise. *Relative size* is the deal's total transaction value divided by the acquirer's market capitalization 20 days prior to the announcement of the deal. *Same industry* is a dummy variable that equals one if the acquirer and the target belong to the same two-digit SIC industry, zero otherwise. *Transaction value* is the natural logarithm of the total transaction value. All other control variables are defined in the Appendix. All regression specifications also include a constant as well as year fixed effects and industry fixed effects (first-digit SIC codes) as in Moeller, Schlingemann, and Stulz (2005) (the respective regression coefficients are not reported for brevity). Robust t-statistics of the regression coefficients (in parentheses) are based on standard errors clustered by acquirer. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

In terms of control variables, our findings are in line with the literature. For example, similar to Fuller, Netter, and Stegemoller (2002) and Moeller, Schlingemann, and Stulz (2005), we find that relative deal size has a significantly positive effect on abnormal announcement returns, while target size is insignificant. Further, in line with Custódio and Metzger (2013), we find no effect of CEO age or tenure on abnormal returns, while acquirer size is found to negatively affect abnormal returns.

To conclude, the M&A event study results provide a strong explanation for our main effect, the positive relation between CEO fitness and firm value. The findings, particularly those for relative deal size and public deals, support the idea that we measure fitness and that fitness facilitates CEO performance and stress coping. Furthermore, the use of the event study methodology is a first attempt to mitigate endogeneity. In the following section, we deal with endogeneity concerns in great detail.

4.4 Robustness and identification

Having identified channels that explain how fitness translates into firm value, we now turn to the robustness of the positive effect of CEO fitness on firm value documented in Section 4.3.1. We address various endogeneity concerns and provide an identification strategy that allows us to draw inferences about causality. Particularly, in Section 4.4.1 we address the concern that we might not measure CEO fitness. In the respective analyses, we also take the endogenous matching between CEOs and firms into account. In section 4.4.2 we address issues of reverse causality and unobserved time-varying heterogeneity due to firm- and industry-specific effects. Finally, in Section 4.4.3 we provide an identification strategy based on CEO sudden deaths. In this analysis, we also extend our definition of fit CEOs.

4.4.1 Do we really measure CEO fitness?

Because the actual fitness level of CEOs is not observable, we have to use publicly available information about CEOs' sports activities to proxy their fitness. Optimally, we would like to have CEOs' medical records or, at least, data about all of a CEO's activities in order not to forego any relevant information. As this is unfortunately not possible, we use data on finished marathons to measure fitness. Yet, this approach raises the question whether we really measure the fitness of CEOs and its consequences. In the following, we deal with this question at length.

4.4.1.1 When fitness matters most

We start with an intuitive test in which we employ variation over different CEO characteristics associated with different levels of the importance of fitness. That means, we identify CEOs for which the positive effect of fitness on job performance and stress coping, and ultimately firm value, should be most evident. In case we really measure fitness, we should find strong, significant effects of the variable *Fit CEO* on firm value for those CEOs for which fitness should matter most, while fitness does not necessarily have to be significantly relevant for other types of CEOs. Yet, if the coefficient of *Fit CEO* is not significant where it should be, this suggests that it does not (primarily) capture fitness. We identify three types of CEOs for which fitness should be most beneficial: older CEOs, high-tenure CEOs, and "busy" CEOs with high responsibility and workload. We motivate the choice of these CEO types in the following.

Several studies suggest that both cognitive and physical abilities decline with age (see, e.g., Verhaeghen and Salthouse (1997)) and that executive functions are especially prone to this negative effect of aging (Rhodes (2004) and Taylor (1975)). Physical fitness, however, has been shown to counteract aging effects. In fact, physical activity and fitness positively affect cognitive functions and executive-control processes (e.g., coordination, planning and working memory) as well as academic and job performance (see, e.g., Colcombe and Kramer (2003), Coe, et al. (2006), Kramer, et al. (1999), and Rhea, Alvar, and Gray (2004)). Thus, we expect a particularly strong effect of CEO fitness on firm value for the group of older CEOs.

For CEO tenure, a reasoning related to and based on that for CEO age can be made. Consistent with anecdotal evidence (see footnote 26), we argue that CEOs get increasingly exhausted over their tenure, both emotionally and physically. In this context, job demands (typically high for CEOs) are found to be positively associated with emotional exhaustion of organizational leaders (Knudsen, Ducharme, and Roman (2009)) and to lead to burnout over time (Schaufeli and Bakker (2004)). Due to its positive effect on performance (Coe, et al. (2006), and Rhea, Alvar, and Gray (2004)) and its moderating effect on stress (see, e.g., Gal and Lazarus (1975), Brown (1991), and Unger, Johnson, and Marks (1997)), we expect fitness to be of particular importance for CEOs who have been on the board for many years. Hence, the effect of fitness on firm value should be particularly strong in the group of high-tenure CEOs.

Finally, given its performance-enhancing and stress-buffering effects as well as the positive impact on work behavior (see, e.g., Folkins and Sime (1981)), we expect fitness to be very relevant for CEOs with high responsibility and workload. We follow the literature on busy directors and CEOs (see, e.g., Fich and Shivdasani (2006), and Perry and Peyer (2005)) and define CEOs as "busy" CEOs if they hold two or more outside board seats. This measure is straightforward as any additional board seats outside the firm impose considerable extra workload (in a different/new firm environment) on CEOs. Further, being members of the board of directors of other companies, CEOs with outside board seats have more responsibility and are exposed to higher stress levels caused, for example, by more unexpected corporate events leading to spontaneous changes in their schedules and the need to take fast actions. Due to the aforementioned aspects, the effect fitness on firm value should be particularly strong for "busy" CEOs.[36]

In Table 4.6 we present the results of our analyses of the aforementioned types of CEOs. We run firm fixed effects regressions similar to those in Section 4.3.1. The dependent variable is the natural logarithm of Tobin´s Q. We first split our sample into older and younger CEOs. Specification (1) shows the results for CEOs who are younger than (or as old as) the sample median (55 years). Specification (2) shows the results for CEOs with above median age. Specifications (3) and (4) show results based on CEO tenure. We again use the sample median to create two groups of CEOs. Finally, specification (5) shows the results for "busy" CEOs and specification (6) shows the results for the "less busy" CEOs.

The results in Table 4.6 clearly corroborate our predictions and provide further evidence consistent with a positive effect of CEO fitness on firm value. The regression coefficients of our main variable of interest, *Fit CEO*, are significantly positive for CEOs with above median age (at the 5% level), for CEOs with above median tenure (at the 1%-level), and for "busy" CEOs (at the 5%-level). The coefficients are also highly significant in terms of their economic relevance. Firm value is at least 8% higher if the variable *Fit CEO* assumes the value of one, taking all control variables into account. That means, relative to the economic effect of the variable *Fit CEO* of 4.6% found for the average CEO in our full sample in Section 4.3.1, the economic effect found in specifications (2), (4) and (5) of Table 4.6 is almost twice as large.

