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Essays on the Real Effects of Financial Markets and the Impact of Role Models on Decision Making

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Chapter 1

Introduction

This dissertation is made up of three empirical papers on corporate governance and gender economics. The first two papers are corporate governance papers about the real effects of investor behaviour on firm decisions. The first paper, "Tolerating CEO Failure: How patient investors support firm innovation", examines the effect of failure tolerant investors on firm innovation (Chapter 2), while the second paper, "A Real Threat? Short Selling and CEO Turnover", looks at the real effects of short selling on CEO turnover (Chapter 3). The third paper, "The impact of role models on women's self-selection into competitive environments", investigates whether female role models can make women more willing to enter into a competitive setting (Chapter 4). Both "Tolerating CEO failure" and "A Real Threat?" look at the effect of investor behaviour—being failure tolerant or shorting stocks—on the behaviour of the firm. In "Tolerating failure", investors' behaviour lessens control over the CEO by making the CEO less likely to be forced out after poor performance and thereby motivating him or her to take on the risk of innovating. By contrast, the chapter on short selling looks at how investors' behaviour tightens control by providing the board with additional information about CEO performance. In the following paragraphs, I will give a brief overview of all three chapters and discuss their motivation, research question, findings, and implications.

Chapter 2, "Tolerating CEO Failure", examines whether failure-tolerant investors motivate innovation in S&P1500 companies. This question is of high importance for two reasons: First, with today's pace of technological change, being innovative is vital for almost any company. Second, large and public companies considerably outspend both private and small firms when it comes to R&D investments. For the most part public companies constitute the only opportunity for average citizens to participate in the returns generated from investments in innovation.

Tolerance for failure has been shown to lead to more innovative outcomes in a laboratory setting (Ederer and Manso, 2013), in academia (Azoulay, Graff Zivin, and Manso, 2011), and in venture capitalist-backed IPO firms (Tian and Wang, 2014).

Chapter 2 contributes to the literature on both the optimal corporate governance structures to foster innovation as well as on long-term investments and managerial short-termism by providing a measure of the failure-tolerance of institutional investors of large and public firms. The chapter contributes to the literature on optimal governance structures, because theoretical and empirical evidence suggests that motivating innovation is especially difficult in both larger companies and in public firms (Holmstrom, 1989; Bernstein, 2015). It, therefore, cannot be assumed that the findings on tolerance for failure in venture capitalist-backed IPO firms by Tian and Wang (2014) also hold for larger and/or public companies. Moreover, in contrast to Baranchuk, Kieschnick, and Moussawi (2014); Chemmanur and Tian (2018), who analyse failure tolerance through anti-takeover provisions and stock option vesting periods, this paper provides evidence for the effect of a non-contractual measure of failure tolerance.

Chapter 2 also contributes to the literature on the role of the stock market in managerial short-termism. The literature currently includes contradictory conclusions on the role of institutional investors. Chapter 2 provides a way to measure ex-ante heterogeneity between investors that can explain different effects on the long-term investment behaviour of the CEO. In addition, this paper also adds to the literature on CEO turnover, by showing that failure-tolerant investors indeed reduce the likelihood of CEO termination after bad performance.

I use a partial model based on the model in Tian and Wang (2014) to demonstrate a positive relation between institutional investors' investment duration and their failure tolerance. Based on this, I calculate a measure of failure tolerance based on how long and how much institutions invested in failing CEOs on average. Using this measure, I find that firms with more failure-tolerant institutional investors are significantly more innovative in terms of quantity, quality, and economic value of innovative output. I control for firm heterogeneity with firm fixed effects and an array of observable firm control variables related to innovation. The finding is also robust to the use of different estimation models and samples. In line with model predictions by Manso (2011) on motivating innovation, an institution's failure tolerance is more important in industries with more opportunities for innovation as well as in industries with higher external governance due to competition.

Further, I look for evidence that excludes the alternative explanation of an endogenous matching between firms with a higher failure tolerance and higher innovation. I find evidence for my explanation and against the alternative explanation by using external variation in the risk of CEO failure as well as by adding controls for institutional investor characteristics and institution fixed effects.

My findings have implications for corporate governance policies and the public debate on institutional investors. In contrast to promoting short-termism, certain institutional investors may provide the right kind of CEO entrenchment necessary for motivating innovation.

The next chapter, "A Real Threat?" (Chapter 3), is also related to CEO turnover and the effects stock market participants can have on corporate decisions. While managers, regulators, and the public often fear the destructive and manipulative effects of short selling on the real economy, most empirical research finds a positive effect of short selling on market efficiency. Chapter 3 therefore examines whether short selling can, by making CEO turnover more efficient, support real efficiency.

Recent literature (e.g., Bond, Edmans, and Goldstein (2012); Edmans, Goldstein, and Jiang (2012)) going back to Hayek (1945) stresses the importance of the informational role of financial markets. As yet, there is not much research on whether short selling can accurately inform decision makers, such as firm managers or boards of directors, in the real economy, and whether this contributes to the efficiency of asset allocation. Findings are varied: Karpoff and Lou (2010) finds that short sellers influence the real economy by enabling financial misrepresentation on the part of firms to be conveyed to the public more quickly. Grullon, Michenaud, and Weston (2015) finds small firms invest less after the lifting of short selling constraints. De Angelis, Grullon, and Michenaud (2017) finds that the loosening of short selling constraints influences CEO compensation contracts. "A Real Threat" contributes to this literature by providing evidence that short selling supplies information to the board that leads to an increased probability of forced turnovers. Furthermore, this increased probability does not seem to be detrimental to the value of firms, but rather a factor for more efficient CEO allocation. It also suggests that short selling is not just about making prices more efficient and, as a result, more informative. Instead, the chapter will argue that the amount of short selling itself is a purveyor of information.

This chapter argues in three steps. Firstly, we show evidence that short sellers have private information on management quality. Specifically, we are able to provide evidence that abnormal short interest increases before forced turnovers and decreases afterward; abnormal short interest is higher before those turnovers that reveal more private information; and short interest predicts forced turnovers. Secondly, using Regulation SHO (Securities and Exchange Commission rules implemented in 2005, which restrict short sales) as a natural experiment, we show that unrestricted short selling increases the probability of forced turnovers for large firms. The effect is *not* driven by a higher informativeness of stock prices. Rather, forced turnovers become more sensitive to short interest during the exogenous decrease in short selling constraints, but not more sensitive to stock price performance. Thirdly, we find that the information likely does not reach the board directly, but rather through shareholder activists.

Our findings imply that short selling can have positive effects on real efficiency by directly providing information on CEO performance. These findings could be used in support of fewer restrictions on short selling.

In the final chapter of this thesis, we examine the effect of female role models on women's decisions to enter into a competition. Several countries especially in Europe have implemented gender quotas to increase the share of women in top supervisory and decision-making bodies of large companies. Still, the fraction of female top managers in Europe, as well as the US, is very low (Adams and Kirchmaier, 2016), likely due to a combination of factors such as career interruptions (Bertrand, Goldin, and Katz, 2010; Keloharju, Knüpfer, and Tåg, 2019), hiring and customer discrimination (Goldin, 2015; Niessen-Ruenzi and Ruenzi, 2019), and harassment (Azmat, Cuñat, and Henry, 2020). Another suggested reason is that women are reluctant to compete against others and even more reluctant to compete against men (Gneezy, Niederle, and Rustichini, 2003a; Niederle and Vesterlund, 2007; Bertrand, 2011). Since top management positions are usually characterized by tough competition, women self-select into less competitive environments.

This preference appears to be the result of nurture rather than nature, exemplified by the observation that women in matrilineal societies do not show the same reluctance to compete (Gneezy, Niederle, and Rustichini, 2003b). Specifically, internalized or recognized gender norms and stereotypes in patriarchal societies likely lead women to think that competitive behavior is either not desired or less likely to bring them success. Specifically, stereotype threat—that is the fear of confirming a negative stereotype about one's own social group, for example "women are bad at math"—may decrease women's confidence and lead them to avoid certain competitive environments. Role models have been shown to be successful in decreasing stereotype threat, raising performance levels (Marx and Roman, 2002; Stout, Dasgupta, Hunsinger, and McManus, 2011), decreasing gender differences in career aspiration, and improving educational attainment (Beaman, Duflo, Pande, and Topalova, 2012), as well as increasing female students' likelihood of choosing mathematical subjects (Bettinger and Long, 2005). In this paper, we investigate whether the availability of competitive female role models can also influence women's willingness to compete.

We explore this question using a 3 (female role model, male role model, no role model) x 2 (subject gender) between-subject experimental design. Our sample consists of 668 American participants recruited through Amazon Mechanical Turk. The dependent variable is the selection into a competitive environment, which we measure by closely following the research design of Niederle and Vesterlund (2007).

Our findings echo the results of earlier research by Niederle and Vesterlund (2011) that shows that women are less willing to enter a tournament than men, despite no significant performance differences. However, we find this gender gap in tournament entry disappears if subjects are exposed to a competitive female role model. By contrast, the gender gap is even larger for women after seeing a male role model compared to a neutral condition. We also analyze the effect of performance on the willingness to compete. While high-performing men compete more often than those with low performance, performance does not impact women's willingness to compete unless they see a female role model. Female role models only increase the propensity to compete for high-performing women. Using survey questions and behavioral evidence, we also find that female role models weaken women's perceived stereotype threat and increase their self-confidence.

With these findings, we contribute to the literature on gender differences in finance and economics (Schubert, Brown, Gysler, and Brachinger, 1999; Bertrand, Goldin, and Katz, 2010; Cadsby, Servátka, and Song, 2013; Gneezy, Leonard, and List, 2009; Niederle and Vesterlund, 2007; Niessen-Ruenzi and Ruenzi, 2019), by studying how preferences for the competition can be altered, as well as to research the effects of female role models on women (Beaman, Duflo, Pande, and Topalova, 2012; Bettinger and Long, 2005; Marx and Roman, 2002; Stout, Dasgupta, Hunsinger, and McManus, 2011; Schier, 2020). In a contemporaneous paper, Schier (2020) finds a positive effect of both male and female role models on women's willingness to compete. In Schier (2020), participants are informed directly before the choice of compensation schemes that either a man or a woman from a previous round of the experiment favored the tournament. This may be interpreted by subjects as a direct recommendation for what to choose. Our paper differs from Schier (2020), because our role models are not presented directly before the choice of a compensation scheme and their actions do not refer directly to the experiment, but to competing in general. We can therefore mitigate experimenter demand effects and this may explain the difference in our findings.

The findings in this final chapter imply that "soft" interventions, such as providing successful and competitive role models, may be suitable to nudge women to pursue competitive careers, increasing the share of women in top management positions. Such "soft" interventions are less intrusive and potentially cheaper than other interventions such as gender quotas (Ahern and Dittmar, 2012). At the same time, our findings suggest that gender quotas may have positive second-round effects, by providing female role models and counter-stereotypes, nudging other highly qualified women to enter competitive careers and thus decreasing the costs of the gender quota over time.

Chapter 2

Tolerating CEO failure: How patient investors support firm innovation

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2.1 Introduction

The innovation level of a company has never been a bigger business imperative. With automation taking over more and more routine jobs, the chance to break free of operational limitations and innovate in new and lucrative directions is a central business theme in this century.[1] But motivating employees and managers to invest their time in innovation is difficult (Manso, 2017), especially when firms are large (Holmstrom, 1989) or public (Bernstein, 2015). The high uncertainty associated with innovative processes makes the standard pay-for-performance incentive scheme unsuitable to motivate the risky act of searching for innovative solutions. While checks and measures are necessary to prevent managers from slacking off when doing routine work or using established technologies, it

[1] Surveys show that companies are under enormous pressure to find ever more ingenious technologies (KPMG, "Now or Never: CEOs Mobilize for the Fourth Industrial Revolution," U.S. CEO Outlook, 2016, https://assets.kpmg.com/content/dam/kpmg/pdf/2016/07/2016-ceo-survey.pdf and PwC, "20 Years Inside the Mind of the CEO... What's Next?," 20th CEO Survey, 2017, https://www.pwc.com/gx/en/ceo-survey/2017/pwc-ceo-20th-survey-report-2017.pdf).

discourages trying out new actions that risk failing in the short term.

Because of this trade-off, there is a public debate about whether and how much managers should be held accountable for their failures. One side of the debate calls for holding managers accountable and criticizes managerial entrenchment, golden parachutes, option repricing, and high CEO pay as rewarding managers for poor performance. In support of this argument, past research has usually interpreted a low performance-turnover sensitivity as a sign of bad governance, because it supposedly does not hold managers sufficiently accountable, hurting shareholder value.

The other side emphasizes the need for less control and more trust in managers even in the face of setbacks and often criticizes institutional investors for thinking too short term. Research on tolerance for failure explains that the aforementioned manager-friendly corporate governance practices may be in the interest of shareholders if they are part of an incentive package that motivates the CEO to invest in innovation.

Both sides have the potential to be correct if there is a trade-off between encouraging innovation by tolerating failure and the lack of manager accountability this entails. The difficulty therein is that the threat of termination discourages both slacking off and exploring new, innovative technologies. Manso (2011) models the incentive problem of motivating an agent to be innovative using a three-armed bandit problem. The agent needs to decide between exploiting known technologies for which the payoff is known or exploring new approaches for which the probabilities of success are unknown. Exploring these new approaches allows the agent to learn about their payoff and thereby find approaches superior to those already known. Manso (2011) shows that when trying to motivate agents to conduct such explorations, a combination of tolerance for failure and the reward for long-term success is the optimal incentive contract.

To further these discussions, this paper seeks to find empirical evidence on whether tolerance for CEO failure motivates innovation. I develop a new measure describing the failure tolerance of institutional investors and analyze how this characteristic influences the innovative output of S&P1500 firms. Investigating the relationship between failure tolerance and innovation in this setting is important for two main reasons: First, while innovation is often associated with start-ups and small firms, large and public companies actually spend the largest amount of money on innovation. The difference between them and small firms is only growing, with large companies having spent \$120 million dollars more on research and development than small companies in 2017. In the 1980s, this difference was only \$20 million.[2] Thus, it is important to understand what makes these investments succeed and what hinders them. Second, public companies, for the most part, constitute the only opportunity for average citizens to participate in the returns generated from investments in innovation.

I argue that institutional investors' failure tolerance is relevant for the innovative outcomes of firms because institutional investors influence the retention and compensation of the CEO. A large part of CEOs' compensation comes from equity and stock options and they are contractually not sufficiently insulated from repercussions. Therefore, both activism and exiting have the potential to oust the CEO or at least hurt their finances and reputation. At the same time, investors can commit to being tolerant of failure by reputation.

My measure is based on a simple partial Bayesian updating model, adapted from Tian and Wang (2014), that models investors' decisions to terminate their investment in a firm-CEO match. In this model, I do not differentiate between ending this investment by trying to oust the CEO or ending the investment by selling their shares in the company. In the model, the investor updates a common prior about the quality of the firm-CEO match by observing a series of performance signals. The investor decides to terminate the investment when the quality that it estimates based on the signals falls below a certain individual threshold. This termination threshold is inversely related to the investment duration in the firm-CEO match and therefore positively related to the investor's tolerance for failure.

Hence, I estimate an institution's failure tolerance from its past tendency to continue to invest in underperforming firm-CEO matches. The intuition of my measure is the following: A failure-tolerant institutional investor is one that continues to invest in a firm-CEO match even though the CEO may encounter setbacks at the firm, such as failed or delayed products. The institution evaluates these signals and either decides to continue its investment or to end it. Firm-CEO matches that eventually fail will have sent negative performance signals (Jenter and Kanaan, 2015; Jenter and Anderson, 2017; Kaplan and Minton, 2012; Kunzmann and Meier, 2018). Investors that nevertheless continued their investment in such a match will have tolerated failure. The longer they held on to this investment despite negative signals, the higher their tolerance for failure.