In sum, fitness appears to be an economically important CEO attribute, particularly if firms are run by older CEOs, those who have been at the helm for several years, and those with several outside board seats. The results are consistent with the literature and hence suggest that the variable *Fit CEO* is very likely to capture fitness. They further help us understand why (and when) CEO fitness matters (most).

[36] Perry and Peyer (2005) find no evidence that "busy" CEOs are generally associated with sender firms (i.e., firms they head as CEOs) with very poor or very good firm performance or corporate governance.

Table 4.6: When fitness matters most: evidence from CEO characteristics

Dep. Var.:	CEO age		CEO tenure		"Busy" CEO	
Ln(Tobin´s Q)	≤ Median	> Median	≤ Median	> Median	1	0
	(1)	(2)	(3)	(4)	(5)	(6)
Fit CEO	**0.0122**	**0.0822****	**0.0105**	**0.0981*****	**0.0831****	**0.0292**
	(0.536)	**(1.992)**	**(0.399)**	**(2.604)**	**(2.315)**	**(0.969)**
CEO characteristics:						
CEO age	0.0023	-0.0029	0.0012	0.0019	0.0007	-0.0011
	(0.963)	(-1.182)	(0.809)	(0.591)	(0.388)	(-0.771)
CEO tenure	0.0018	-0.0084	0.0040	-0.0108	0.0014	0.0039
	(0.164)	(-0.736)	(0.385)	(-0.253)	(0.105)	(0.377)
CEO duality	-0.0057	0.0387**	0.0136	-0.0072	0.0013	0.0184
	(-0.351)	(2.142)	(0.920)	(-0.327)	(0.068)	(1.094)
Founder CEO	-0.0630	-0.0402	-0.0262	-0.0723*	-0.0682	-0.0298
	(-1.466)	(-0.961)	(-0.252)	(-1.856)	(-1.266)	(-0.899)
Firm characteristics:						
Firm age	-0.0223	0.0866*	0.0659	-0.0030	0.0482	0.0186
	(-0.514)	(1.800)	(1.329)	(-0.100)	(1.267)	(0.355)
Firm size	-0.1758***	-0.1794***	-0.1630***	-0.1635***	-0.1771***	-0.1768***
	(-8.393)	(-8.284)	(-8.576)	(-6.735)	(-7.049)	(-9.947)
Book leverage	-0.0539	-0.1302*	-0.1233*	-0.1051	-0.0868	-0.0968
	(-0.712)	(-1.873)	(-1.775)	(-1.492)	(-1.255)	(-1.466)
R&D	0.0927***	0.1251***	0.1031***	0.0113	0.0977*	0.1170***
	(10.297)	(16.715)	(23.022)	(0.260)	(1.696)	(21.768)
CapEx	-0.0865	-0.1160	-0.0581	-0.1164	0.0382	-0.1783**
	(-1.205)	(-1.149)	(-0.681)	(-1.478)	(0.526)	(-2.216)
Operating cash flow	0.4599***	0.3674***	0.4204***	0.4312***	0.3027***	0.5030***
	(5.245)	(3.700)	(4.783)	(4.713)	(2.969)	(6.550)
Business segments	-0.0132	0.0088	-0.0119	0.0068	-0.0006	-0.0084
	(-1.265)	(0.982)	(-1.248)	(0.635)	(-0.059)	(-0.838)
Governance characteristics:						
Board size	-0.0127	-0.0233	-0.0060	-0.0026	-0.0397	-0.0031
	(-0.344)	(-0.574)	(-0.162)	(-0.057)	(-1.017)	(-0.079)
% indep. directors	-0.0310	0.0122	0.0291	-0.0007	-0.0096	0.0076
	(-0.864)	(0.363)	(0.862)	(-0.019)	(-0.325)	(0.211)
E-Index	-0.0074	-0.0231***	-0.0145**	-0.0190***	-0.0061	-0.0242***
	(-1.152)	(-3.323)	(-2.272)	(-2.601)	(-0.946)	(-3.562)
Institutional majority	0.0247*	0.0414***	0.0266**	0.0230	0.0324**	0.0243*
	(1.947)	(3.332)	(2.141)	(1.635)	(2.541)	(1.887)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
NObs	4,824	4,725	5,231	4,318	3,970	5,579
Within R-Squared	0.293	0.285	0.276	0.283	0.275	0.307

Notes: This table reports coefficients from firm fixed effects regressions of the natural logarithm of Tobin´s Q on the *Fit CEO* dummy and other control variables for different subsamples. All regression specifications include year fixed effects and a constant (not reported). "Busy" CEOs are defined as CEOs with two or more outside board seats. All variables are defined in the Appendix. Robust t-values of the regression coefficients (in parentheses) are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

4.4.1.2 Unobserved CEO heterogeneity

One of the most important concerns when dealing with CEO attributes and firm outcomes, such as performance, is unobserved CEO heterogeneity. In the context of our study, it is possible that fit CEOs (generally) differ from less fit CEOs. In this case, our variable *Fit CEO* might not measure CEO fitness, but a shared attribute of fit CEOs that affects firm value. Alternatively, it might capture fitness but also another CEO attribute relevant for firm value (i.e., fitness and another attribute correlate). For example, fit CEOs could generally be more disciplined or more talented. This might enable them to successfully manage their firms *and*, at the same time, be/stay fit.[37] An advantage of our study is that we can account for much unobserved CEO heterogeneity, including general discipline or innate talent. Specifically, as our measure of CEO fitness is time-variant, we are able to exploit observable variation in our main variable of interest, *Fit CEO*, over the same CEOs.

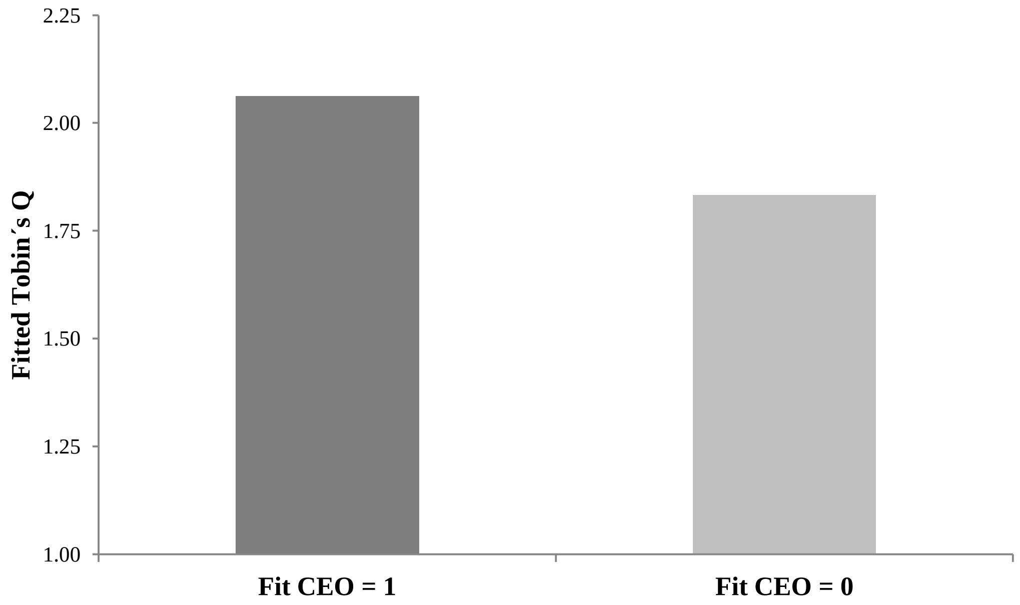
In a first step, we address unobserved CEO heterogeneity by considering only those CEOs who finished at least one marathon over the sample period. Figure 4.4 shows the fitted values of Tobin's Q (from a regression of Tobin's Q on the variables shown in Table 4.3, excluding *Fit CEO*) for the group of marathon runners split by the time-variant variable *Fit CEO*. This way, we only consider changes in observable fitness within the group of CEOs who have demonstrated to be able to finish a marathon. As can be seen from Figure 4.4, the fitted values for Tobin's Q are considerably higher if the variable *Fit CEO* equals one. The difference in firm value between fit and less fit CEOs is statistically significant at the 1% level, as suggested by a t-test on mean differences (not reported).

In unreported multivariate regressions where we restrict the sample to CEOs with at least one finished marathon, we find a positive and statistically significant coefficient of *Fit CEO*. We further find that our results from Table 4.3 do not change when we additionally include a time-invariant variable for fit CEOs, which is set to one if a CEO ran at least one marathon over the sample period. We conclude that the positive relation between CEO fitness and firm value is unlikely the outcome of an unobserved characteristic shared by fit CEOs. As a second, more general way of addressing the concern of unobserved CEO heterogeneity, we repeat the regressions shown in Table 4.3 and Table 4.6 using CEO-firm fixed effects. This way, we take any time-invariant CEO heterogeneity into account. The method brings with it another advantage: as long as the matching between CEOs and firms is based on

[37] In particular, one might argue that the group of fit CEOs is generally characterized by a higher level of discipline due to, for example, an athletic background or prior military service. This is consistent with the anecdotal evidence mentioned in footnote 39, which suggests that many fit CEOs get up very early for morning runs before they go to office.

time-invariant unobservable CEO and firm characteristics, using CEO-firm fixed effects also addresses a potential endogenous matching between firms and (fit) CEOs (see Custódio and Metzger (2014), and Bertrand and Schoar (2003)). Regression results are shown in Table 4.7.[38]

Figure 4.4: CEO fitness and firm value within the treatment group



Notes: This figure shows the mean *Fitted Tobin´s Q* for firms with and without a *Fit CEO* within the treatment group (i.e., those CEOs who finish at least one marathon over the sample period). The fitted values of Tobin's Q are from a regression of Tobin's Q on the variables shown in Table 4.3 (including firm and year fixed effects), excluding the variable *Fit CEO*. Variables are defined in the Appendix.

As can be seen from Table 4.7, our main results do not change when we use CEO-firm fixed effects instead of firm fixed effects (as done in Section 4.3.1 and 4.4.1.1). In fact, the results remain significant, both statistically and economically. The *Fit CEO* dummy is positive and significant at the 10% level in the full sample regression shown in specification (1) and at the 5% level in all of the three subsamples where we expect particularly strong effects of CEO fitness on firm value (see specifications (3), (5) and (6)). Even after controlling for unobserved CEO heterogeneity, the economic magnitude of CEO fitness remains meaningful: firm value is about 4% higher in the full sample and at least 8% higher in the subsamples.

To conclude, the evidence presented in this section suggests that our results are very unlikely caused by unobserved CEO heterogeneity. It thus appears that our variable *Fit CEO* indeed measures the (time-varying) fitness of CEOs.

[38] Regressions are run with standard errors clustered at the firm level. We alternatively cluster standard errors at the CEO-firm level in unreported regressions. The results are similar. Please note that as we use CEO-firm fixed effects, the indicator variable Founder CEO is excluded in the regressions shown in Table 4.7.

Table 4.7: Unobserved CEO heterogeneity: CEO-firm fixed effects

Dep. Var.: Ln(Tobin´s Q)	Full sample (1)	CEO age ≤ Median (2)	CEO age > Median (3)	CEO tenure ≤ Median (4)	CEO tenure > Median (5)	„Busy“ CEO 1 (6)	„Busy“ CEO 0 (7)
Fit CEO	**0.0421***	**0.0116**	**0.0936****	**0.0086**	**0.0785****	**0.0818****	**0.0248**
	(1.944)	**(0.569)**	**(2.357)**	**(0.413)**	**(2.060)**	**(2.013)**	**(0.983)**
CEO characteristics:							
CEO age	-0.0149***	-0.0067	-0.0255***	-0.0017	-0.0203***	-0.0082	-0.0214***
	(-4.219)	(-1.250)	(-4.318)	(-0.244)	(-3.060)	(-1.553)	(-4.045)
CEO tenure	0.0223	-0.0160	0.0758***	-0.0380*	0.1292	0.0002	0.0363
	(1.404)	(-0.757)	(2.773)	(-1.648)	(1.475)	(0.009)	(1.605)
CEO duality	-0.0087	0.0063	0.0068	0.0101	-0.0343	-0.0259	0.0060
	(-0.629)	(0.355)	(0.348)	(0.663)	(-1.299)	(-1.243)	(0.332)
Firm characteristics:							
Firm age	0.0154	-0.0299	0.0867	0.0147	0.0044	0.0136	-0.0088
	(0.505)	(-0.533)	(1.576)	(0.258)	(0.132)	(0.309)	(-0.220)
Firm size	-0.1755***	-0.1977***	-0.1849***	-0.1719***	-0.1694***	-0.1718***	-0.1783***
	(-11.457)	(-9.038)	(-7.316)	(-8.185)	(-7.099)	(-6.588)	(-8.694)
Book leverage	-0.0948*	-0.0230	-0.0893	-0.1131	-0.0588	-0.0241	-0.0806
	(-1.770)	(-0.296)	(-1.100)	(-1.469)	(-0.811)	(-0.325)	(-1.147)
R&D	0.0817	0.0905	-0.0393	0.1022	0.0035	0.1149**	0.0667
	(1.378)	(1.302)	(-0.410)	(1.058)	(0.082)	(2.145)	(0.996)
CapEx	-0.1271**	-0.1284	-0.2179**	-0.1316	-0.1126	-0.0101	-0.2297**
	(-2.116)	(-1.602)	(-2.113)	(-1.625)	(-1.451)	(-0.159)	(-2.449)
Operating cash flow	0.2966***	0.3165***	0.2432**	0.1253	0.3905***	0.1457	0.3720***
	(4.792)	(3.615)	(2.516)	(1.626)	(4.369)	(1.574)	(4.948)
Business segments	0.0008	-0.0067	0.0048	-0.0086	0.0061	0.0018	-0.0042
	(0.115)	(-0.636)	(0.452)	(-0.888)	(0.601)	(0.155)	(-0.435)
Governance characteristics:							
Board size	-0.0077	-0.0005	-0.0124	-0.0019	-0.0029	-0.0513	0.0108
	(-0.278)	(-0.015)	(-0.269)	(-0.056)	(-0.063)	(-1.240)	(0.274)
% indep. directors	-0.0076	-0.0206	-0.0195	0.0320	-0.0237	0.0011	-0.0120
	(-0.312)	(-0.529)	(-0.597)	(0.989)	(-0.643)	(0.037)	(-0.333)
E-Index	-0.0115**	-0.0032	-0.0178**	-0.0059	-0.0158**	-0.0042	-0.0200***
	(-2.393)	(-0.499)	(-2.227)	(-0.952)	(-2.090)	(-0.587)	(-2.891)
Institutional majority	0.0252***	0.0225*	0.0280**	0.0163	0.0254*	0.0364***	0.0115
	(2.666)	(1.716)	(2.078)	(1.408)	(1.759)	(2.751)	(0.879)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CEO-firm fixed effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
NObs	9,549	4,824	4,725	5,231	4,318	3,970	5,579
Within R-Squared	0.266	0.278	0.266	0.245	0.280	0.266	0.280