I, therefore, calculate investment duration as the number of quarters an institution was invested in a firm-CEO match where the CEO was eventually forced out and weight each

[2] "The Gap Between Large and Small Companies Is Growing. Why?", *Harvard Business Review*, August 16, 2019.

quarter with its portfolio weight at that point in time. This takes the specific risk this investment poses to the investor into account. For every quarter, I then take the average of these weighted investment durations per investor over the past 5 years. This gives me the average weighted investment duration in failed firm-CEO matches for each investor and each quarter. The measure, therefore, varies over time. While the investor does not have to be invested in the firm when the CEO is fired, the ousting needs to occur within this 5-year window so that the measure is not forward-looking.

I then link the individual investor's failure tolerance to the firm by averaging the failure tolerance of all institutional investors invested in a particular firm at a particular time. I weight each failure tolerance with the size of the investment relative to all institutional investors. This measure reflects the overall failure tolerance exhibited by the institutional shareholders of the firm. The average firm is faced with an investor failure tolerance of 1.1 quarters with a maximum of 1.9 quarters.

In contrast to Tian and Wang (2014), I am able to validate the measure by testing whether it is negatively related to the CEO turnover-performance sensitivity. If the measure proxies for failure tolerance towards the CEO, a CEO in a firm with higher failure tolerance should be less likely to be fired after bad firm performance than a CEO in a firm with lower failure tolerance. Indeed, managers are less likely to be fired after bad firm performance if they have a more failure-tolerant investor base. However, the failure tolerance of investors does not impact the overall likelihood of forced turnover. This finding confirms that the measure does not reflect a general leniency of investors, but specifically a higher tolerance for bad performance.

My main finding is a robust positive association between innovation and the failure tolerance of investors, even after controlling for firm fixed effects and other confounding variables. Conditional on the level of institutional ownership and firm size, these S&P1500 companies produce more patents, more impactful patents, and patents with higher economic value. I measure quality using citation-weighted patent counts and economic value with a measure by Kogan, Papanikolaou, Seru, and Stoffman (2017) of the stock market response to news about patent grants. Conditional on the same amount of past R&D investment, a change in ownership that increases the firm's *Failure tolerance* by one standard deviation is associated with 15.6 percent more patents. The same change in *Failure tolerance* is related to 17.1 percent more citation-weighted patents and a 12.4 percent higher expected dollar value of patents. More failure-tolerant investors have a positive effect on the productivity of R&D, i.e., for the same level of past R&D investment, firms with more failure-tolerant investors generate more innovative and profitable patents.

This finding is robust even when all alternative measures, samples, and estimation models are applied. Therefore, the results are not driven by particular specifications of my measures, but instead, hold when changing the measurement period for *Failure tolerance* or when using only the largest investor's *Failure tolerance*. My results are also not driven by the large number of firms that do not have any approved patents, since the results hold when excluding these firms from the sample. They are also not driven by my choice of estimation model, since they also hold when using a different model to the Poisson estimation model used in my main specification.

I use exogenous variation in the cost of shirking and the possibilities of innovation to test further predictions of the model. According to Manso (2011), the optimal contract depends on the cost of shirking and the costs of innovating. When the principal is worried that the manager will slack off, a credible threat of termination is optimal. If the principal is more worried about the manager playing it safe, tolerance for failure is optimal. Using product market competition as an exogenous variation for the cost of shirking, I show that in situations where the CEO is more likely to exploit known actions than to shirk, *Failure tolerance* is more strongly associated with innovation. The same trade-off applies when innovation is not the main organizational goal, for example, when there are very few possibilities for innovation. In this case, the principal would not want the agent to waste effort on innovation but rather needs a credible threat of termination to motivate higher performance. I use industry variation in innovative outcomes to proxy for the possibilities for innovation and find that *Failure tolerance* is more relevant in more innovative industries.

My baseline results are consistent with the hypothesis that more failure-tolerant investors motivate firm innovation. However, they are also consistent with the alternative hypothesis that investors self-select into firm-CEO combinations with high ex-ante potential and it is this potential that results in higher innovative output. In contrast to Tian and Wang (2014), I can partially address this alternative hypothesis by including firm-fixed effects, which control for the ex-ante time-invariant quality of the firm, but they also do not control for the time-variant quality of the firm-CEO match. I deploy three further strategies to deal with the endogeneity problem.

First, I use exogenous variation in the ex-ante risk of firm-CEO failure to differentiate between the two hypotheses. When CEOs start their tenure during a recession, their risk of failure is higher. I find that the marginal effect of *Failure tolerance* is larger for these recession-CEOs, lending support to my causal interpretation of the relation between innovation and *Failure tolerance* and contradicting the alternative explanation: Being tolerant towards failure is even more important to produce innovation when the risk of failure is very high. By contrast, one would expect a lower marginal effect under the alternative hypothesis, because the likelihood of converting higher ex-ante potential into innovation should be lower during a recession.

Second, I control for different investor investment styles, skills, and preferences. Any of these may result in a matching between investors with high *Failure tolerance* and firm-CEO matches with a higher ex-ante potential. To control for investment styles, I include the percentage of dedicated and quasi-indexer investors according to the classification by Bushee (1998). The coefficient on *Failure tolerance* remains highly significant. To control for time-varying and -invariant investor characteristics, I calculate the *Failure tolerance* of the largest investor (*Failure tolerance* (*LI*)) and control for its age, portfolio concentration, the number of firms held as well as its portfolio liquidity and momentum. Age, portfolio concentration, and the number of firms held proxy for investors' skills and experience in picking firm-CEO matches with higher ex-ante potential. The endogeneity problem occurs because this same skill would also likely lead an investor to hold on to a firm-CEO match longer. The coefficient on *Failure tolerance* (*LI*) is slightly reduced in size and significance but remains statistically significant. I further add investor fixed effects to control for unobservable and time-invariant investor characteristics. I find that the size of the relation between *Failure tolerance* (*LI*) and the most widely used measure of innovation—citation-weighted patents—decreases some more, but stays significant at the 5% level. The relation to the plain number of patents as well as to the economic value is no longer statistically significant. This evidence supports a causal relationship between *Failure tolerance* and the quality of innovative output, but not for the quantity or economic value. Therefore, the relationship with the quality of innovative output cannot be fully explained by the matching of investors with higher *Failure tolerance* with firm-CEO matches with higher ex-ante potential.

Past research has found evidence that failure tolerance leads to more innovative outcomes in a laboratory setting (Ederer and Manso, 2013), in academia (Azoulay, Graff Zivin, and Manso, 2011), and in venture capitalist-backed IPO firms (Tian and Wang, 2014). While tolerance for failure has been proxied for by the existence of anti-takeover provisions (Chemmanur and Tian, 2018; Baranchuk, Kieschnick, and Moussawi, 2014), to the best of my knowledge, a direct measurement of failure tolerance and its effect in large or publicly traded companies is not available. At the same time, it is not clear whether the findings by Tian and Wang (2014) on venture capitalist IPO firms also hold for large and/or public companies for two reasons. First, as Holmstrom (1989) explains, motivating innovation in large companies is different than in small companies because attention needs to be allocated between heterogeneous tasks, whereas small companies are more focused and therefore the tasks more alike. In large firms, there are also tasks that are less exploratory and therefore carry less risk for the employee being judged unfairly. Similarly, shareholders may also prefer managers to invest in short-term rather than long-term projects because short-term projects lead to less noise when it comes to assessing the manager (Thakor, 2020). Second, the decision for small firms to go public is endogenous and may be related to innovation. According to the model by Ferreira, Manso, and Silva (2014), because the stock prices of publicly traded securities react quickly to good news, insiders in public companies have more incentives to exploit existing ideas than to innovate. In line with this result, Bernstein (2015) finds that going public negatively affects the internal innovation of firms. This finding may also be related to the shrinking of the U.S. stock market and a shift to privately held companies (Ljungqvist, Persson, and Tag, 2018; Doidge, Karolyi, and Stulz, 2017; Doidge, Kahle, Karolyi, and Stulz, 2018). For these reasons, it is unclear whether failure tolerance matters in large firms that have selected into being a public company, as this decision may be related to less desire or ability to innovate. This paper, therefore, fills this gap by providing the first direct measure of tolerance for failure for large and public companies and showing that more failure-tolerant institutional investors contribute to better innovative outcomes within this subgroup.

2.2 Related research

My paper contributes to two parallel streams of research: the growing strand of the empirical literature on optimal corporate governance structures to foster innovation and the literature on long-term investments and managerial short-termism.

The paper most closely related to mine is Tian and Wang (2014). They develop a measure of failure tolerance of venture capitalists (VCs) based on the VCs' past investment behavior and find that IPO firms backed by more failure-tolerant VCs are more innovative. I use their approach for measuring the failure tolerance of VC as a starting point and develop a similar measure of failure tolerance for institutional investors of large and public firms. Although innovation is often associated with small, start-up firms, large companies spend much more on innovation and the differences are growing. Whereas large U.S. companies spent $20 million more on R&D than small companies in the 1980s, this difference has grown to $120 in 2017 (numbers are inflation-adjusted).[3] Similarly, large companies in Germany spent around 68 € billion more on innovation than small and medium firms and this difference grew to 117,2 € billion more in 2021. When adjusting for sales, large companies still spent twice as much on innovation as small companies.[4] Analysing how to motivate innovation in large and public firms is therefore economically highly relevant, both because much can be gained through successful innovation, but also because many more employees are at stake when a firm goes under for example because it failed to be innovative. Moreover, since large and public firms differ from smaller firms both in terms of regulation, complexity, and challenges in motivating innovation, it is not clear whether the findings of Tian and Wang (2014) hold in this setting.

Other empirical papers on motivating innovation in large and public firms have analyzed the relation with tolerating failure using contractual governance measures that can either make termination less likely, such as through anti-takeover provisions (Baranchuk, Kieschnick, and Moussawi, 2014; Chemmanur and Tian, 2018) or less costly through shorter vesting periods for employee stock options (Baranchuk, Kieschnick, and Moussawi, 2014). Both papers find a positive relationship between these contractual measures and the innovative output of firms. My paper contributes to these findings by showing that a "soft", non-contractual tolerance for failure can have a significant effect on the innovation of large, public companies. In addition, it shows that institutional investors cannot only serve as an external control mechanism but can also serve to motivate innovation.

Lastly, in contrast to other papers, I do not only test whether failure tolerance increases the number of patents (i.e., the quantity of innovation) (Baranchuk, Kieschnick, and Moussawi, 2014) or citation-weighted patents (i.e., the quality of innovation) (Aghion, van Reenen, and Zingales, 2013), but test my hypothesis on both measures. In addition, I also test whether failure tolerance increases the economic value of a firm's innovation. By testing my hypothesis on all three measures, I analyze which aspects of these aspects of innovation failure tolerance motivates.

[3] The Gap Between Large and Small Companies Is Growing. Why?, *Harvard Business Review*, August 16, 2019.

[4] ZEW Innovation Survey 2022: Innovation Behaviour in the German Economy, January 24, 2023.

My paper also adds to the literature on the role of the stock market in managerial short-termism or myopia. Central for this literature is Stein (1989)'s model, in which stock market pressure pushes managers to prefer actions that bring immediate returns to shareholders at the expense of long-term value creation.[5] Several empirical papers provide evidence that public firms underinvest (Derrien, Kecskés, and Thesmar, 2013; Asker, Farre-Mensa, and Ljungqvist, 2015), especially in long-term projects such as innovation (Gao, Hsu, and Li, 2018; Bernstein, 2015).[6] Other theoretical papers also explain why short-termism can be optimal depending on a firm's debt structure or the labor market competition (Thakor, 2020; Hackbarth, Rivera, and Wong, 2022).

The role of institutional investors in managerial myopia is controversial: Some blame them for it (Bushee, 1998; Gao, Hsu, and Li, 2018). In Graham, Harvey, and Rajgopal (2005), CFOs argue that institutional investors promote short-termism as they "sell first and ask questions later". Other researchers counter that informed long-term institutional investors actually insulate managers from short-termism (Aghion, van Reenen, and Zingales, 2013; Edmans, 2009). The literature has started to explore these different views by differentiating between different categories of investors (financial vs. non-financial, private vs. non-private, short term vs. long term, and Bushee (1998)'s classification of institutions into "dedicated", "transient", and "quasi-indexers"). However, these classifications only allow for categorical results and proxy for a number of different characteristics, partially related to, but not directly measuring, tolerance for failure. I contribute to this literature by focusing on the effect of ex-ante heterogeneity in investor preferences.

My paper also adds to the literature on CEO turnover. Past results on the relation between institutional investors and the likelihood of forced CEO turnover are mixed: Kaplan and Minton (2012) find an insignificant or negative relationship, whereas Aghion, van Reenen, and Zingales (2013) find a positive significant relationship. This paper contributes a possible explanation for these mixed findings: Differences in failure tolerance amongst institutional investors lead to differences in the sensitivity of forced turnover to firm performance. By not controlling for this characteristic, past conflicting results may have stemmed from different levels of failure tolerance in the respective samples.

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[5] Theoretically, firms should go private to circumvent short-term pressures from the stock market if they want to explore new ideas (Ferreira, Manso, and Silva, 2014).

[6] Analyst coverage (He and Tian, 2013) and a greater threat of termination to CEOs Gao, Harford, and Li (2017) are possible channels through which stock market pressure influences firm investment.

2.3 Theoretical framework and key predictions

My definition of an institutional investor's failure tolerance assumes a standard Bayesian updating model in which the estimated quality of a firm-CEO match, α is defined as:

$$\alpha = \theta + u, \tag{2.1}$$

where θ is the average firm-CEO match quality and u is the firm-CEO match's individual quality. I assume that u is normally distributed with zero mean and precision h_u and that this distribution is known to all investors. By observing private and public signals, δ_n, that depend on the firm-CEO's idiosyncratic quality, u, as well as a random element, ϵ_n, the institutional investor subsequently updates its prior estimate of the quality of this match. Like Tian and Wang (2014), I assume that ϵ_n is normally distributed with zero mean and precision h_ϵ.

The investor will abandon her investment in the firm-CEO match when the posterior estimate of the match falls under a certain threshold, ϕ. Investors can decrease their investment in a firm-CEO match either by selling shares, voting, or by direct intervention to fire the CEO. Following Tian and Wang (2014), I assume this threshold is below the initial estimate of the firm-CEO match quality, such that $\phi < \theta$. Thus, the institution will terminate its investment after receiving the first signal, n, that brings the estimated quality below its threshold. Different investors will have different termination thresholds. I define institutions with a lower threshold to be considered more failure tolerant and investors with a higher threshold to be less failure tolerant. Following Tian and Wang (2014), I do not assume that this threshold depends on the rationality of the investor, but that investors behave rationally with respect to their preferences. Thus, the intuition is that a more failure-tolerant investor endures negative signals for a longer period in the belief that the actual quality of the firm-CEO match may still be above the average quality.

According to standard Bayesian updating, an institutional investor will abandon its investment in the firm-CEO match after having received a sufficient number of negative performance signals pushing the estimated quality of the project beneath its threshold. The investment duration is therefore inversely related to the institution's threshold. The lower its threshold, the longer the institution will wait to terminate its investment:

$$n^j >= \frac{h_u}{h_\epsilon} \frac{\theta - \phi^j}{(-\bar{\delta}) - (\theta - \phi^j)}. \tag{2.2}$$

Besides the termination threshold, the investment duration also depends on the precision of the signal. The higher the precision of the—in this case negative—signal, the sooner the investor will terminate the investment. Therefore, if institutional investors also differ concerning the average precision of the signals they receive, their investment duration will not only differ concerning their failure tolerance but also concerning the precision of their information. For the derivation of these conclusions from the model, see Tian and Wang (2014).