Notes: This table reports coefficients from CEO-firm fixed effects regressions of the natural logarithm of Tobin´s Q on the *Fit CEO* dummy and other control variables for the full sample (column 1) and different subsamples (columns 2-7). All regression specifications include year fixed effects and a constant (not reported). All variables are defined in the Appendix. Robust t-values of the regression coefficients (in parentheses) are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

4.4.1.3 Permutation tests: random assignment of pseudo fitness

As a last step to provide evidence that we measure CEO fitness and its consequences, we perform a permutation test and assign each CEO a random (pseudo) fitness status. We use 10,000 random draws, i.e., we repeat the random procedure of assigning a pseudo fitness status to CEOs 10,000 times and rerun our multivariate regression for the full sample and the subsamples of CEO characteristics discussed in Section 4.4.1.1 for each random draw. The results are shown in Table 4.8. We apply the described procedure using both firm fixed and CEO-firm fixed effects in Panel A and Panel B, respectively.

In both panels, we only show the coefficient of our main variable of interest, *Fit CEO*, and the p-value resulting from the permutation test. The p-value is calculated as the fraction of randomly permutated datasets that yield a regression coefficient larger than or equal to the reported coefficient for *Fit CEO* relative to the total number of 10,000 permutations. The results in Table 4.8 confirm our earlier findings for both firm fixed and CEO-firm fixed effects. The null hypothesis that there is no effect of the variable *Fit CEO* can be rejected in all specifications of interest (Column (1), (3), (5), (6)) in both panels. For example, the p-value for the coefficient of *Fit CEO* resulting from the firm fixed effects regression using the full sample (= 0.0461) is 0.025. This means that only 250 of 10,000 permutations yield a similar or larger coefficient for our fitness measure.

Overall, the results suggest that our main findings are statistically reliable. We thus conclude that the positive coefficient of *Fit CEO* is not a statistical artifact.

Table 4.8: Permutation tests: random assignment of pseudo fitness

Panel A: Firm fixed effects

Dep. Var.:	Full sample	CEO age		CEO tenure		„Busy“ CEO	
Ln(Tobin´s Q)		≤ Median	> Median	≤ Median	> Median	1	0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fit CEO	0.0461	0.0122	0.0822	0.0105	0.0981	0.0831	0.0292
p-value	***[0.025]***	***[0.646]***	***[0.014]***	***[0.686]***	***[0.004]***	***[0.012]***	***[0.259]***
CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Governance characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NObs	9,549	4,824	4,725	5,231	4,318	3,970	5,579
Permutations	10,000	10,000	10,000	10,000	10,000	10,000	10,000

(Continued)

L

Table 4.8: Continued

Panel B: CEO-firm fixed effects

Dep. Var.:	Full sample	CEO age		CEO tenure		„Busy“ CEO	
Ln(Tobin´s Q)		≤ Median	> Median	≤ Median	> Median	1	0
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Fit CEO	0.0421	0.0116	0.0936	0.0086	0.0785	0.0818	0.0248
p-value	***[0.038]***	***[0.648]***	***[0.007]***	***[0.723]***	***[0.019]***	***[0.021]***	***[0.337]***
CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Governance characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CEO-firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NObs	9,549	4,824	4,725	5,231	4,318	3,970	5,579
Permutations	10,000	10,000	10,000	10,000	10,000	10,000	10,000

Notes: This table reports p-values from a Monte Carlo permutation test with 10,000 random draws. The reported p-value is the fraction of randomly permutated datasets that yield a regression coefficient larger than or equal to the reported coefficient for the variable *Fit CEO* from our regressions of the natural logarithm of Tobin´s Q on the *Fit CEO* dummy and other control variables for the full sample (column 1) and different subsamples (columns 2-7) relative to the total number of permutations. The null hypothesis that there is no effect of the variable *Fit CEO* can be rejected in specifications (1), (3), (5) and (6). Panel A (Panel B) reports results for firm fixed effects (CEO-firm fixed effects) regression. All regression specifications also include year fixed effects and a constant. For sake of brevity, we only report the coefficients for the *Fit CEO* dummy. All variables are defined in the Appendix.

4.4.2 Reverse causality and unobserved time-varying heterogeneity

Although the results from Section 4.4.1 support the view that we measure CEO fitness, so far we cannot conclude that we really measure its consequences. In particular, some alternative explanations for our main result – CEO fitness has a positive effect on firm value – remain. The most likely alternative explanation appears to be reverse causality which might lead us to (falsely) conclude that CEO fitness has a positive effect on firm value, while instead CEOs can just afford the time to get fit when their firms perform well.

For example, one could imagine that after presenting good firm results a CEO is more likely to do sports (either as she allows herself more time outside the office or as those people involved in monitoring do so). Although CEOs are free to decide to run independent of firm performance, and although all of our regressions shown so far already include controls for corporate governance, past operating performance and year fixed effects, we now address concerns of reverse causality and unobserved firm- and industry-specific heterogeneity in more detail. While the analyses provided in the following cannot entirely rule out these concerns, they at least considerably mitigate the related endogeneity problems.

4.4.2.1 Do fit CEOs have the time to be fit?

We start with the general concern that CEOs might not have the time to do sports frequently (and only do so when their firm has performed well). There is much academic and anecdotal evidence against this point of view. For example, Bandiera, Prat, and Sadun (2013) analyze the working hours of 354 CEOs for an exogenously chosen work week. They find that CEOs spend about 10 percent of their total working hours for personal activities. That means, CEOs can generally afford some time for running or recreational activities, even over their work week. Consistently, Neck, et al. (2000) document that many CEOs and other people in leading, time-consuming positions manage to run several times a week and participate in marathons. Anecdotal evidence strongly supports this result.[39] It even suggests that doing sports frequently gives executives more (instead of less) time because it increases their productivity.[40]

Next, we conduct an intuitive test to address the concern of reverse causality (as explained above). If CEOs tend to be fit (e.g., run) when their firm has performed well, then we would expect to find a positive effect of firm performance on CEO fitness. Therefore, we run regressions of our variable *Fit CEO* on the control variables used in the previous analyses and add the variable *Tobin's Q lagged*. Results are shown in Table 4.9.

As can be seen from specifications (1) to (4) of Table 4.9, we find no significant effect of firm performance, neither for *Tobin's Q lagged* nor for *Operating cash flow*, on the dependent variable *Fit CEO*. This result holds independent of whether we use industry fixed effects (two-digit SIC codes) in specifications (1) to (3) or firm fixed effects in specification (4). When we use *ROA lagged* (either separately or in addition to *Tobin's Q lagged*) in unreported regressions, we come to the same conclusion. This suggests that CEOs are not more likely to be fit (i.e., run a marathon) when their firm has performed well. The result is consistent with both the aforementioned anecdotal evidence and the view that a CEO's decision to spend time for fitness does not depend crucially upon firm performance. It provides an indication that reverse causality is unlikely to drive our results.

[39] In the article "Marathon running – A hobby of global CEOs" (in *Global* CEO), Rao (2006) lists several CEOs of large, global firms who run frequently. He states that *"[…] running CEOs manage the challenge of time management.*" For example: "*Nike's Bill Perez […] is up at 4:00 a.m. He heads out, at 5:00, for a four-mile run […].*" and "*Greg Brenneman of Burger King trains most mornings by 4:30 a.m. with an eight-mile run.*" Furthermore, in "CEO fitness: the performance plus" (in *Psychology Today*), Rippe (1989) cites Ken Resse, former executive Vice-president at Tenneco INC.: "*I'm a morning runner, and that sets the tone for the whole day. By the time I get to the office, I'm relaxed.*"

[40] In "The fittest CEOs in America?" (from May 5, 2015) Fortune Magazine reports about CEOs who do sports several days a week. It cites Richard Branson, CEO of Virgin Group and a marathon finisher, who says that work out gives him four extra hours of productivity a day.

Table 4.9: Do fit CEOs have the time to be fit?

Dep. variable:	Fit CEO			
	(1)	(2)	(3)	(4)
Tobin´s Q lagged	**0.0017**	**0.0017**	**0.0020**	**0.0018**
	(0.892)	**(0.889)**	**(1.026)**	**(1.286)**
Board meetings		**-0.0010**		**-0.0034**
		(-0.239)		**(-0.761)**
Board meetings lagged			**-0.0001**	**0.0029**
			(-0.034)	**(0.620)**
CEO characteristics:				
CEO age	-0.0005*	-0.0005*	-0.0004*	-0.0004
	(-1.906)	(-1.878)	(-1.740)	(-1.006)
CEO tenure	-0.0013	-0.0014	-0.0015	-0.0006
	(-0.588)	(-0.679)	(-0.699)	(-0.208)
CEO duality	0.0044	0.0042	0.0047	-0.0014
	(1.137)	(1.063)	(1.190)	(-0.355)
Founder CEO	-0.0096*	-0.0093*	-0.0097*	-0.0119
	(-1.892)	(-1.802)	(-1.857)	(-1.523)
Firm characteristics:				
Firm age	0.0001	0.0002	-0.0000	0.0118
	(0.058)	(0.112)	(-0.008)	(1.097)
Firm size	-0.0019	-0.0018	-0.0020	-0.0011
	(-1.281)	(-1.174)	(-1.270)	(-0.279)
Book leverage	-0.0100	-0.0103	-0.0091	0.0163
	(-0.908)	(-0.928)	(-0.823)	(0.997)
R&D	-0.0063	-0.0062	-0.0066	-0.0015
	(-1.604)	(-1.602)	(-1.625)	(-1.344)
CapEx	0.0411	0.0410	0.0429	0.0159
	(1.355)	(1.327)	(1.413)	(1.637)
Operating cash flow	-0.0031	-0.0026	-0.0055	-0.0155
	(-0.201)	(-0.165)	(-0.348)	(-0.925)
Business segments	-0.0012	-0.0013	-0.0014	-0.0011
	(-0.517)	(-0.543)	(-0.574)	(-0.402)
Governance characteristics:				
Board size	-0.0068	-0.0073	-0.0067	-0.0264***
	(-0.961)	(-1.017)	(-0.933)	(-2.872)
% indep. directors	-0.0032	-0.0030	-0.0049	-0.0002
	(-0.315)	(-0.283)	(-0.473)	(-0.019)
E-Index	-0.0007	-0.0008	-0.0007	0.0017
	(-0.567)	(-0.610)	(-0.521)	(0.983)
Institutional majority	-0.0025	-0.0028	-0.0023	0.0001
	(-0.758)	(-0.821)	(-0.680)	(0.018)
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	No
Firm fixed effects	No	No	No	Yes
NObs	9,542	9,384	9,409	9,273
Adj. R-Squared	0.017	0.017	0.017	0.270

Notes: This table reports regression coefficients from OLS regressions – using the linear probability model – of the *Fit CEO* dummy on Tobin´s Q lagged, Board meetings, Board meetings lagged and other control variables. Industry fixed effects (two-digit SIC codes) are included in specifications (1) to (3), while firm fixed effects are included in specification (4). All regression specifications include year fixed effects and a constant (not reported). All variables are defined in the Appendix. Robust t-values of the regression coefficients (in parentheses) are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

In Table 4.9 we perform another test to address the concern that CEOs might tend to be fit and run when they have the time to. In specifications (2) to (4) we additionally include the number of a firm's current and lagged board meetings. Assuming that board meetings are a good (and general) measure of time that needs to be spent with the firm, we can conclude that CEOs are not more likely to run when they have more time to do so. Neither current nor lagged board meetings affect the dependent variable *Fit CEO*.