How is a lower termination threshold, i.e., tolerance for failure, related to innovative output? As in Manso (2011), I define innovation as finding new, superior actions by exploring new possibilities. Manso (2011) models the innovation process using a three-armed bandit problem[7] and embeds it in a principle-agent framework. The agent can choose between shirking, exploiting known actions, or exploring new actions. The distribution of outcomes from new actions is unknown, but the agent can learn about the probability of success of a new action by trying it out. If the action is superior to known actions, the agent can achieve higher outcomes in the long run by trying out new actions early. However, the agent may be discouraged from doing so, when she has to fear termination after poor performance. Specifically, Manso (2011) shows that if the principal needs to incentivize the agent to explore new actions instead of exploiting known actions, the optimal contract will protect the agent against early failures by committing to a lower termination threshold than ex-post efficient.

In a parallel research stream, Edmans (2009) lays out a model that shows how blockholders tolerate negative performance signals in terms of weak earnings because they have the incentive to find out what was the cause of the weak earnings. If the weak earnings are the result of long-term investments, the blockholder will not sell, lessening the stock price decline due to the weak earnings. The model in Edmans (2009) relates to my model in that investments into innovation, i.e., exploring, are a subgroup of long-term investments. In that sense, my model is a specific case of Edmans (2009)'s model. At the same time, the above model is more general since it considers the investment durations of all institutional investors, not just blockholders. Blockholders' increased information acquisition is captured in my model through a higher signal-to-noise ratio of their signals.

I argue failure tolerant institutional investors can achieve the desired excessive continuation because they have power over the retention of the CEO and because CEOs are not already contractually sufficiently insulated from repercussions due to early failure.

[7]Bandit problems are a class of Bayesian decision models.

Regarding the first reason, if an institutional investor is unhappy with the management of a company, it can pressure the board to fire the CEO (voice) or sell shares of the company (exit). In practice, both measures are highly prevalent as well as effective in costing the CEO her job: In a survey, 45% of investors stated that they hold private discussions with the boards of companies without management present and 49% that they had exited a portfolio firm over the past five years because of dissatisfaction with CEO performance (McCahery, Sautner, and Starks, 2016).

Second, CEOs are not completely contractually insulated from repercussions due to early failure. The majority of CEOs are employed 'at will', meaning that they do not have explicit employment agreements and thus face a permanent dismissal threat (Schwab and Thomas, 2006; Gillan, Hartzell, and Parrino, 2009; Chen, Cheng, Lo, and Wang, 2015). In addition, only around 35% of CEOs have stand-alone severance agreements (Schwab and Thomas, 2006). The exit strategy can also have a sizeable impact on CEOs' compensation: Equity compensation made up an average of 52% of total compensation in 2005 (Chhaochharia and Grinstein, 2009). In a survey of executives, Graham, Harvey, and Rajgopal (2005) finds that managers are also concerned with the volatility of their earnings. In line with these results, they also find that 78% of surveyed executives state that they would sacrifice long-term value to meet earnings targets (Graham, Harvey, and Rajgopal, 2005).

To provide reliable protection against termination, investors must not only have the power to punish failure, but they must also be able to commit to being failure tolerant. I argue that institutional investors can do so using their reputation. For this, CEOs must be aware of the identity of institutional investors, which they are through their investor relations departments or shareholder intelligence firms (Beatty, 2017; Kempf, Manconi, and Spalt, 2017). Corporations, represented by the Association of Corporate Secretaries, even petitioned to reduce the reporting lag on their investor basis (Christoffersen, Danesh, and Musto, 2018), suggesting that information in 13F filings is used by companies.[8] In addition, research also suggests that managers would be informed about the reputation and intentions of their investors: McCahery, Sautner, and Starks (2016) finds that 63% of large, long-term investors hold direct discussions with top management. These interventions typically occur before a potential exit (McCahery, Sautner, and Starks, 2016), suggesting that management would also be informed about the threat of exit. Burr (2012) provide further anecdotal evidence on behind-the-scenes activism.

[8]https://www.sec.gov/rules/petitions/2013/petn4-659.pdf

Additional interactions will take place at conference calls and annual meetings, providing ample possibilities for observing investors' failure tolerance.

Differences in the failure tolerance of investors between firms can exist as optimal reactions to differing circumstances. First, while tolerating failure is optimal to motivate innovation, investors may not want the agent to innovate if the expected gains from innovation are relatively low. If exploration is not desired, Manso (2011)'s three-armed bandit problem reduces to a standard principle agent model in which the principal must keep the agent from shirking and being failure tolerant is not optimal. Second, according to Manso (2011), if the principle wants the agent to innovate, the principle must keep the agent not only from shirking but also from using conventional technologies, i.e., from exploiting. In this case, tolerating failure is optimal if the agent is more likely to exploit than shirk because the costs of shirking are already relatively high compared to the costs of exploring. Vice versa, if the costs for exploring are very high, the agent will either shirk or exploit a conventional work method. In this case, it is optimal for the principle to prevent the agent from shirking by showing less tolerance for failure.

Cremers and Nair (2005) find that external and internal governance mechanisms interact with each other. Therefore, even in situations where tolerance for failure is the optimal contract form, it may be cheaper to reduce the threat of termination through explicit contracts or through other corporate governance mechanisms that give the manager job security through managerial entrenchment.

2.4 Data and variables

2.4.1 Main independent variable: Failure tolerance

Failure tolerance on an institutional level

My main variable of interest is a firm-level measure of how tolerant a representative institutional investor is towards the failure of a CEO in a particular firm in a given period. I call this variable *Failure tolerance*. In section 2.3, I refer to the formal model in Tian and Wang (2014) showing how the investment duration into an ex-post failed investment is positively related to failure tolerance. Since I cannot observe the current failure tolerance of an investor, I use this insight to construct *Failure tolerance* such that I consider institutions that invest for a longer time into firm-CEO matches for which I know, ex-post, that they must have sent negative performance signals, as having a higher tolerance for failure. A higher value of *Failure tolerance* thus implies that the investor has a lower termination threshold and thus will tolerate negative performance signals for a longer time before ending or reducing the investment. Specifically, I approximate institutions' failure tolerance by their past investment duration into firm-CEO matches where the CEO was terminated. In addition, I account for the weight this investment has in the institution's portfolio, by weighting the investment duration with the portfolio weight.

More precisely, *Failure tolerance* (NA) of institution i in quarter q is the weighted number of quarters within a rolling window that the institution invested in firms with CEOs who were forced out, or:

$$Failure\,tolerance\,(NA)_{i,q} = \sum_{q=-z}^{q=0} \sum_{k=1}^{k=K} w_{k,q} Forced_{k,q}. \tag{2.3}$$

Here, k indexes firm-CEO matches in which the institution invests and z denotes the length of the rolling window in quarters. $Forced_{k,q} \in \{0,1\}$ is a dummy equal to 1 in all quarters that an institution was invested in a firm-CEO match where the CEO was fired from her CEO position within the rolling window and 0 otherwise. Since the turnover occurs within the rolling window, my measure is not forward-looking. In plain terms, the above equation states that in every quarter and for every institution-firm observation, I go back z quarters. If the CEO of the firm was fired between $-z$ and the current quarter, I sum up the weighted number of quarters the institution was invested in the firm within the z quarters while this CEO was in office.

I define forced turnover as any turnover due to performance reasons as opposed to voluntary turnover and operationalize it using the common classification procedure by Parrino (1997). I first obtain data on CEOs of S&P1500 firms from Compustat's Execucomp database from 1993-2018. I then mark all observations as turnovers if the person classified as CEO changed from one fiscal year to the next. Because CEOs are rarely openly fired, the classification scheme classifies turnovers as forced not only if the company or the press states that the CEO was fired for performance reasons, but also by the process of elimination of alternative reasons such as another position, illness, death, or retirement. Reasons are taken from news and press release searches on Lexis Nexis.[9] I define the turnover quarter to be the quarter in which the turnover is announced and not

[9] I have kindly received classifications based on this method for turnovers between 1993 and 2009. I hand-collect reasons and perform the classification myself for turnovers between 2010 and 2017.

the quarter in which the CEO left the office; this quarter more closely reflects the time point of the decision to oust the CEO.[10]

I obtain data on institutional holdings from the Thomson Reuters institutional holdings database. This database contains the holdings of all large institutional investors that are required to file Form 13F with the SEC. Beginning in 1980, large institutional investors, i.e. those exercising investment discretion over at least $100 million in market value, must report the number and market value of each share they hold on a quarterly basis. Filings must occur within 45 days and may exclude small holdings of less than ten thousand shares or $200,000 in value. I merge the holdings data with stock data from CRSP.[11]

Further, $w_{k,q}$ captures the weight the CEO's firm had in the institution's portfolio of firms in the Execucomp database at the time of the investment. I consider only the institution's investments in firms in the Execucomp database since I only have information on the CEOs of these firms. Specifically, I calculate the weight as:

$$w_{k,q} = \frac{P_{k,j,q} * SharesOwned_{k,j,q}}{\sum_{j=1}^{j=J} P_{j,q} * SharesOwned_{j,q}}, \tag{2.4}$$

Where $P_{k,j,q}$ is the price of a share in firm j of the CEO-firm match k at the end of quarter q and $SharesOwned_{k,j,q}$ are the number of shares of firm j institution i owns at the end of the quarter.

Figure 2.1 illustrates the calculation of $Failure\,tolerance_{i,q}$ for two hypothetical institutions in $q = 2$. For this example, I assume a universe of three firms and use a rolling window of $z = 2$. $z = 2$ means that I use the past 2 quarters, i.e. a rolling window of 2, to estimate the institutions' $Failure\ tolerance$. In the example, two turnovers take place, and they are both forced turnovers. Therefore, in all other periods, the firm-CEO matches stay the same. $Failure\ tolerance$ is calculated at $q = 2$. In both $q = 1$ and

[10] Announcement dates are not recorded in Execucomp. For the period 1993-2009, I kindly received information on announcement dates from Jenter and Kanaan (2015) and Peters and Wagner (2014). I hand-collect the remaining dates for 2010-2017 using Lexis Nexis.

[11] Some adjustments must be made with the data from Thomson Reuters 13F (formerly Spectrum). First, the institution identifier (MGRNO) is not unique to an institution but is reassigned after an institution disappears. I, therefore, use the permanent identifiers assigned by Brian Bushee, available on his personal website (http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html). The permanent identifiers assume that the MGRNO was reassigned by Spectrum every time there are more than two quarters without holding information for a manager number. If this is the case, it is understood to be a different institution and assigned a new permanent identifier. Further, the database often contains multiple entries per institution for one reporting period. If this is the case, I use the first entry, since it tends to be less erroneous. I adjust shares for stock splits using the filing date. Moreover, if there is a one-quarter gap in the reporting, I fill in the missing observation with interpolated shares outstanding. I drop firm-quarters for which the institutional ownership exceeds 101%.

$q = 2$, institution 1 invested 50% of its portfolio into portfolio firms 1 and 2, each. Of the two, only portfolio firm 2 experienced a forced turnover during the rolling window, namely in $q = 2$. I thus add up the number of periods the institution had invested in this firm-CEO match and weight it with its portfolio weight in each period, resulting in $Failure\,tolerance_{1,2} = 1$. Institution 2 also only invested in portfolio firms 1 and 2. Only firm 2 had a forced turnover within the rolling window and the institution was invested 100% in quarter 1. Therefore, $Failure\,tolerance_{2,2} = 1$.

$Failure\ tolerance\ (NA)$ of an individual institution can thus vary between 0 and z. It is 0 if the institution did not invest in any firm in which the CEO was forced out within the past z quarters. It is equal to z if the institution invested only in firms where the CEO was forced out within the past z quarters over the whole measurement period. Thus, my measure reflects failure tolerance in two ways: First, by summing up the quarters an institution is invested in a firm with a CEO who fails, I account for the investment duration. Second, by value-weighting each invested quarter, I additionally account for the importance of this investment in the institution's portfolio. The measure differs in this respect from the measure by Tian and Wang (2014), who only know the values of the investment for each investment round of the VC-backed firms.

Picking the length of the window involves a trade-off: On the one hand, the longer the time window, the better the chances of capturing the full extent of the behavior that I want to measure. For example, using a window of just one quarter, i.e., $z = 1$, I would capture only the variation of whether an institution is invested in a failed CEO in a particular quarter. This measure would leave out any variation in how long the institution was invested in a CEO. A CEO's tenure constitutes the maximum time an institution can invest in the CEO and thus constitutes an upper bound on the variation I want to capture. A CEO's tenure in years served as the CEO of a company covered by the Execucomp database is on average 4.77 years ($std.dev. = 3.7$, $max = 24$ years).[12] Moreover, Taylor (2010) shows that the probability of being fired is highest in the second and third year of a CEO's tenure, decreases rapidly after that until the seventh year, and becomes extremely small after eleven years. Therefore, most of the variation will be captured using a 5-year window.

On the other hand, past behavior will be less indicative of current behavior the further it is in the past. This problem becomes more severe the faster the underlying characteristics of the institution cause the behavior changes and less severe the slower the characteristics

[12] This number does not necessarily reflect the actual tenure of CEOs since it excludes years not covered by the database or for which the firm was not covered by the database.

change. The characteristics and investment behavior of an institution are tied to the characteristics and behavior of asset managers working there. Assuming that the failure tolerance remains relatively constant over the tenure of an individual asset manager, the failure tolerance of an institution changes mostly when managers with a certain failure tolerance leave the institution and managers with a different failure tolerance start working at the institution. According to Chemmanur, Loutskina, and Tian (2014), the average mutual fund manager's tenure in an institution is 3.35 years ($std.dev. = 4.69$). This suggests that observed behavior three to five years in the past will be indicative of current behavior, with the significance gradually fading from then on. Last, arguing from a practical measurement standpoint, the longer the measurement period, the shorter the sample period for which I have enough information to calculate $Failure\ tolerance$.

I opt for a rolling window length z of 5 years (20 quarters). That is, at every quarter for each institution, I look back 20 quarters to observe the investment behavior of fired CEOs during this period. For an unbiased measure of $Failure\ tolerance$, I exclude any institution that is younger than 5 years old, measured from the first time the institution appears in the data. As a robustness check, I also calculate $Failure\ tolerance\ (10y)$ over 10 years in the same way (i.e., excluding institutions younger than 10 years from the sample). The correlation between the two measures on an institutional level is 0.78 and is highly significant. Robustness tests in section 2.5 also show that my results are not influenced by the choice of measure.

Table 2.1 reports descriptive statistics of $Failure\ tolerance\ (NA)$ by institutional investors. The average $Failure\ tolerance\ (NA)$ is 1.10 quarters, meaning that out of five years or 20 quarters, institutional investors, on average, invest 100% of their portfolio for 1.10 quarters in CEOs that are forced out within the rolling window. The minimum $Failure\ tolerance\ (NA)$ is 0.00, meaning that in the past 5 years, the institution did not invest in any CEO that would be forced out within the rolling window. The maximum $Failure\ tolerance\ (NA)$ in my sample is 17.59 quarters.

[Insert Table 2.1 about here]

Figure A.1 in the Appendix shows the fraction of institution-firm-quarters per year with forced turnovers and the average number of quarters out of 5 years institutions invested in a forced-out CEO. Table A.1 shows the mean and median development of $Failure\ tolerance\ (NA)$ over time.