Next, as another way of addressing the concern of reverse causality, we identify fit CEOs with fast marathon finish times. These CEOs must have spent a considerable amount of (weekly) time to prepare for the marathons (as fast times necessitate much practice). Thus, for these CEOs the concern that they are fit because their firm is simply doing very well and they can afford the time for practice is most apparent. Put differently, our results could be driven by the fittest CEOs. To identify them, we collect all finish times for the fit CEOs in our sample. We then run our baseline regression model shown in Table 4.3 and exclude the fittest CEOs, i.e., CEOs who finish a marathon (in a given year) in less than 3 hours and 30 minutes or, alternatively, less than 4 hours.[41] Results are shown in Table 4.10. As can be seen from Table 4.10, our results are robust to excluding the fittest CEOs. The coefficient of the variable *Fit CEO* remains significant independent of the finish time threshold (3.30h or 4h) we use and in both firm fixed and CEO-firm fixed effects regressions.

4.4.2.2 Unobserved firm- and industry-specific heterogeneity

In this section, we address alternative explanations based on time-varying firm and industry heterogeneity. Specifically, we rerun our regressions on firm value and include additional control variables that capture relevant firm and industry characteristics. We do so to address the concern that CEO fitness and high firm value might both be the outcome of positive firm or industry trends.

Consequently, we include *Tobin's Q lagged* and the variables *Current operating cash flow* and *Sales growth* in our extended regression model. All variables are expected to positively affect firm value. Apart from past stock performance, we control for the firm's current operating performance and its sales growth to further address concerns of reverse causality. Although it is rather unlikely that within a given year CEOs decide to run a marathon (which is hardly done ad-hoc as it needs about 15-20 weeks of preparation) when

[41] According to www.marathonguide.com, only about 10% of all runners finished in less than 3.30h in the year 2011. The average U.S. marathon finish time was 4.26h (for males with an average age of 40 years). The average finish time for fit CEOs is 4.39h. Our results remain qualitatively unchanged when we exclude the slowest CEOs, for example, those who finish in less than 6h.

Table 4.10: Excluding fit CEOs with fast marathon finish times

Dep. Var.: Ln(Tobin´s Q)	Finish time > 3.30h	Finish time > 4.00h	Finish time > 3.30h	Finish time > 4.00h
	(1)	(2)	(3)	(4)
Fit CEO	**0.0418***	**0.0482****	**0.0366***	**0.0449****
	(1.870)	**(1.971)**	**(1.728)**	**(2.026)**
CEO characteristics	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes
Governance characteristics	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	No	No
CEO-firm fixed effects	No	No	Yes	Yes
NObs	9,537	9,516	9,537	9,516
Within R-Squared	0.291	0.291	0.268	0.269

Notes: This table reports coefficients from firm fixed effects regressions (columns 1 and 2) and CEO-firm fixed effects regressions (columns 3 and 4) of the natural logarithm of Tobin´s Q on the *Fit CEO* dummy and other control variables. All regression specifications include year fixed effects and a constant. For sake of brevity, we only report the coefficients for the *Fit CEO* dummy. All variables are defined in the Appendix. Robust t-values of the regression coefficients (in parentheses) are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively. "Finish time > 3.30h" (see columns 1 and 3) means that fit CEOs who finished a marathon in less than 3 hours and 30 minutes (in a given year) are excluded from the sample. "Finish time > 4.00h" uses a finish time of 4 hours as the respective threshold.

the operating performance shows a good trend, our variable *Fit CEO* might capture a good current performance or trend (or just the CEO's knowledge about that). As a consequence, the positive relation between CEO fitness and firm value might simply reflect the increased likelihood of CEOs to run marathons when the performance of their firm shows a good trend.

Furthermore, the variable *Fit CEO* might measure the effect of industry competition on firm performance. On the one hand, CEOs could have (or take) more time to run if competition (and pressure to perform) is low. In this regard, Bandiera, Prat, and Sadun (2013) find that CEOs reduce their working hours, due to increased (opportunity) costs of working, only in firms exposed to relatively less competition. Low competition might further be associated with higher product prices and margins and, ultimately, higher firm values. Yet, the literature on the effects of competition is not unambiguous. Thus, on the other hand, one may also argue that CEOs have more need to care for their fitness and engage in activities that help them perform on a high level each day if they have to face high industry competition. The latter has been shown to have a positive effect on corporate performance (see, e.g., Nickell (1996)). To address the concern that *Fit CEO* captures the effect of industry competition on firm value, we additionally control for the variable *Competition*.

Finally, some CEOs might run because they are managing firms that belong to industries which show a very good performance in specific years. The variable *Fit CEO* might include these CEOs and they might actually cause the positive effect on firm value. Because the use of firm fixed and year fixed effects does not accurately account for this concern, we use two-digit SIC *industry interacted with year dummies* in addition to the aforementioned controls. This way, we take year-specific industry effects into account and are able to draw cleaner inferences.

The results of the regressions with the additionally included controls are presented in Table 4.11. Panel A shows the results for regressions using firm fixed effects and Panel B shows the results for CEO-firm fixed effects. For brevity, we only report the regression coefficients for *Fit CEO* and the new controls, which are defined in the Appendix. As can be seen from Table 4.11, our main result does not change: the coefficient of *Fit CEO* remains statistically significant in all specifications of interest (i.e., specifications (1), (3), (5) and (6)). Importantly, the economic magnitude of CEO fitness does not considerably change. For fit CEOs, firm value is still 3.5% higher in the full sample and at least 7% in the subsamples, regardless of whether we use firm or CEO-firm fixed effects. In terms of our additional control variables, we find that *Tobin's Q lagged* and *Current operating cash flow* have significantly positive regression coefficients, as expected. *Sales growth* has a positive effect, but it is only significant in some regressions. In line with the rather ambiguous effect of industry competition on firm value, we find that the coefficient of the variable *Competition* switches signs and is insignificant in most regression specifications.[42]

In sum, the results of Section 4.4.2 suggest that the positive effect of CEO fitness on firm value is unlikely caused by reverse causality or other alternative explanations.

[42] In additional unreported regressions, we include the squared values of CEO age and firm size to take important non-linear effects on firm value into account. All results remain qualitatively similar.