In the next step, I split all observations into two groups with below and above median $Failure\ tolerance\ (NA)$. Table 2.2 Panel A shows summary statistics of the institutions' characteristics in each group. Institutions with a high *Failure tolerance* (NA) tend to be slightly, but significantly, older, have more firms in their portfolio, and a lower portfolio concentration measured by a normalized Herfindahl index. They also tend to have much larger portfolios in market values ($6.1 bn vs. $4.7 bn). In line with the lower portfolio concentration, they are also less likely to be a blockholder in their portfolio firms. Following the current literature, I define a blockholder as any institutional investor holding at least 5% of shares outstanding. Institutions with high *Failure tolerance* (NA) are more likely to be classified as quasi-indexers in the classification scheme by Bushee (1998) and less likely to be a dedicated or transient investors. However, the two subsamples do not coincide with Bushee (1998)'s classification: All three of Bushee (1998)'s categories can be found in both the high and low samples with an overall similar distribution in both samples. Institutions with a high *Failure tolerance* (NA) are also more likely to be banks, investment companies, or pension funds and less likely to be insurance companies, independent advisors, or university or foundation endowments. But again, differences in the distribution of these investor types in the two samples are small. *Failure tolerance* (NA), therefore, seems to be a new characteristic, so far not measured in the literature of public companies.

[Insert Table 2.2 about here]

Panel B shows the mean values of the average firm in the portfolios of institutions with a high *Failure tolerance* (NA) and of institutions with a low *Failure tolerance* (NA). The mean firm in the portfolio of institutions with high and low *Failure tolerance* (NA) differs statistically on all dimensions except for the percentage owned by blockholders, but economic differences are very small: Portfolio firms in institutions with high *Failure tolerance* (NA) statistically have lower institutional ownership (with 71.2% vs. 71.3%). Institutions with high *Failure tolerance* (NA) on average hold 0.3% of the shares outstanding of their portfolio firms, amounting to a stake of $ 17.1 million. This is less than what low-failure tolerant institutions hold in their portfolio firms (0.4%, $19.9 million). Compared to the preceding literature, investors in both groups hold a slightly smaller fraction of their portfolio firms but have a larger absolute investment size. This is due to the sample being restricted to observations with investments in S&P1500 firms. Institutions with high *Failure tolerance* (NA) also hold tentatively older (22.6 vs. 22.3 years), less volatile (0.09 vs. 0.10) firms with a higher share turnover. Whereas the current-quarter momentum is slightly larger, momentum over the past 2 quarters is slightly smaller. All values are comparable to sample statistics in the previous literature (Bushee, 2001; Baik, Kang, and Kim, 2010; Christoffersen, Danesh, and Musto, 2018).

Failure tolerance aggregated on firm level

Next, I aggregate the $Failure tolerance\,(NA)_{i,q}$ of all institutional investors in a firm to derive $Failure\ tolerance$ on a firm level, such that CEOs in firms owned by institutions that will endure more negative performance signals face a higher $Failure\ tolerance$. Specifically, a firm j's $Failure\ tolerance$ in calendar quarter q is:

$$Failure\,tolerance_{j,q} = \sum_{i=1}^{i=I} w_{i,q} * Failure\,tolerance\ (NA)_{i,q}, \tag{2.5}$$

where $Failure\ tolerance_{i,q}$ denotes the failure tolerance of institution i in calendar quarter q. I denote the weight of institution i in firm j as $w_{i,q}$, measured as the number of shares invested in the firm in relation to the total number of shares held by all institutional investors in the firm. I use a weight relative only to the institutional investors and not relative to all shares outstanding. The latter would assume a $Failure\ tolerance$ of zero for all non-institutional investors, whereas, in fact, I do not have information about their $Failure\ tolerance$. Also, I assume that the marginal investor that sets prices as well as makes the decisive vote in a proxy fight will be an institution. Since Aghion, van Reenen, and Zingales (2013) shows that ownership constitution influences innovation, I later control for the overall level of institutional ownership. Firms on average face a $Failure\ tolerance$ of 1.1, meaning that the average institutional investor in a firm invests its whole portfolio for 1.1 quarters in failing firm-CEO matches.

Validating Failure tolerance: Evidence from forced CEO turnover

In this section, I validate my proxy for failure tolerance by relating it to the likelihood of CEO turnover. A firm's $Failure\ tolerance$ describes how long its institutional investors in the past were invested in firms with CEOs who were fired. I test whether firms with investors with a higher $Failure\ tolerance$ are also more failure tolerant towards their current CEO. Previous literature on firm performance and CEO turnover finds a robust but smaller-than-expected inverse relationship between stock returns and accounting variables such as ROA. The relationship increases with stronger corporate governance, attributing the weak relation to CEO entrenchment (Taylor, 2010; Hermalin and Weisbach, 1998).[13] I, therefore, hypothesize that the CEO of a firm will be less likely to be fired after bad performance if the firm's institutional investors have a higher *Failure tolerance*.

I test this hypothesis by running the following firm-year-level regression:

$$\begin{aligned} Forced_{j,t+1} = \beta_0 + \beta_1 \text{IO} + \beta_2 \text{Idiosyncratic return}_{jt} + \beta_3 \text{IO} * \text{Idiosyncratic return}_{jt} \\ + \beta_4 \text{Failure tolerance}_{jt} + \beta_5 \text{Failure tolerance} * \text{Idiosyncratic return}_{jt} \\ + \beta_6 \text{CONTROLS}_{jt} + \text{Industry}_{j,t} + \text{Year}_t + \epsilon_{jt}, \quad (2.6) \end{aligned}$$

where *Forced* is a dummy variable that is equal to one if a forced turnover occurred within this fiscal year and equal to zero otherwise. My measure of failure tolerance varies quarterly because I have monthly information on institutional holdings. Similar to Jenter and Kanaan (2015), I average this quarterly measure of *Failure tolerance* over one year preceding the quarter of the turnover or the fiscal year end if there was no turnover. I also follow Jenter and Kanaan (2015) and use idiosyncratic stock return, derived as the residuals from a regression of 12-month cumulative holding period return on 12-month cumulative value-weighted industry holding period returns as my measure of firm performance. To ease interpretability, I center all interaction variables. To exclude that *Failure tolerance* picks up the effect of institutional ownership (*IO*), I control for *IO* as well as its interaction with idiosyncratic return in columns 3 and 4. I follow the standard literature (e.g., Aghion, van Reenen, and Zingales (2013)) and define *IO* as the percentage of shares outstanding owned by institutional investors. In addition, I again follow Jenter and Kanaan (2015) and also control for industry stock return, CEO stock ownership, and CEO age. To control for industry and time trends, I further include year and industry fixed effects in all regressions.

Based on the previous literature, I expect β_2 will be negative, i.e., there is an inverse relationship between firm performance measured by *Idiosyncratic return* and the likelihood of forced turnover. Based on my theoretical framework, I further hypothesize that this relationship will be weakened by the presence of failure-tolerant investors and therefore that β_5 will be positive: Holding institutional ownership constant, forced turnover is less likely after bad performance if institutions have a higher failure tolerance.

[13]See Weisbach (1988), Warner, Watts, and Wruck (1988), Denis and Denis (1995), Yermack (1996), Denis, Denis, and Sarin (1997), Huson, Parrino, and Starks (2001), Goyal and Park (2002), Adams and Funk (2009), Kaplan and Minton (2012), and Jenter and Kanaan (2015).

[Insert Table 2.3 about here]

Table 2.3 shows the results of these probit regressions.[14] As a benchmark, I first regress *Forced* only on *IO* and controls in column 1 and exclude *Failure tolerance*. In line with the findings by Del Guercio, Seery, and Woidtke (2008), *IO* is significantly negatively related to the likelihood of forced turnover. In column 2, I additionally add *Failure tolerance*. In contrast to *IO*, there is no significant effect of *Failure tolerance* on the likelihood of forced turnover, whereas the relationship with *IO* remains significant. According to this result, having more failure-tolerant institutional investors—in contrast to a higher share of institutional investors in general—is not directly related to the likelihood of forced turnover. In other words, replacing a less failure-tolerant institution with a more failure-tolerant institution, while keeping the overall share of institutional investors constant, does not alter the likelihood that the CEO will be ousted.

In columns 3 and 4 of Table 2.3, I examine the performance-sensitivity of forced turnovers to institutional investors and *Failure tolerance*. Again, I first run a regression without *Failure tolerance* as a benchmark: In column 3, I regress *Forced* on *IO* as well as on its interaction with *Idiosyncratic return*. I find that at a mean level of *Idiosyncratic return*, *IO* is still negatively related to forced turnover. In addition, the interaction is negatively significant, such that for firms with greater *IO*, the relation between *Idiosyncratic return* and forced turnover is stronger. This result is in line with the findings of Kaplan and Minton (2012).

In column 4, I add *Failure tolerance* as well as its interaction with *Idiosyncraticreturn* as explanatory variables. The interaction of *IO* and *Idiosyncratic return* is still negatively significant, whereas the interaction with *Failure tolerance* is positively significant. This result suggests that coherent with my theoretical framework, firms with more failure-tolerant investors are less likely to fire their CEO after bad performance. This provides evidence that *Failure tolerance* is a valid proxy for an investor base which allows the CEO more room for trial and error.

2.4.2 Dependent variables: Innovation proxies

For my main dependent variables, I use firm-level patent data for U.S. firms from Kogan, Papanikolaou, Seru, and Stoffman (2017) provided on Dimitris Papanikolaou's website to

[14]Because my main prediction is about an interaction effect, I cannot report marginal effects for this non-linear model. This section's main purpose is to test whether there is a significant relation between performance sensitivity and less about the economic size of this relation.

proxy for the innovative output of firms.[15] The authors downloaded the complete history of U.S. patent documents between 1926 and 2019 from Google Patents and matched them with corporations in the CRSP database. They then extracted the number of citations from this data and complemented it with the hand-collected reference data from Nicholas (2008).

From this data, I construct three variables to measure innovation. The first, *Patents*, simply describes the number of eventually successful patent applications per year. This measure, however, does not capture the quality and impact of firms' innovations. I, therefore, use two further measures: *Citations* weights patent counts by future citations per patent and is widely used in the literature. Citations can be received over indefinite periods of time in the future, but I can only observe the citations made during my sample period. Therefore, *Citations* scales the citations received by each patent with the average number of forward citations received by the patents that were granted in the same year (see equation (9) in Kogan, Papanikolaou, Seru, and Stoffman (2017) and Hall, Jaffe, and Trajtenberg (2005)).

To differentiate between scientifically important and economically important innovations to the firm, I also use a new measure developed by Kogan, Papanikolaou, Seru, and Stoffman (2017), which I will call *Market value*. *Market value* captures a patent's impact on firm profits by weighting each patent by the firm's stock market reaction upon the patent being granted. Effectively, the authors perform an event study with a 3-day window consisting of the day of the announcement and the two following days using market-adjusted returns. The estimated return due to the value of the patent is subsequently multiplied by the market value of the firm before the announcement. Since the market knows the probability that a patent will be granted in advance, the value estimated from the event study underestimates the total value of the patent. The authors, therefore, adjust the value for the probability that patent applications are granted by multiplying it by 2.27. To obtain a yearly measure, I then sum up the values for all patents per fiscal year.

To decrease the risk that my results are driven by a few outliers, I follow He and Tian (2013) and winsorize all three measures at the 99th percentile.[16] Table 2.4 shows summary statistics of the innovation variables.

[15] Noah Stoffmann, https://iu.app.box.com/v/patents, 2014. Downloaded in September 2020.

[16] For count data where the dependent variable takes on a non-trivial number of zeros, Wooldridge (2010) advises against applying a natural log transformation to this type of data and rather choose an appropriate count data model.

2.4.3 Other explanatory variables

I follow extended literature on the patent production function and control for the firm's past history of R&D spending (here the natural logarithm of *R&D stock*), as well as the natural logarithms of firm sales, *Sales* (Compustat: sale) and the capital-labor ratio (Compustat: ppe / number of employees), K/L (Hall and Ziedonis, 2001; Aghion, van Reenen, and Zingales, 2013). *R&D stock* is calculated using the perpetual inventory method as in Hall, Jaffe, and Trajtenberg (2005).[17] I further control for a number of firm characteristics taken from the financial reporting data by Compustat. I control for firm size with total assets (item: at), firm age with the years since the firm first appears in CRSP, ROA (Operating income before depreciation (item: oibdp)/ Total assets (item: at)), and $Tobin'sQ$. $Tobin'sQ$ is the ratio of the market value to the book value of assets. I provide a complete and more detailed list of variable definitions in Appendix section A.1.

2.4.4 Sample

Because I can detect CEO turnover for all firms in Execucomp starting in 1994 and I need 5 years of history to calculate $Failure\ tolerance$, the sample for my main analysis is restricted from the bottom to start in 1999. The availability of the patent data restricts my sample from the top so that it ends in 2019. The sample contains 26,706 observations of 2,706 individual firms over the period 1999-2019.

2.4.5 Econometric modelling

The conditional expectation of a count-based measure of innovation, such as $Patents$, $Citations$, or $Market\ value$, in firm j in year t can be expressed as:

$$\begin{aligned} &E[Y_{j,t+1}|\text{Failure tolerance}_{j,t}, \text{CONTROLS}_{j,t}, \text{Firm}_j, \text{Year}_t] = \\ &\qquad exp(\beta_0 + \beta_1 \text{Failure tolerance}_{j,t} + \beta_3 \text{CONTROLS}_{j,t} + \text{Firm}_j + \text{Year}_t), \end{aligned} \tag{2.7}$$

where Y is one of the three innovation variables: $Patents$, $Citations$, and $Marketvalue$, $Firm_j$ is a firm fixed effect, and $Year_t$ are time dummies. The year dummies capture

[17] As in Hall, Jaffe, and Trajtenberg (2005), I calculate *R&D stock* as $G_{it} = R_{it} + (1-\delta)G_{it-1}$, where R is the R&D spending in year t and a depreciation rate, δ, of 0.15. I use linear interpolation to fill in missing values of R&D spending.

aggregate trends in patents and citations and control for a possible truncation bias in patent counts. I also include a set of industry dummies to capture industry trends, such as greater possibilities for innovation in some industries. Including *R&D stock* controls for the amount of resources, which a firm has invested into innovation. The coefficient, β_1, therefore, captures the relation between a higher *Failure tolerance* and innovation, keeping the level of *R&D* investment up to this point constant. Because the paper seeks to differentiate the effects of different institutional investors, I also control for IO, the share of institutional ownership.

Following the standards in the innovation literature, I estimate dynamic count data models (Hausman, Hall, and Griliches, 1984; Blundell, Griffith, and Van Reenen, 1999; Aghion, van Reenen, and Zingales, 2013). Poisson regression models account for the count-based nature of the innovation data and the nontrivial amount of zeros in the innovation variables (Wooldridge, 2010). The Poisson regression model is fully robust and efficient. Linear models sometimes combined with logarithmic transformations have well-known properties and often provide good approximations. In the case of count data with a large proportion of zeros in the dependent variable, (Wooldridge, 2010) nevertheless advocates to model $E(y|\mathbf{x})$ directly using an exponential function. In section 2.5.3, I show my results also hold when using the Negative Binomial regression model as another count data regression model.

To account for unobservable, time-invariant heterogeneity between firms, I follow the standard in the literature (Aghion, Blundell, Griffith, Howitt, and Prantl, 2009; Aghion, van Reenen, and Zingales, 2013; Bloom, Schankerman, and Van Reenen, 2013) and include firm fixed effects, Firm_j, using the "presample mean scaling" method introduced by Blundell, Griffith, and Van Reenen (1999). This method exploits the long history of pre-sample information on patenting behavior starting in 1926 to calculate what the authors call the "initial innovation stock".[18] The model relaxes the strict exogeneity assumption of the approach by Hausman, Hall, and Griliches (1984), who first introduced a fixed effects Poisson model. Using Monte Carlo simulations, Blundell, Griffith, and Van Reenen (1999) demonstrate that this method performs well compared to alternative estimators for dynamic panel models with weakly endogenous variables.

[18] I follow Blundell, Griffith, and Van Reenen (1999) and calculate the initial innovation stock as $G_{it} = I_{it} + (1-\delta)G_{it-1}$, with a knowledge depreciation rate, δ, of 30 percent.

2.5 Main results: Failure tolerance and innovation output

2.5.1 Descriptive statistics

Table 2.4 describes firm-level summary statistics of all firm-level variables used throughout my analyses. A forced turnover occurs in 2.6% of firm years. A firm has on average 4.8 granted patents per year and 2.6 patents weighted with citations. In total, these patents have an average market value of 94.1 million dollars per year. Firms on average face a $Failure\,Tolerance$ of 1.1, meaning that the firms' institutional investors invest their whole portfolio for 1.1 quarters in a failing CEO. The average firm in my sample is 17 years old and has 12.7 billion dollars in assets. These numbers are comparable to other studies using an ExecuComp sample, but by construction much larger than in Tian and Wang (2014), who study failure tolerance in IPO firms. On average 64.5% of shares belong to institutional investors.

2.5.2 Baseline results

In this section, I test whether $Failure\ tolerance$ is related to more innovative output.

Table 2.5 shows the Poisson regression results. Columns 1 and 2 (3 and 4, 5 and 6) have $Patents$ ($Citations$, $Market\,value$) as the dependent variable. In all columns, I control for a comprehensive set of firm characteristics, including IO. I also include a full set of year and industry dummies in all regressions to control for time trends and differences across industries. In columns 2, 4, and 6, I additionally control for firm-level heterogeneity by including firm fixed effects following the method of Blundell, Griffith, and Van Reenen (1999).

[Insert Table 2.5 about here]

For all measures of innovation, I find strong evidence in favor of my hypothesis: In all specifications, keeping past R&D investments constant, higher $Failure\ tolerance$ is associated with higher innovative output measured as $Patents$, $Citations$, and $Market value$. This means that firms with more failure-tolerant investors have a higher R&D productivity—they produce more innovation with the same amount of investment. I also control for the level of IO. I confirm the results of Aghion, van Reenen, and Zingales (2013) and find that higher IO increases innovation. I additionally find that for the same level of

IO, firms with more failure-tolerant investors tend to produce more patents, and these patents are scientifically and economically more relevant.

Including firm fixed effects only slightly decreases the size of the coefficient on *Failure tolerance*, which remains significant for all three dependent variables. By including firm fixed effects, I exclude alternative explanations for my result by which the ex-post more innovative firms already differed from the less innovative firms ex-ante in any time-invariant characteristics. For example, this would exclude alternative explanations hinging on differences such as the headquarters of the firm, state of incorporation, or general ability to innovate.

The results are also economically significant. They indicate that for the same level of R&D investment, a difference in ownership that increases the average *Failure tolerance* by one standard deviation corresponds to 6.3 percent (.333*.190) more patents. More concretely, this amounts to approximately half a patent per year. Second, firms with one standard deviation higher *Failure tolerance* on average have an 11.0 percent (.333*.330) higher number of citation-weighted patents. With an average of 1.77 citation-weighted patents per year, this is approximately one-third of a weighted patent per year. Third, firms with higher *Failure tolerance* (while keeping *IO* constant) on average have 10.0 percent (.333*0.320) higher expected dollar value of patents per year.

While these results illustrate the level of variation between firms, it does not imply that changes in *Failure tolerance* would result in the above changes in innovative output. According to the model by Manso (2011) and as explained in 2.3, different levels of tolerance for failure are optimal to motivate innovation depending on the costs and gains for innovation and for shirking. I assume firms in equilibrium have the optimal level of *Failure tolerance*, such that deviations from this equilibrium would not result in a gain.

The coefficient on *IO* is positive and significant in all specifications. The coefficient found in columns 3 and 4 further closely match the coefficient reported by Aghion, van Reenen, and Zingales (2013), who also use *Citations* as a dependent variable, in size and significance ($\beta_{Aghion} = .007, p = 0.002$). I, therefore, conclude that my results are likely not derived from anomalies in my sample.

Regarding the control variables, firms with a larger *Ln*(*R&D stock*) have more innovative output both in quantity and quality. This variable controls not only for the R&D investment in the current period but also for the complete history of R&D investments in the past. Further, firms with higher *Sales* tend to have lower innovative output in the following year, measured in *Patents* and *Citations*. As expected, *Assets*, *ROA*, and $Tobin's\,Q$ are also positively associated with a higher innovative output. However, contrary to the findings in He and Tian (2013), I find a negative relation with $Firm\,age$. Consistent with my hypothesis, the coefficient on $Failure\ tolerance$ is always positive and significant, even when controlling for these variables.

These baseline results show a positive relation between investors' tolerance for failure and the innovative output of their portfolio firms. The findings thereby lend support to Manso (2011)'s theory that tolerance of failure motivates innovation. Of course, as explained in my theoretical framework, the observed distribution of $Failure\ tolerance$ are equilibrium outcomes such that an increase in $Failure\ tolerance$ in a specific firm will not necessarily result in higher innovative output if the previous level was already optimal.

2.5.3 Robustness

Alternative Failure tolerance measure

In section 2.4.1, I argue from an empirical and a practical perspective for measuring $Failure\ tolerance$ based on the institutional investor's behavior over the previous five years. I argue that this period strikes the appropriate balance between capturing the full information and being an appropriate proxy for the present, while at the same time allowing a long enough time series for model estimations. That being said, two points speak for a longer estimation period. First, the average tenure of CEOs in my sample is just under 5 years. By restricting the measurement period to 5 years, I am not capturing the variation in failure tolerance stemming from investors investing in firm-CEO matches with above 5-year tenure for more than 5 years. Second, while I argued that the measurement period should not be too long because failure tolerance is a characteristic of the investment managers working at institutional investors and therefore may change when they leave, this change may happen more slowly if new managers are hired according to a culture including failure tolerance.

Therefore, I rerun my main specification with an alternative $Failure\ tolerance$ (10) measure using the 10-year estimation period. Table 2.6 describes the results. For the sake of brevity, I only show the coefficient and t-stats of $Failure\ tolerance$ and omit the coefficients of the control variables. The relation between $Failure\ tolerance$ and innovation is robust to this alternative measurement: All coefficients are very similar in size to those in section 2.5 as well as highly significant. For example, a change in ownership that increases *Failure tolerance* (10) by one standard deviation is associated with an increase in *Patents* of 7.5% (.635*.225).

Alternative subsamples

To exclude that my results are driven by the large number of firms who do not have any approved patents, I replicate my main analysis using a subsample of firms that have at least one patent in my sample period. Table 2.7 describes the results. The sample is reduced by over 40% to 14,875 observations. Still, my main results barely change in size or significance across all three innovation measures as well as with and without firm fixed effects. Similar to my main results, a change in ownership that increases *Failure tolerance* by one standard deviation is associated with an increase in *Patents* by 5.7% (.333*.170), in *Citations* by 10.6% (.333*.317), and in *Marketvalue* by 9.3% (.333*.280).

Alternative estimation model

To show that my results are not an artifact of the Poisson regression model, I repeat my main analysis using a Negative Binomial regression model. The Negative Binomial model relaxes the assumption of the Poisson model that the conditional mean of the dependent variable equals its conditional variance. Table 2.8 displays the results of this analysis. In all models, the coefficient on *Failure tolerance* is similar to the Poisson results; only the statistical significance drops slightly to a 5-10 percent level for some specifications. My results, therefore, do not depend on the specific assumptions of the Poisson model.

2.5.4 Testing further model predictions

My baseline specification in the subsection 2.5.2 shows a positive relation between *Failure tolerance* and innovation, which is in line with the model predictions of Manso (2011) that tolerating failure leads to more innovation. In this subsection, I test whether my data also supports additional predictions of the model.

Is Failure tolerance more important when the CEO is likely to exploit known actions?

As described in section 2.3, threatening termination can be optimal if the principal wants the agent to exploit conventional actions. Excessive termination, i.e., being intolerant to failure, will keep the agent from shirking. By contrast, if the principal wants the agent to innovate, i.e., explore, the threat of termination may have different effects depending on circumstances. On the one hand, the threat prevents the agent from shirking, but on the other hand, it may also encourage the manager to play it safe and focus on exploiting already known actions. Whether it is optimal to implement excessive continuation, i.e., failure tolerance, depends on which of the two effects is more important.

In this section, I use cross-sectional variation in product market competition as variation in the importance of these two effects. Based on the work by Hart (1983) and Schmidt (1997), I assume that with higher product market competition, managers have less slack. Therefore, the shirking constraint in Manso (2011)'s model becomes binding. In this case, the model predicts excessive continuation as the optimal contract to foster innovation.

I follow Giroud and Mueller (2010) and measure the yearly competitiveness of an industry using the Herfindahl-Hirschman index (HHI), defined as the sum of squared market shares (Tirole and Jean, 1988):

$$HHI_{kt} = \sum_{i=1}^{N_k} s_{ikt}^2,$$

where s_{ikt} is the market share of firm i in industry k year t. I calculate market shares using Compustat data on firm sales (item: sale). Industries are defined based on 3-digit SIC codes.[19] I also follow Giroud and Mueller (2010) and drop observations with $HHI >= 0.99$.[20] Higher HHI implies a more concentrated and, hence, less competitive industry.

I then partition my sample into two subsamples with higher and lower than median HHI and estimate the same models as in Table 2.5 for each subsample. Table 2.9 displays the results. Again, for the sake of brevity, I only show the coefficient and t-stats of $Failure\ tolerance$ and IO. In line with the predictions from the theory, the coefficients in columns 1 and 3 in the competitive industry sample are more than twice the size of the coefficients in columns 2 and 4 in non-competitive industries. At the same time, they are highly significant, while the coefficients in non-competitive industries are only

[19] Giroud and Mueller (2010) consider the 3-digit industry classification as an appropriate compromise between the too coarse classifications of 2-digit industry codes and the too-narrow classification of 4-digit industry codes. I refer to their paper for further discussions and robustness checks of this choice.

[20] Giroud and Mueller (2010) observe a "spike" at the right endpoint of their HHI distribution and take a closer look at these observations. They find that these monopolies are caused by very narrow industry definitions, causing the industry to be made up of a single firm even though this firm could easily also be classified within another industry. After dropping observations as described above, the distribution of HHI in my sample does not show a "spike" at the right endpoint.

marginally or not at all statistically significant. The difference in coefficients between the two samples is statistically significant at the one percent level. The coefficient in column 5, with *Market value* as the dependent variable is also almost double the size of the coefficient in column 6. However, the statistical significance is almost equal.

Overall, these results show that the relation between *Failure tolerance* and innovative output in the form of patents or citation-weighted patents is concentrated in competitive industries. This finding supports the empirical validity of *Failure tolerance* and provides supporting evidence for the theory that tolerance of failure motivates innovation, especially when outside governance mechanisms already prevent managers from shirking.

Is Failure tolerance more important when innovation is desired?

Manso (2011)'s model describes how to solve the incentive problem when the principal wants to motivate the agent to innovate. If the principal does not want the agent to innovate, i.e., because innovation is not as profitable in a particular industry or because innovation is so costly that it is too expensive to motivate the agent to do it, the three-armed bandit problem in his model is reduced to a two-armed bandit, which is equal to a standard principle-agent problem. In these settings, it is more important to keep the agent from shirking, and setting incentives to motivate innovation is less profitable. I explore whether this pattern can also be found within my data using the *Failure tolerance* measure. I assume that some industries hold more potential for innovation than others and that *Failure tolerance* will be more effective in this setting. To test this, I follow Hirshleifer, Low, and Teoh (2012) and define an industry as innovative if average industry *Citations* in year t are above the average *Citations* over all industries in the year $t+1$.

I expect that *Failure tolerance* will have a larger effect in industries with good opportunities for innovation. I test this hypothesis by splitting the sample into more and less innovative industries. I then separately test the effect of *Failure tolerance* on innovation in each. Following Hirshleifer, Low, and Teoh (2012), I define an industry as innovative if the mean level of *Citations* in the industry is above the median level of *Citations* over all industries using 2-digit SIC industry classifications.

Table 2.10 shows the coefficients from Poisson regressions of the three innovation measures on *Failure tolerance* in innovative and non-innovative industries, using the same specification as in columns 1, 3, and 5 of Table 2.5. *Failure tolerance* is only associated with more innovation in innovative industries. The size and significance of all three coefficients in the innovative industries are similar to the results in Table 2.5, despite the smaller sample size. A one standard deviation increase in *Failure tolerance* is associated with a 6.0, 10.3, and 10.1 percent increase in *Patents*, *Citations*, and *Market value*, respectively. By contrast, the coefficients on *Failure tolerance* are statistically insignificant or only marginally significant in the non-innovative industries. This suggests that failure-tolerant investors only lead to more innovation if there are opportunities to innovate. Since I include industry and year fixed effects, this result is not due to higher innovation in this industry or in this year in general.

[Insert Table 2.10 about here]

These results show that the importance of *Failure tolerance* depends on the industry. In addition to testing whether the industry is important, these results also provide more evidence for the empirical validity of the *Failure tolerance* measure as well as for the validity of the theory that failure tolerance motivates innovation.

2.6 Identification

Based on the model by Tian and Wang (2014) and as mentioned in section 2.3, the investment duration of investors depends not only on their termination threshold but also on the precision of their private signals relative to the noise and on the ex-ante known quality of the firm-CEO match, θ. Therefore, the positive correlation between *Failure tolerance* and innovation may also be driven by selection. A causal interpretation of my results in section 2.5 rests on the assumption that the effect of *Failure tolerance* on firms' innovative outcomes is not driven by other ex-ante firm or investor characteristics that may drive both the investment duration in failing CEOs as well as the innovative output of firms.

In this section, I test this assumption. First, in section 2.6.1, I seek to understand the identification problem on the basis of my theoretical framework in section 2.3. I then respond to the identification problem in two ways: First, in section 2.6.2, I use exogenous variation in the risk of a firm-CEO failure to differentiate between the failure tolerance and the ex-ante quality hypotheses. I find that the marginal effect of *Failure tolerance* is larger when the CEO joined the firm during a recession, which does not support the hypothesis that the higher innovative output is caused by the endogenous matching of investors with higher *Failure tolerance* and firm-CEO matches with higher ex-ante potential. Second, I control for various time-varying and time-invariant investment selection preferences and abilities that could affect ex-ante CEO-firm characteristics. I find that these characteristics cannot fully explain my baseline results.

Controlling for investor fixed effects does also not absorb the impact of *Failure tolerance* on *Citations*. However, they do absorb the *Failure tolerance* effect on *Patents* and *Market value*. This may be due to *Failure tolerance* only being important to the quality and not necessarily the quantity or economic value of innovation.

2.6.1 Omitted variable problems

Recall equation 2.2, describing the determinants of an institutional investor's investment duration in a firm-CEO match, derived from the partial model by Tian and Wang (2014). According to this equation, an investor's investment duration in eventually failed CEOs depends on three other factors besides the termination threshold, ϕ^i: the average quality of the firm-CEO match, θ, the precision of the signal, and the average signal over time, $\overline{\delta}$. If any of these factors are also related to the termination threshold, they pose an omitted variable problem.