Table 4.11: Alternative time-variant explanations

Panel A: Firm fixed effects

Dep. Var.: Ln(Tobin´s Q)	Full sample (1)	CEO age ≤ Median (2)	CEO age > Median (3)	CEO tenure ≤ Median (4)	CEO tenure > Median (5)	„Busy" CEO 1 (6)	„Busy" CEO 0 (7)
Fit CEO	**0.0347****	**0.0229**	**0.0690*****	**0.0178**	**0.0804*****	**0.0813*****	**0.0059**
	(2.069)	**(0.949)**	**(2.662)**	**(0.794)**	**(3.008)**	**(2.804)**	**(0.249)**
Additional controls:							
Tobin´s Q lagged	0.0938***	0.0681***	0.0860***	0.0931***	0.0666***	0.0879***	0.0749***
	(11.683)	(7.323)	(5.960)	(9.701)	(4.800)	(7.653)	(7.202)
Current opr. cash flow	0.6110***	0.5752***	0.6003***	0.5419***	0.6734***	0.5491***	0.5973***
	(8.922)	(5.539)	(6.266)	(5.619)	(6.705)	(5.312)	(6.963)
Sales growth	0.0139	0.0234*	0.0096	0.0037	0.0238**	0.0045	0.0259*
	(1.617)	(1.691)	(0.799)	(0.342)	(2.528)	(0.441)	(1.779)
Competition	0.1064	-0.0003	0.1901	0.1782	0.0392	-0.0288	0.3169***
	(1.191)	(-0.002)	(1.460)	(1.550)	(0.228)	(-0.206)	(2.836)
CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Governance characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
NObs	9,510	4,802	4,708	5,208	4,302	3,953	5,557
Within R-Squared	0.505	0.522	0.540	0.521	0.551	0.547	0.544

Panel B: CEO-firm fixed effects

Dep. Var.: Ln(Tobin´s Q)	Full sample (1)	CEO age ≤ Median (2)	CEO age > Median (3)	CEO tenure ≤ Median (4)	CEO tenure > Median (5)	„Busy" CEO 1 (6)	„Busy" CEO 0 (7)
Fit CEO	**0.0351****	**0.0291**	**0.0751*****	**0.0219**	**0.0676****	**0.0889****	**0.0229**
	(2.009)	**(1.257)**	**(3.033)**	**(0.966)**	**(2.401)**	**(2.541)**	**(1.055)**
Additional controls:							
Tobin´s Q lagged	0.0671***	0.0504***	0.0590***	0.0641***	0.0525***	0.0743***	0.0478***
	(8.710)	(5.497)	(3.956)	(7.042)	(4.043)	(6.602)	(4.397)
Current opr. cash flow	0.5520***	0.4941***	0.5385***	0.4516***	0.6320***	0.4513***	0.6029***
	(7.630)	(4.542)	(5.555)	(4.148)	(6.408)	(4.348)	(6.831)
Sales growth	0.0202**	0.0390**	0.0186	0.0082	0.0265***	0.0060	0.0309*
	(2.091)	(2.492)	(1.552)	(0.626)	(2.698)	(0.526)	(1.848)
Competition	0.1441	-0.1269	0.3446**	0.0962	0.2246	-0.0321	0.4403***
	(1.500)	(-0.901)	(2.416)	(0.686)	(1.389)	(-0.227)	(3.831)
CEO characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Governance characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CEO-firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Year FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
NObs	9,510	4,708	4,802	4,302	5,208	3,953	5,557
Within R-Squared	0.471	0.517	0.519	0.547	0.474	0.535	0.522

Notes: This table reports coefficients from firm fixed effects regressions (Panel A) and CEO-firm fixed effects regressions (Panel B) of the natural logarithm of Tobin´s Q on the *Fit CEO* dummy and other control variables for the full sample (column 1) and different subsamples (columns 2-7). All regression specifications include year as well as year*industry fixed effects (two-digit SIC codes) and a constant. For sake of brevity, we only report the coefficients for the *Fit CEO* dummy and the additionally included control variables. All variables are defined in the Appendix. Robust t-values of the regression coefficients (in parentheses) are based on standard errors clustered by firm. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

4.4.3 Sudden deaths and the value of fitness

As a final solidification of our results, we use sudden deaths as an identification strategy allowing for causal inference. Given the exogeneity of sudden deaths and the comparison of each firm to itself when we consider the stock market reaction to announcements of sudden deaths, we can infer whether CEO fitness really has a positive effect on firm value.

To identify sudden deaths, we follow Nguyen and Meisner Nielsen (2014) and search for keywords (such as 'CEO' and 'president' as well as 'death', 'deceased', 'died' and 'passed away') on the internet using Edgar Online, Lexis-Nexis and Google searches. We restrict our sample to sudden deaths of CEOs and presidents. We use the period 1990 to 2012 to be able to identify enough cases. Deaths have to be described as 'sudden' (or 'unexpected' or a comparable term). If we find evidence that a death was not sudden, we exclude it (e.g., if a CEO or president was known to suffer from cancer or a heart disease). The event date is defined as the trading day of the first public announcement of the sudden death or the first trading day following the death announcement if it occurred on a non-trading day.

As we only handle a small sample in this analysis, we are now able to hand-collect all information about activities to classify the deceased as fit (or not). That means, we do not limit our definition of fitness to marathon finishers. This allows us to provide more general empirical evidence for the effects of fitness. We use a conservative approach in defining the deceased as fit. Specifically, consistent with how we have identified fitness in this study, a deceased is defined as fit if she can be identified as fit *around* the time of her death, i.e., the CEO or president has to be an active sportsman around the time of her death. For example, if a deceased was a sportsman at college (i.e., athletic background), but cannot be identified as active around the time of death, she is considered not to be fit. We use information from news around deaths, including obituaries, and additionally search the internet for information about the activities of the deceased.

Of course, the depth of information we require limits the number of sudden deaths we can use in our analysis. From 91 cases of sudden deaths for which an abnormal stock return can be calculated and for which data about the characteristics of the deceased as well as firm characteristics are available, we find information that allows us to classify the deceased as fit or not for 50 cases. The deceased CEOs (or presidents) classified as fit are active tennis and ice hockey players, mountaineers and hunters, skiers, and aerialists. For the 50 cases, we provide regression results in Table 4.12. As our main dependent variable (in specification (1)), we use the abnormal stock return around the announcement of the sudden death, denoted

CAR [0,1], i.e., the abnormal return on the announcement date and the next trading day. For robustness purposes, we also use *CAR [-1,1]* and *CAR [0,2]* as dependent variables.

Table 4.12: Sudden deaths and the value of fitness

Dep. variable:	CAR [0,1] (1)	CAR [-1,1] (2)	CAR [0,2] (3)
Fit CEO	**-0.0567***** **(-2.795)**	**-0.0471*** **(-1.837)**	**-0.0499**** **(-2.294)**
Age	0.0012 (1.064)	0.0026 (1.603)	0.0018 (1.271)
CEO	-0.0645** (-2.104)	-0.0546 (-1.683)	-0.0569* (-1.801)
Duality	0.0356 (1.308)	0.0191 (0.652)	0.0223 (0.848)
Founder	0.0090 (0.378)	-0.0192 (-0.700)	0.0077 (0.257)
Tenure	0.0004 (0.428)	0.0008 (0.924)	-0.0002 (-0.224)
Ln(total assets)	0.0117** (2.435)	0.0132** (2.268)	0.0104** (2.034)
Market-to-book	-0.0052 (-1.420)	0.0034 (0.700)	-0.0077* (-1.723)
ROA	-0.0450 (-0.816)	-0.0125 (-0.172)	-0.0529 (-0.844)
Constant	-0.1054 (-1.311)	-0.2288* (-1.969)	-0.1161 (-1.152)
NObs	50	50	50
Adjusted R-squared	0.347	0.348	0.380