The first factor is the quality of the firm-CEO match. In section 2.3, I assume that the quality of the firm-CEO match is unknown to the institutional investor and that all institutions initially assume an average quality of the match, θ. However, if I relax this assumption and firm-CEO matches are not assigned to institutions randomly, then institutions might differ systematically in their selection procedure. In this case, as Tian and Wang (2014) point out, the quality of the firm-CEO match an investor invests in becomes $\alpha = \theta^j + u$, where θ^j is the average quality of firm-CEO matches of investor j. Due to this endogenous matching, an omitted variable problem arises. On the one hand, a higher average ex-ante firm-CEO match quality is likely related to better innovation outcomes ex-post. On the other hand, investors will hold on to higher-quality investments longer even in the face of negative performance signals. This is the mechanism Aghion, van Reenen, and Zingales (2013) describe in their model through which institutional investors insulate managers from negative consequences due to bad performance signals because they know about the manager's ability. If we assume that firm-CEO matches with higher ex-ante quality are also more likely to transform opportunities for innovation into ex-post innovation, this alternative explanation is in line with my main findings in section 2.5.2 as well as with the findings in 2.5.4, where I find the effect of *Failure tolerance* is concentrated in industries with high innovation potential.

The second factor is the signal-to-noise ratio h_u/h_ϵ. The investment duration depends on the precision of the signal on CEO quality. The more noisy, i.e., less precise, the longer will be the investment duration because learning about the CEO quality takes more time. The precision may depend on the characteristics of the investor as well as on the characteristics of the selected investments. For example, some investors may spend more effort or have better abilities to receive a more precise signal, leading to shorter investment durations. If more precise information also allows investors to make better investment decisions (Edmans, 2009), then this would work against my finding and the relation I find would be an underestimation of the true relation.

On the other hand, as Tian and Wang (2014) also point out, the precision of signals may also vary considerably by industry, depending on the uncertainty in an industry. This may result in differences in the average signal-to-noise ratios of firm-CEO matches across investors so that investors concentrated in more uncertain industries will invest longer in failed projects. If one believes that more innovative companies also have more uncertainty, then the signal-to-noise ratio is also an omitted variable (Holmstrom, 1989). I, therefore, include industry fixed effects in all regressions to control for the time-invarying portion of industry uncertainty.

Last, the average signal $\overline{\delta}$ about the quality of a specific firm-CEO match u, also influences the investment duration in failed investments. However, the model assumes that the errors of the signals are independent over time with a mean of zero. With this assumption, the idiosyncracies of the performance signals of an investor's past investments are not correlated with future investments. Also, while the investor's estimated quality of firm-CEO matches is correlated through θ^j, the specific qualities of firm-CEO matches are assumed to be independent of each other, i.e., the quality of a past firm-CEO match does not predict the special quality of the next firm-CEO match. The average signal about the specific quality component is therefore not an omitted variable in my regression.

2.6.2 Failure tolerance in high failure risk environments

In this section, I make use of variations in CEOs' ex-ante failure risk. As outlined in the previous subsection, an alternative explanation for the relation between *Failure tolerance* and innovative outcomes of firms is that differences in the quality of firm-CEO matches between investors create differences in my measure of *Failure tolerance* as well as in the likelihood of successful innovation. In other words, investors with high *Failure tolerance* have longer investment durations because they invest in CEO-firm matches with higher ex-ante quality. According to this alternative explanation, the marginal effect of *Failure tolerance* on innovation reflects the effect a higher ex-ante potential has on ex-post innovative outcomes.

I use recessions as an external variation to a firm-CEO match's failure risk. During a recession, uncertainty is high, access to resources is restricted, and demand is low, leading to a higher risk of failure, exemplified in more bankruptcies and high CEO turnover. Since CEOs are particularly vulnerable to turnover at the beginning of their tenure, starting a position during a recession puts them at a higher risk of forced turnover.

If the assumption holds that *Failure tolerance* captures an investor's attitude towards failure and this attitude towards *Failure tolerance* motivates innovation, then this characteristic should be especially important in environments where the risk of failure is high. In other words, the marginal effect of *Failure tolerance* should be higher if a CEO starts her tenure at a firm during a recession and lower otherwise.

By contrast, the likelihood to convert a higher ex-ante potential into innovative outcomes should be lower during times of high risk. Thus, under the alternative explanation of *Failure tolerance* capturing higher ex-ante potential to produce innovation, the marginal effect of *Failure tolerance* should be lower when starting during a recession.

To test these alternative assumptions, I use NBER-based Recession Indicators to classify a CEO-firm match as starting in a high-risk environment if any month during the first year of a CEO's tenure was classified as a recession period. I then divide the sample into two subsamples according to this classification. About one-fifth of the observations start during a recession. I then estimate the same models as in Table 2.5 separately for each subsample. Table 2.11 displays the results. The coefficient on *Failure tolerance* is larger and more significant for all three innovation outcomes when the CEO-firm match was formed during a recession even though the sample size is much smaller than the sample of non-recession CEOs. The coefficient estimating the relation with *Patents* and *Citations* for non-recession starters becomes insignificant. In both models, the coefficient is more than twice as large for the recession starters than for the non-recession starters. A one standard deviation increase in *Failure tolerance* is associated with a 23.0% (.333*.769) increase in *Citations* if the CEO started in a recession. Interestingly, the same pattern does not hold for *IO*.

This analysis of recession-starters shows that the marginal effect of *Failure tolerance* is larger when the risk of failure is higher. This is in line with the assumption that the coefficient on *Failure tolerance* identifies the effect of a lower termination threshold of investors on the innovative outcome of their firms and contradicts the assumption of the effect of *Failure tolerance* being driven by an ex-ante higher quality potential of firms owned by more failure tolerant investors. The results, therefore, lend support to the empirical validity of my measure and for Manso (2011)'s theory that tolerance for failure motivates innovation.

2.6.3 Investor fixed effects, investment style and skill

In this section, I control directly for differences in time-variant and -invariant investor characteristics that may be correlated with the innovative outcome of portfolio firms as well as with *Failure tolerance* by influencing the ex-ante quality of the firm-CEO match, θ^j, or the signal-to-noise ratio h_u/h_ϵ.

Controlling for institutional investment styles

Institutional investment styles may influence the ex-ante quality of the firm-CEO match, θ^j, and the signal-to-noise ratio h_u/h_ϵ. Bushee (1998) sorts investors into three categories based on a set of characteristics describing their past investment behavior, such as portfolio turnover, diversification, and momentum trading. "Quasi-indexers" are highly diversified and have a low portfolio turnover. "Dedicated" investors have a high portfolio concentration and low portfolio turnover. "Transient" investors trade frequently in and out of individual stocks. For example, Aghion, van Reenen, and Zingales (2013) find that higher levels of institutional ownership are associated with more citation-weighted patents, but that this effect stems from "dedicated" and "transient" investors. Quasi-indexers do not increase innovative output.

I want to exclude that *Failure tolerance* is simply another proxy for firms with these already known investment types. I therefore run the same regressions as before and additionally control for the share of institutional investors which are dedicated investors and quasi-indexers. Table 2.12 displays the results. The coefficient on *Failure tolerance* increases slightly in size and significance for all three dependent variables compared to Table 2.5. Therefore, when keeping the share of investment types constant, the *Failure tolerance* of these investors is still related to the innovative output of firms.

Controlling for time-varying and -invarying investor characteristics

Investment skills and expertise are two observable investor characteristics that could influence the ex-ante firm-CEO characteristics. Both could contain a time-varying and a time-invariable component: Some investors may have general skills or preferences that could influence ex-ante firm-CEO characteristics. At the same time, this skill or preference could vary over time as the investor gains experience. One could also assume that more specialized investors are better at selecting high-potential firm-CEO matches because they can focus their efforts better. I, therefore, control for the investor expertise, specialization, and different investment strategies as time-varying investor characteristics.

As discussed in section 2.3, blockholders or firms with larger stakes may have the incentive to acquire additional information that could mitigate negative signals. I therefore also control for the fraction of outstanding shares held by the largest investor.

To be able to measure these investor characteristics, I focus on the largest institutional investor in the firm in the preceding year, measured by the share of ownership. This allows me to control for the investor's observable characteristics as well as include investor fixed effects. I assume that the institutional investor owning the largest share of stock will on average also have the highest influence on the firm, making its failure tolerance the most influential for firm decisions. Instead of using the weighted average $Failure\ tolerance$ (NA) of all institutional investors in the firm, I use only the $Failure\ tolerance$ (NA) of the largest investor. I call this variable $Failure\ tolerance$ (LI). Same as with my standard measure, I also winsorize the $Failure\ tolerance$ (LI) at the 99th percentile. While the largest investor may have the largest influence, I also exclude information about the other investors, possibly resulting in a noisier proxy.

I proxy for investor expertise with $Investor\ age$, measured as the number of quarters after the institutional investor first appears in Thomson Reuters 13F filings. My measures of institution specialization are $Portfolio\ concentration$, measured as the normalized Herfindahl-Hirschman Index, and $Firmsinportfolio$, measured as the number of different stocks in an investor's portfolio. I further control for investment strategies that may be correlated with $Failure\ tolerance$ using $Portfolio\ volatility$ and $Portfolio\ momentum$. For detailed variable definitions, see Appendix section A.1.

Table 2.13 shows the results of Poisson regressions of the three innovation measures on $Failure\ tolerance$ (LI). Panel A (B, C) shows results for $Patents$ ($Citations$, $Market\ value$) as the dependent variable. In each panel, I first replicate the results of columns 2, 4, and 6 in Table 2.5 (i.e., including firm fixed effects) but using the $Failure\ tolerance$ of the largest investor instead of the average. I also control for the size of the largest investor's stake. The coefficient on $Failure\ tolerance$ (LI), therefore, measures the effect of the largest investor's failure tolerance keeping its size and therefore influence constant. The coefficients on $Failure\ tolerance\ (LI)$ in columns 1 in Panel A, B, and C are smaller in size but still statistically significant in all panels. This suggests that it is not only the $Failure\ tolerance\ (NA)$ of the largest investor that contributes to the increase in innovation but that the overall distribution of $Failure\ tolerance\ (NA)$ over all institutional investors plays a role.

In column 2, I then include the investor control variables. This slightly reduces the size of the coefficient on $Failure\ tolerance\ (LI)$, but it remains statistically significant at the 1% and 5% levels. The measures of experience and specialization are all insignificant, except for a small, marginally significant relation of $Firms\ in\ portfolio$ with $Patents$ and $Citations$. By contrast, both proxies of investment strategies are highly significant. Firms with investors trading in more liquid stocks and with higher portfolio momentum also have a higher innovative output.

Finally, I also control for unobservable time-invarying investor characteristics by including investor fixed effects. For example, if investors have certain investment selection skills or preferences that are time-invariant, the investor fixed effects should partially exclude this explanation. I run the same models as in the previous specification, controlling for various firm and investor characteristics, industry and year dummies, as well as firm fixed effects. As would be expected, this again somewhat reduces the size of the coefficients as well as the statistical significance. The size of the coefficient in all three panels is smaller, making it insignificant for $Patents$ and $Market\ value$. The coefficient on $Failure\ tolerance\ (LI)$ in the model with $Citations$ proxying for innovation remains statistically significant at the 5% level.

It follows that time-invariant components of institutional characteristics such as investment skills cannot explain the effect of failure tolerance on the innovative output of firms.

2.7 Conclusion

I examine how institutional investors' failure tolerance affects firm innovation. To do so, I develop a measure of institutional investors' failure tolerance toward the CEO based on their past investment behavior. I provide evidence for the validity of my measure by showing that it is associated with a decrease in CEO turnover-performance sensitivity, but not with an overall decrease in forced turnover. CEOs in firms with more failure-tolerant investors indeed face a lower risk of termination after bad performance. Based on the theoretical literature, I argue that institutional investors with a higher failure tolerance will lead to more innovation in their portfolio firms. My empirical results show that firms whose institutional investors are more failure-tolerant are more innovative in terms of the quantity, quality, and economic value of their patents. These results are robust to a wide set of firm and investor control variables including the share of institutional investors as well as firm fixed effects. The effect on the quality of innovation remains even after controlling for institutional investor fixed effects.

My findings have implications for corporate governance policy work. Since tighter corporate governance in the form of less tolerance for failure stifles innovation, worrying too much about entrenchment in industries where innovation is important may be misleading. This holds especially in industries with a very competitive product market, which provides a strong external control mechanism.

Moreover, this research also adds to the public debate on the social advantages and disadvantages of rising institutional ownership. Managers have complained that institutions force them to myopic behavior while the public blames institutional investors for undermining the economy and preventing managers from following their vision.[21] My findings give evidence that institutional investors differ in terms of their failure tolerance and more failure-tolerant investors allow managers to be more innovative.

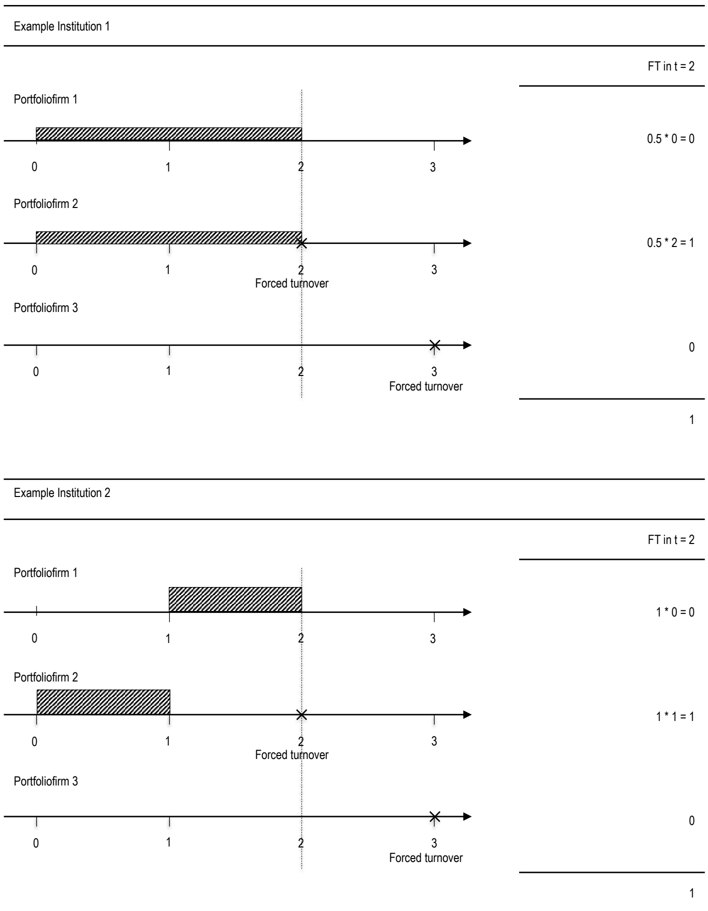
Immediate avenues for future research are inspecting causes and effects for being more or less failure tolerant from the perspective of the institutional investors. For example, what makes institutional investors more or less failure tolerant? Is this an optimal choice for them? Future research could also consider how institutional failure tolerance interacts with other corporate governance measures such as board independence or incentive contracts for CEOs.

[21]E.g., the former CEO of IBM, Sam Paimisano, stated that "you're still pressured to do things that aren't necessarily in the long-term interests of the entity to make your numbers. If you miss by a penny, the market knocks your stock down by 4% to 8%", *Harvard Business Review*, June 14, 2014.

2.8 Figures Chapter 2

Figure 2.1: Example of institutional failure tolerance

This figure illustrates the calculation of *Failure tolerance* (NA) (FT) for two hypothetical institutions each with three firms in their portfolio.



2.9 Tables Chapter 2

Table 2.1: Descriptive statistics of Failure tolerance

This table reports descriptive statistics of the *Failure tolerance NA* of institutional investors. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix A.1.

Variable name	N	Mean	Median	Std. dev.	Min	Max
Failure tolerance (NA)	130,633	1.103	0.964	0.868	0.000	17.590

Table 2.2: Institutional characteristics by Failure tolerance (NA)

This table reports descriptive statistics for my sample of institutional investors split by high and low $Failure\ tolerance$ (NA). Panel A shows mean values of institutional investor characteristics as well as the difference in means between those with high and low $Failure\ tolerance$ and the corresponding t-statistic. Panel B shows mean values for the average characteristics of the firms in an institution's portfolio as well as, again, the difference in means and the corresponding t-statistics. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix A.1.

Panel A: Institutional characteristics by $Failure\ tolerance$

	Low $Failure\ tolerance\ NA$		High $Failure\ tolerance\ NA$			
	N	Mean	N	Mean	Difference	t-stat
Institution's age	63379	13.639	65032	13.785	-0.146	-3.52***
Firms in portfolio	63379	548.610	65032	617.214	-68.604	-16.79***
Portfolio concentration	59312	0.067	63515	0.045	0.022	33.56***
MV portfolio ($ m)	65317	4661.437	65316	6084.020	-1422.583	-7.35***
Is blockholder	65317	0.006	65316	0.005	0.001	8.70***
Dedicated	64794	0.048	65286	0.022	0.027	26.18***
Quasi-indexer	64794	0.655	65286	0.721	-0.066	-25.63***
Transient	64794	0.296	65286	0.257	0.039	15.74***
Bank	65317	0.079	65316	0.094	-0.015	-9.57***
Insurance company	65317	0.034	65316	0.031	0.003	2.71***
Investment company	65317	0.024	65316	0.026	-0.002	-2.71***
Independent advisor	65317	0.777	65316	0.737	0.040	16.96***
Private pension fund	65317	0.015	65316	0.019	-0.004	-5.72***
Public pension fund	65317	0.008	65316	0.013	-0.005	-8.01***
University endowments	65317	0.007	65316	0.005	0.002	4.51***
Miscellaneous	65317	0.056	65316	0.075	-0.019	-13.90***

Table 2.2: Institutional characteristics by Failure tolerance (NA) cont'd

Panel B: Portfolio firm characteristics by *Failure tolerance*

	Low *Failure tolerance NA*		High *Failure tolerance NA*			
	N	Mean	N	Mean	Difference	t-stat
IO	65297	0.713	65316	0.712	0.001	2.56**
% shares owned	63379	0.004	65032	0.003	0.001	14.75***
% owned by blockholders	65317	5.4	65316	5.4	-0.000	-0.38
MV stake ($ m)	63379	19.906	65032	17.113	2.793	5.98***
Firm age	65317	22.288	65316	22.680	-0.392	-15.66***
CEO age	65253	56.159	65301	56.057	0.102	14.79***
Tenure	65249	7.402	65301	7.258	0.144	23.65***
Volatility (q-8, q-1)	65316	0.102	65316	0.094	0.007	42.40***
Share turnover (q-1)	65317	0.206	65316	0.213	-0.008	-19.71***
Momentum (q)	65317	0.032	65316	0.035	-0.003	-4.92***
Momentum (q-3, q-1)	65317	0.110	65316	0.100	0.010	9.07***

Table 2.3: Failure tolerance and forced turnover

This table reports probit regression results. The dependent variable is a binary variable equal to 1 if the CEO was forced out in the fiscal year and 0 otherwise. *t*-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix A.1.

Dep. Var.: *Forced*	(1)	(2)	(3)	(4)
IO	–0.0031***	–0.0025***	–0.0041***	–0.0037***
	(–3.95)	(–2.94)	(–4.48)	(–3.88)
Idiosyncratic return	–0.7116***	–0.6849***	–0.7378***	–0.6966***
	(–9.50)	(–8.01)	(–10.42)	(–8.98)
Failure tolerance		–0.0199		0.0315
		(–0.18)		(0.28)
Idiosyncratic return × IO			–0.0052**	–0.0067***
			(–2.18)	(–2.60)
Idiosyncratic return × Failure tolerance				0.4574**
				(2.22)
Industry return	–0.4679***	–0.5662***	–0.4752***	–0.6038***
	(–5.13)	(–5.50)	(–5.28)	(–5.93)
High CEO ownership	–0.3578***	–0.3243***	–0.3569***	–0.3248***
	(–5.40)	(–4.47)	(–5.46)	(–4.54)
Retirement age	–0.5269***	–0.5003***	–0.5293***	–0.5060***
	(–9.18)	(–8.06)	(–9.25)	(–8.27)
Pseudo R^2	0.086	0.083	0.087	0.086
Observations	35,144	28,108	35,144	28,108
Year FE	Y	Y	Y	Y
Industry FE	Y	N	Y	N
Firm FE	N	Y	N	Y

Table 2.4: Summary statistics for firms

This table reports descriptive statistics by Execucomp firms for the sample period between 1999 and 2017. Variables are defined in detail in Appendix A.1.

Variable name	N	Mean	Median	Std. dev.	Min	Max
Failure tolerance	27,984	1.131	1.099	0.333	0.460	1.901
Forced	44,147	0.025	0.000	0.155	0.000	1.000
Patents	44,147	4.766	0.000	9.388	0.000	29.000
Citations	44,147	2.645	0.000	6.369	0.000	20.397
Market value	44,147	94.142	0.000	203.917	0.000	639.133
IO	39,472	64.548	68.164	22.860	0.000	100.984
R&D stock ($ million)	22,903	789.086	72.244	3,434.205	0.000	61,670.336
K/L	41,943	251.461	40.596	1,786.049	0.000	135,623.188
Sales ($ million)	44,126	4,952.212	1,090.812	16,277.231	0.000	483,521.000
ROA	41,333	0.150	0.140	0.154	-4.117	8.060
Tobin's Q	42,917	2.007	1.461	2.126	0.298	105.090
Idiosyncratic returns	42,787	0.025	-0.038	0.583	-1.713	27.719
Industry Return	42,787	0.155	0.156	0.223	-0.750	2.240
Assets ($ million)	44,141	12,738.146	1,442.301	77,746.922	1.446	2,573,126.000
Leverage	38,360	0.355	0.327	0.736	-94.406	45.282
Firm age	44,147	16.944	16.167	9.542	0.333	39.667
CEO tenure	42,512	7.567	5.000	7.486	0.000	61.000
High ownership	42,611	0.116	0.000	0.321	0.000	1.000
Retirement age	43,917	0.175	0.000	0.380	0.000	1.000
% dedicated investors	43,863	0.017	0.012	0.015	0.000	0.214
% transient investors	43,863	0.382	0.389	0.085	0.000	0.725
% quasi-index investors	43,863	0.600	0.596	0.080	0.255	1.000

Table 2.5: Failure tolerance and innovation

This table reports Poisson regression results. In columns 1 and 2, the dependent variable is simple patent counts, in columns 3 and 4, the dependent variable is future citation weighted patents, and in columns 5 and 6, the dependent variable is stock market weighted patent counts. z-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix A.1.

Dep. Var.:	$Patents_{t+1}$		$Citations_{t+1}$		$Market\ value_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Failure tolerance	0.2197**	0.1901**	0.3702***	0.3304***	0.3285***	0.3016***
	(2.28)	(1.99)	(2.99)	(2.65)	(3.20)	(2.92)
IO	0.0051***	0.0054***	0.0074***	0.0077***	0.0088***	0.0088***
	(4.17)	(4.39)	(4.31)	(4.46)	(5.47)	(5.49)
Ln(R&D stock)	0.2252***	0.2184***	0.3033***	0.2873***	0.1196***	0.1255***
	(6.56)	(6.66)	(6.84)	(6.69)	(3.85)	(4.01)
Ln(K/L)	0.0549	0.0500	0.0281	0.0208	0.0694	0.0664
	(1.48)	(1.35)	(0.59)	(0.44)	(1.54)	(1.49)
Ln(Sales)	-0.0279	-0.0454	-0.0706	-0.1011	0.0531	0.0535
	(-0.55)	(-0.92)	(-1.11)	(-1.64)	(0.82)	(0.83)
Ln(Assets)	0.2161***	0.2284***	0.2819***	0.3044***	0.3815***	0.3815***
	(3.47)	(3.82)	(3.67)	(4.15)	(5.66)	(5.79)
Ln(Firm age)	-0.0831	-0.3235***	-0.1396*	-0.4011***	-0.0802	-0.2527***
	(-1.43)	(-4.35)	(-1.81)	(-4.17)	(-1.22)	(-2.90)
ROA	0.0296	0.0161	0.0793	0.0764	0.1658	0.1474
	(0.24)	(0.13)	(0.57)	(0.61)	(1.15)	(1.02)
Tobin's Q	0.0402***	0.0396***	0.0441***	0.0436***	0.0570***	0.0566***
	(6.35)	(6.20)	(6.28)	(6.11)	(6.16)	(6.09)
$Pseudo R^2$	0.524	0.528	0.519	0.523	0.555	0.558
Observations	26,575	26,575	26,575	26,575	26,575	26,575
Year dummies	Y	Y	Y	Y	Y	Y
Industry dummies	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y

Table 2.6: Failure tolerance with 10-year estimation window and innovation

This table reports Poisson regression results. In columns 1 and 2, the dependent variable is simple patent counts, in columns 3 and 4, the dependent variable is future citation weighted patents, and in columns 5 and 6, the dependent variable is stock market weighted patent counts. z-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix A.1.

Dep. Var.:	$Patents_{t+1}$		$Citations_{t+1}$		$Market\ value_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Failure tolerance (10y)	0.2295***	0.2247***	0.3328***	0.3230***	0.3474***	0.3449***
	(3.28)	(3.24)	(3.66)	(3.57)	(4.28)	(4.23)
$PseudoR^2$	0.519	0.522	0.518	0.521	0.562	0.564
Observations	19,045	19,045	19,045	19,045	19,045	19,045
Year dummies	Y	Y	Y	Y	Y	Y
Industry dummies	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y

Table 2.7: Firms with at least one patent in the sample period

This table reports results from Poisson regressions from a restricted sample containing only observations from firms that filed at least one patent in the sample period. In columns 1 and 2, the dependent variable is simple patent counts, in columns 3 and 4, the dependent variable is future citation weighted patents, and in columns 5 and 6, the dependent variable is stock market weighted patent counts. z-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix A.1.

Dep. Var.:	$Patents_{t+1}$		$Citations_{t+1}$		$Market\ value_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Failure tolerance	0.1969**	0.1696*	0.3534***	0.3167***	0.2981***	0.2801***
	(2.14)	(1.87)	(2.87)	(2.58)	(3.05)	(2.87)
$PseudoR^2$	0.401	0.405	0.411	0.415	0.484	0.486
Observations	14,809	14,809	14,809	14,809	14,809	14,809
Year dummies	Y	Y	Y	Y	Y	Y
Industry dummies	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y

Table 2.8: Failure tolerance and innovation with negative binomial model

This table reports results from negative binomial regressions. In columns 1 and 2, the dependent variable is simple patent counts, in columns 3 and 4, the dependent variable is future citation weighted patents, and in columns 5 and 6, the dependent variable is stock market weighted patent counts. z-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix A.1.

Dep. Var.:	$Patents_{t+1}$		$Citations_{t+1}$		$Market\,value_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Failure tolerance	0.2346**	0.1955*	0.3132***	0.2701**	0.2625**	0.2073*
	(2.25)	(1.93)	(2.87)	(2.50)	(2.32)	(1.85)
IO	0.0029**	0.0033***	0.0035**	0.0038***	0.0027**	0.0032**
	(2.35)	(2.74)	(2.56)	(2.87)	(1.99)	(2.43)
Ln(R&D stock)	0.2733***	0.2526***	0.3528***	0.3247***	0.2741***	0.2408***
	(8.72)	(7.92)	(10.45)	(9.24)	(8.16)	(6.80)
Ln(K/L)	0.0822**	0.0738*	0.0603	0.0480	0.0944**	0.0818*
	(2.09)	(1.92)	(1.37)	(1.11)	(2.06)	(1.86)
Ln(Sales)	-0.0386	-0.0637	-0.0487	-0.0857	-0.0258	-0.0607
	(-0.76)	(-1.28)	(-0.90)	(-1.62)	(-0.46)	(-1.11)
Ln(Assets)	0.1824***	0.1985***	0.2258***	0.2524***	0.2499***	0.2694***
	(3.24)	(3.65)	(3.79)	(4.38)	(4.01)	(4.53)
Ln(Firm age)	0.0010	-0.2960***	-0.0840	-0.3795***	0.0496	-0.2819***
	(0.02)	(-3.95)	(-1.26)	(-4.63)	(0.69)	(-3.37)
ROA	0.0076	0.0100	0.1234	0.1343	0.0866	0.0856
	(0.05)	(0.06)	(0.69)	(0.85)	(0.59)	(0.64)
Tobin's Q	0.0381***	0.0373***	0.0414***	0.0410***	0.0484***	0.0475***
	(7.79)	(7.53)	(7.65)	(7.47)	(8.52)	(8.32)
$Pseudo R^2$	0.177	0.180	0.207	0.209	0.117	0.119
Observations	26,575	26,575	26,575	26,575	26,575	26,575
Year dummies	Y	Y	Y	Y	Y	Y
Industry dummies	Y	Y	Y	Y	Y	Y
Firm FE	N	Y	N	Y	N	Y

Table 2.9: Failure tolerance in competitive and non-competitive industries

This table reports Poisson regression results. I classify firms according to whether they belong to a competitive industry. A competitive industry is one where industry competition measured using a Herfindahl-Hirschman Index is above the median level of industry competition across all industries and years. The dependent variable in columns (1)-(2) is $Patents_{t+1}$, in (3)-(4) $Citations_{t+1}$, and in (5)-(6) $Market\,value_{t+1}$. z-statistics are provided in parentheses. Robust standard errors are clustered at the 3-digit industry level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix A.1.

Dep. Var.:	$Patents_{t+1}$		$Citations_{t+1}$		$Market\,value_{t+1}$	
	Competitive ind. (1)	Non-comp. ind. (2)	Competitive ind. (3)	Non-comp. ind. (4)	Competitive ind. (5)	Non-comp. ind. (6)
Failure tolerance	0.4473***	0.1120	0.6356***	0.2237*	0.4923***	0.2791***
	(4.86)	(1.05)	(5.07)	(1.93)	(2.65)	(2.68)
IO	0.0059***	0.0049***	0.0075***	0.0075***	0.0113***	0.0076***
	(3.77)	(3.75)	(3.36)	(4.59)	(4.60)	(3.93)
$PseudoR^2$	0.514	0.530	0.508	0.529	0.535	0.571
Observations	12,249	14,325	12,249	14,325	12,249	14,325
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table 2.10: Failure tolerance in innovative and non-innovative industries

This table reports Poisson regression results. I classify firms according to whether they belong to an innovative industry. An innovative industry is one where mean $Citations_t$ is above the median level of $Citations_{t+1}$ across all industries. The dependent variable in columns (1)-(2) is $Patents_{t+1}$, in (3)-(4) $Citations_{t+1}$, and in (5)-(6) $Market\,value_{t+1}$. z-statistics are provided in parentheses. Robust standard errors are clustered at the 3-digit industry level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix A.1.

Dep. Var.:	$Patents_{t+1}$		$Citations_{t+1}$		$Market\,value_{t+1}$	
	Innovative ind. (1)	Non-inno. ind. (2)	Innovative ind. (3)	Non-inno. ind. (4)	Innovative ind. (5)	Non-inno. ind. (6)
Failure tolerance	0.1808**	0.4076	0.3101***	0.7553*	0.3024***	0.2523
	(2.06)	(1.55)	(2.93)	(1.68)	(3.28)	(1.15)
IO	0.0052***	0.0041	0.0078***	0.0026	0.0092***	0.0081
	(4.40)	(0.95)	(5.08)	(0.61)	(5.77)	(1.37)
$Pseudo R^2$	0.386	0.487	0.398	0.529	0.495	0.555
Observations	12,842	13,733	12,842	13,733	12,842	13,733
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table 2.11: The failure tolerance effect in recessions

This table reports Poisson regression results. Recession is a dummy variable equal to 1 if any month in the first year of the CEO-firm match is a recession and 0 otherwise. Recessions are classified according to the NBER based Recession Indicators. The dependent variable in columns (1)-(2) is $Patents_{t+1}$, in (3)-(4) $Citations_{t+1}$, and in (5)-(6) $Market\ value_{t+1}$. z-statistics are provided in parentheses. Robust standard errors are clustered at the 3-digit industry level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix A.1.