Notes: This table reports coefficients from regressions of abnormal stock returns in reaction to sudden deaths of CEOs and presidents on the variable *Fit CEO (or president)* (defined below) and other control variables. *CAR [0,1]* is the cumulative abnormal return (CAR) around the first announcement of a sudden death over the two-day event window, where day 0 is the event date. *CAR [-1,1]* and *CAR [0,2]* are defined accordingly. CARs are estimated using the market-model event study approach with the CRSP index as the market index. Deceased CEOs and presidents are defined as being fit if they can be identified as active sportsmen around the time of the sudden death. The number of CEOs (and presidents) identified as fit is seven. The variable *Age* measures the age of the deceased, the variable *CEO* equals one if the deceased was the CEO of the company that employed him (zero if he or she was the president), the variable *Duality* equals one if the deceased was also the chairman of the company that employed him or her (zero otherwise), the variable *Founder* equals one if the deceased was the founder of the company that employed him (zero otherwise), and the variable *Tenure* measures the tenure of the deceased CEO or president. Firm-level controls include firm size (i.e., *ln(total assets)*), firm growth opportunities (i.e., *Market-to-book*) and firm profitability (i.e., *ROA*). The t-statistics of the regression coefficients (in parentheses) are based on robust standard errors. ***, **, and * denote statistical significance at the 1%-, 5%-, and 10%-level, respectively.

The results shown in Table 4.12 include important controls used in the extant literature, i.e., age, CEO, duality, founder and tenure as well as firm size, market-to-book ratio and ROA (defined in Table 4.12). We find that abnormal returns are between 4.7 and 5.7 percentage points lower for fit CEOs (consistent with our estimates for Tobin's Q). The coefficient of the variable *Fit CEO* is significant (at least at the 10% level) in all three regression specifications which use cumulative abnormal returns (CAR) based on different event windows.[43]

The above results, which are based on a broader definition of fitness, suggest that firms lose significantly more firm value around the announcement of a sudden death when the deceased CEO (or president) was physically fit. Put differently, the results indicate that the contribution to firm value is significantly higher when CEOs (and presidents) are fit. Thus, we can conclude that CEO fitness indeed has a positive effect on firm value.

4.5 Conclusion

Despite the growing interest of economists in CEO attributes, the literature has remained relatively silent about physical aspects of CEOs. One reason is that data about CEOs' physical attributes is generally not available. In this study, we use hand-collected data on U.S. marathons to measure CEO fitness. Due to its buffering effect on stress and its positive effect on cognitive functions, executive control processes, work behavior and job performance, fitness should play an important role for CEOs as their jobs are characterized by high demands and high stress. Fit CEOs should be better able to cope with stress, should be less exhausted, more efficient and better performing. This should lead to better firm performance.

Using a panel of S&P 1500 companies over the period from 2001 to 2011 we provide evidence suggesting that fitness is indeed an important CEO attribute. Fit CEOs are associated with higher firm profitability and higher M&A announcement returns, especially in large and public M&As, likely to cause much stress. We find that the aforementioned effects translate into significantly higher firm values for firms run by fit CEOs. Regression results suggest that firm value is almost 5% higher on average. It is at least 8% higher when CEOs' fitness is particularly important, i.e., for CEOs with above-median age, above-median tenure and for CEOs with several outside board seats. Our findings for firm value remain significant, both statistically and economically, when we address important endogeneity concerns including unobserved CEO and firm heterogeneity and reverse causality. Evidence from sudden deaths supports our findings and suggests that the effect of fitness on firm value is causal.

The results of this study can explain the increasing importance of fitness in the managerial labor market and the trend for fitness among executives. In particular, the results provide a rationale for why executive recruiting firms look for physically fit candidates. They

[43] When we use all 91 observations in unreported regressions, and define a deceased as not being fit when we are unable to gather information about her activities, results remain statistically significant.

further suggest that investments which help CEOs cope with the high demands and stress of their job, some of them might be (falsely) labeled as perquisites, may be valuable and thus in the interest of shareholders. Finally, we argue that our findings have general implications for executives (beyond the CEO) as fitness is likely to be highly relevant in jobs resembling that of the CEO, such as investment managers or lawyers.

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Appendix to Chapter 4

Variable definitions

The table shows the definitions of the variables used in this study. Accounting data is from Compustat. CEO and governance data is from the Corporate Library's Board Analyst database.

Variable	Definition
% indep. directors	Percentage of directors on the board classified as independent directors.
Board meetings	Natural logarithm of the number of a firm's board meetings.
Board size	Natural logarithm of the number of directors on the firm's board of directors.
Book leverage	(Long-term debt + current liabilities)$_{t-1}$ / Total assets$_{t-1}$.
Business segments	Natural logarithm of the number of business segments.
Busy CEO	Defined as a CEO with two or more outside board seats, zero otherwise. The definition follows Fich and Shivdasani (2006).
CapEx	Capital expenditures$_{t-1}$ / Sales$_{t-1}$.
CEO age	Age of the firm's CEO in years.
CEO duality	Indicator variable equals one if the CEO is also the chairman of the board, zero otherwise.
CEO tenure	Natural logarithm of the number of years of service of the firm's CEO.
Competition	Herfindahl index of sales (on annual basis) for all firms in the Compustat universe that belong to the same 2-digit SIC industry.
E-Index	The Bebchuk, Cohen, Ferrell (2009) entrenchment index of six IRRC provisions.
Firm age	Natural logarithm of the number of years the company has been in business, i.e., the firm's age since foundation.
Firm size	Natural logarithm of total assets$_{t-1}$.
Fit CEO	Indicator variable equals one if a CEO finishes a marathon in a given year, zero otherwise. Data sources: official marathon websites and www.marathonguide.com
Founder CEO	Indicator variable equals one if the CEO is the founder of the company, zero otherwise.
Free cash flow (FCF)	FCF = (EBITDA – CapEx – (Working capital$_t$ – Working capital$_{t-1}$)) / Total assets. Information about Working capital not available for all Compustat firms.
Institutional majority	Indicator variable equals one if the majority of a firm's outstanding shares is held by institutions, zero otherwise. In The Corporate Library database the variable is available for the years 2003 and later; the dummy for the years 2001 and 2002 is created using the variable 'InstitutionPctg' reported in The Corporate Library.
Operating cash flow	Annual cash flow from operations$_{t-1}$ / Total assets$_{t-1}$.
R&D	R&D expense$_{t-1}$ / Sales$_{t-1}$.
Return on Assets (ROA)	ROA = EBITDA / Total assets.
Sales growth	Annual change in net sales divided by prior year's net sales: Sales$_t$ / Sales$_{t-1}$ – 1.
Tobin's Q	Tobin's Q = (Total assets - Book equity + Market value of equity)/Total assets.

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