Dep. Var.:	$Patents_{t+1}$		$Citations_{t+1}$		$Market\ value_{t+1}$	
	$Recession = 1$	$Recession = 0$	$Recession = 1$	$Recession = 0$	$Recession = 1$	$Recession = 0$
	(1)	(2)	(3)	(4)	(5)	(6)
Failure tolerance	0.3984**	0.1190	0.6910***	0.2103	0.4128**	0.2528**
	(2.43)	(1.13)	(2.97)	(1.44)	(2.42)	(2.13)
IO	0.0059**	0.0048***	0.0102***	0.0063***	0.0079***	0.0081***
	(2.38)	(4.13)	(3.13)	(4.34)	(2.67)	(4.21)
$PseudoR^2$	0.520	0.538	0.518	0.534	0.587	0.565
Observations	5,908	20,667	5,908	20,667	5,908	20,667
Controls	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y

Table 2.12: Controlling for investor types

This table reports Poisson regression results. The dependent variable in columns 1, 2, and 3 is $Patents_{t+1}$, $Citations_{t+1}$, and $Market\ value_{t+1}$, respectively. z-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix A.1.

Dep. Var.:	$Patents_{t+1}$	$Citations_{t+1}$	$Market\ value_{t+1}$
	(1)	(2)	(3)
Failure tolerance	0.1936**	0.3416***	0.3199***
	(2.00)	(2.72)	(3.05)
IO	0.0052***	0.0074***	0.0088***
	(4.25)	(4.37)	(5.36)
% dedicated investors	-14.1316***	-18.8757***	-29.6781***
	(-2.87)	(-2.92)	(-4.83)
% quasi-index investors	-0.0714	-0.2568	0.2022
	(-0.14)	(-0.34)	(0.34)
$PseudoR^2$	0.529	0.524	0.562
Observations	26,369	26,369	26,369
Year dummies	Y	Y	Y
Industry dummies	Y	Y	Y
Firm FE	Y	Y	Y

Table 2.13: Failure tolerance of the largest investor and innovation

This table reports Poisson regression results. In Panel A, I use simple patent counts as the dependent variable, while Panels B and C use citation-weighted patent counts and stock market weighted patent counts, respectively. z-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix A.1.

Panel A			
Dep. Var.: $Patents_{t+1}$	(1)	(2)	(3)
Failure tolerance (LI)	0.0960***	0.0779**	0.0485
	(2.64)	(2.12)	(1.56)
% owned by largest investor	-0.8000	-0.6807	0.0721
	(-1.28)	(-1.08)	(0.16)
Investor age		-0.0028	-0.0031*
		(-1.19)	(-1.91)
Portfolio concentration		0.0688	-0.2996
		(0.21)	(-1.27)
Firms in portfolio		0.0000*	0.0000*
		(1.86)	(1.71)
Portfolio liquidity		0.2943***	0.2643***
		(5.44)	(4.97)
Portfolio momentum		0.0621*	0.0297
		(1.72)	(0.82)
$PseudoR^2$	0.501	0.503	0.532
Observations	26,019	25,971	26,715
Year dummies	Y	Y	Y
Industry dummies	Y	Y	Y
Investor dummies	N	N	Y
Firm FE	Y	Y	Y

Table 2.13: Failure tolerance of the largest investor and innovation cont'd

Panel B			
Dep. Var.: $Citations_{t+1}$	(1)	(2)	(3)
Failure tolerance (LI)	0.1721***	0.1454***	0.0941**
	(3.52)	(2.90)	(2.04)
% owned by largest investor	-0.9703	-0.8407	-0.9895
	(-1.12)	(-0.94)	(-1.46)
Investor age		-0.0051*	-0.0049**
		(-1.70)	(-2.19)
Portfolio concentration		-0.0017	-0.6357
		(-0.00)	(-1.63)
Firms in portfolio		0.0000**	0.0000*
		(2.07)	(1.68)
Portfolio liquidity		0.3979***	0.3628***
		(6.91)	(6.25)
Portfolio momentum		0.1490***	0.1239**
		(3.30)	(2.56)
$PseudoR^2$	0.493	0.496	0.534
Observations	26,019	25,971	25,969
Year dummies	Y	Y	Y
Industry dummies	Y	Y	Y
Investor dummies	N	N	Y
Firm FE	Y	Y	Y

Table 2.13: Failure tolerance of the largest investor and innovation cont'd

Panel C			
Dep. Var.: $Market\,value_{t+1}$	(1)	(2)	(3)
Failure tolerance (LI)	0.1417***	0.1261***	0.0438
	(3.38)	(3.11)	(1.33)
% owned by largest investor	-1.4965***	-1.5599***	-1.4979**
	(-2.61)	(-2.66)	(-2.47)
Investor age		0.0009	-0.0018
		(0.35)	(-1.01)
Portfolio concentration		0.3001	0.2001
		(1.16)	(0.75)
Firms in portfolio		0.0000	0.0000
		(0.56)	(0.91)
Portfolio liquidity		0.3701***	0.3386***
		(6.38)	(5.87)
Portfolio momentum		0.2003***	0.1435***
		(4.53)	(3.21)
$PseudoR^2$	0.538	0.541	0.584
Observations	26,019	25,971	25,969
Firm controls	Y	Y	Y
Year dummies	Y	Y	Y
Industry dummies	Y	Y	Y
Investor dummies	N	N	Y
Firm FE	Y	Y	Y

Chapter 3

A real threat? Short selling and CEO turnover

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3.1 Introduction

> *[Elon Musk] was bracing for "at least a few months of extreme torture from the short-sellers, who are desperately pushing a narrative that will possibly result in Tesla's destruction."*
>
> \- *The New York Times*, August 16, 2018[1]

Managers, regulators, and the public fear the destructive and manipulative effects of

[1] *The New York Times*, "Elon Musk Details 'Excruciating' Personal Toll of Tesla Turmoil", August 16, 2018, `https://www.nytimes.com/2018/08/16/business/elon-musk-interview-tesla.html`

short selling on the real economy. While two papers provide theoretical evidence to justify this fear (Goldstein and Guembel, 2008; Khanna and Mathews, 2012), most empirical research on short selling points towards the benefits of short selling for market efficiency and its ability to forecast prices.[2] Short selling provides speculators with negative information about a stock and the possibility to trade on this information without having to own the stock, incorporating their information into prices. Some researchers also argue that simply having the possibility to sell short creates a looming threat that negative information will be incorporated into prices and that this threat may discipline managers.[3] Besides making prices more efficient, short sales could also directly impact real efficiency by serving as a signal for negative information to firm decision makers. Yet, even though recent literature (e.g., Bond, Edmans, and Goldstein (2012); Edmans, Goldstein, and Jiang (2012)) going back to Hayek (1945) stresses the importance of the informational role of financial markets, little is known about whether short selling provides information to real decision makers and whether this contributes to or deters the efficient allocation of assets. In this paper, we contribute to the debate on the real effects of short selling by looking at CEO turnover decisions.

Following Bond, Edmans, and Goldstein (2012), financial markets promote real efficiency if they support real decision makers in the efficient allocation of assets. Since CEOs shape firm behavior and performance (Bertrand and Schoar, 2003), we view the placement of a CEO as the allocation of an important asset in the firm's production process. We analyze a sample of 31,862 firm-years including 2,074 voluntary and 730 forced CEO turnovers from 1993 to 2015. We focus on forced turnover decisions because they provide an ideal setting to better understand the effect of short selling on the allocation of assets: First, they allow us to analyze firms for which we know an important and comparable asset was changed because the original allocation was poor. Second, this change is publicly announced. Third, since the relation between stock returns and forced turnover is well established and the SEC's Regulation SHO provides an exogenous shock to short selling restrictions, we can pick apart the direct effects of short selling on CEO turnover decisions from the indirect effects through prices.

We hypothesize that short sellers possess private negative information on the quality of the CEO-firm match so that their trades serve as a signal to shareholders or the board

[2] An exception is Grullon, Michenaud, and Weston (2015), who analyze the impact of short sale restrictions on investments. For literature on short selling and market efficiency, see Diamond and Verrecchia (1987), Diether, Lee, and Werner (2009a), Saffi and Sigurdsson (2011), or Boehmer and Wu (2013).

[3] See Fang, Huang, and Karpoff (2016); Massa, Zhang, and Zhang (2015); He and Tian (2015).

about CEO performance. The negative information contained in the signal can lead to shareholder activism and to an eventual dismissal of the CEO. Past research unanimously supports the notion that short sellers are on average informed traders, acting on value-relevant information not yet incorporated into prices.[4] Additionally, anecdotal evidence suggests that short sellers also have information on mismanagement. In an extreme example, the CEO of the Spanish telecom company Gowex was fired days after a short seller revealed information that management was responsible for fraudulent accounting.[5] Moreover, short selling is by no means a rare event. According to the samples in Diether, Lee, and Werner (2009b) and Boehmer, Jones, and Zhang (2008), short sales constitute from 13% (Boehmer, Jones, and Zhang, 2008) to 31% (Diether, Lee, and Werner, 2009b) of total trading volume, aggregating the information of many speculators. In addition, while short sales are not directly publicly available, the fraction of shares sold short in a company, also called short interest, is published by exchanges on a monthly basis. In line with short interest carrying important information, a considerable amount of attention is paid to it by the press and managers.[6]

We find three pieces of evidence in favor of short sellers having private information on management quality. First, abnormal short interest increases steadily for three years before a forced turnover and decreases again afterward.[7]

Second, we find a negative relation between short interest in the year before a turnover and forced turnover announcement returns. According to previous literature, CEO turnover announcement returns reflect a combination of two potentially opposing components: The "real" component reflects the expected impact of a new CEO on future firm performance. The "informational" component reflects information about past managerial decisions that are revealed with the announcement (Warner, Watts, and Wruck, 1988). Thus, positive, negative or no abnormal announcement returns may occur depending

[4] For literature stating that and why short sellers are informed see Diamond and Verrecchia (1987) and Boehmer, Jones, and Zhang (2008). Accordingly, short selling activity predicts negative future returns and firm events (Desai, Ramesh, Thiagarajan, and Balachandran, 2002; Cohen, Diether, and Malloy, 2007; Boehmer, Jones, and Zhang, 2008; Christophe, Ferri, and Angel, 2004; Desai, Krishnamurthy, and Kumar, 2006; Karpoff and Lou, 2010; Akbas, Boehmer, Erturk, and Sorescu, 2017). Moreover, there is anecdotal evidence that short sellers were among the first to address severe problems in firms including Enron Corporation, the Lehmann Brothers, and Sino-Forest Corp.

[5] Spruce Point Capital Management, a NY-based hedge fund, published a list of CEO departures that occurred at target companies after the fund's engagement.

[6] The attention paid by the media and executives is exemplified by the vast amount of news coverage on Elon Musk and short positions in Tesla.

[7] As Akbas, Boehmer, Erturk, and Sorescu (2017) argue, short sellers do not necessarily have short-term investment horizons. In fact, the authors provide examples of short sellers with investment horizons of up to several months or years, which is in line with our observation.

on which component outweighs. Overall, we find negative announcement returns in our sample of forced turnovers, suggesting that, on average, the informational component outweighs the real component in these turnovers. In other words, forced turnover decisions are at least partially based on private information not known to the market. Following the above argument, the negative relation between short interest and forced turnover announcement returns means that short sellers were most present in those firms, where the most negative information was revealed during the turnover announcement. This suggests that short sellers were better informed about the extent of past management's failure than the market.

To understand whether the negative abnormal returns are indeed caused by a negative information component and not by the turnover having been a value-destroying decision, we also analyze long-term operating and stock performance after the turnover. We split our sample of turnovers into two groups depending on whether the turnover was preceded by high or low short interest. Using calendar time portfolio returns, we find significantly positive abnormal performance in the year following a forced turnover in both the high and low short interest groups. There is no reversal over the subsequent two years and also no robust difference between the two groups. Changes in operating performance also do not show any decrease in performance after forced turnovers for both high and low short interest groups. There is no significant difference in the three years after and the year before the turnover for both groups and no difference between the groups.

Third, short interest predicts forced CEO turnover, controlling for linear and non-linear measures of a firm's idiosyncratic stock performance, industry performance, accounting performance measures, several information proxies as well as unobserved firm heterogeneity. This effect is statistically and economically significant, with a one standard deviation increase in short interest being associated with a 20% higher turnover probability compared to the unconditional probability of forced turnover of 2.3% in our sample.

We next ask whether short selling also triggers the board to force out the CEO. Since short selling is endogenous to CEO turnover, we use a natural experiment known as Regulation SHO for exogenous variation in the possibility to sell short. In this regulation, the SEC lifted short selling constraints for a randomly selected group of firms. Because the regulation treated large and small firms differently, we treat the regulation as two separate experiments, one on small and one on large firms. We find that when short selling bans were lifted, the probability of forced turnover increased by 2.7 percentage points in the sample of large firms. We do not find a significant effect in our sample of small firms.

However, in line with prior literature, our results also show that the absolute levels of short interest did not increase for treated firms during Regulation SHO. To understand how Regulation SHO nevertheless influenced turnover decisions (and in past literature also other corporate actions), we analyze changes in the slope coefficients of short interest and idiosyncratic stock returns during the experiment. We find that the sensitivity of forced turnover to short interest increases for treated firms while there is at the same time no significant change in the sensitivity to idiosyncratic returns. The rise in sensitivity to short interest indicates that, due to short sale restrictions being lifted, the informational content of short interest with regard to the turnover decision increased.

Last, we seek to understand how the information in short interest triggers the decision by the board to dismiss the CEO. We use cross-sectional variation in board characteristics to find evidence for the board observing short interest directly. We predict that if boards pay attention to short interest when deciding on whether to dismiss the CEO, we should find a higher sensitivity for less entrenched boards, boards with a higher need for or ability to use information from financial markets, and less diverse boards. We do not find any significant evidence to support these predictions although all estimates go into the expected direction. This non-result could occur due to measurement problems or because the board does not directly react to the information in short interest.

Following research by Attari, Banerjee, and Noe (2006) and Gantchev and Jotikasthira (2018) on the relation between institutional selling and shareholder activism, we consider activist shareholders may also react to increased short selling. Shareholder activism may then, in turn, lead to a higher probability of forced CEO turnovers. We find that short interest is significantly related to activism and that the effect of short interest on forced turnover more than triples in the presence of shareholder activism. We thus infer that the information contained in short interest may not affect the board's decision directly but is transmitted through shareholder activism. Activist shareholders of course aim at increasing shareholder value, which at first sight is at odds with the negative announcement effects of the forced turnovers. However, the negative returns are reversed about two months after the forced turnover and, as explained above, become significantly positive in the year after the turnover. With hedge fund activists' average holding period of close to two years (Brav, Jiang, Partnoy, and Thomas, 2008), activist shareholders will profit from the eventual value increase caused by the turnover. Further, if shareholder activism is the main channel through which short interest influences CEO dismissal, it could explain the missing effect of Regulation SHO on CEO turnover in our sample of small firms, since the regulation did not impact the level of shareholder activism in this sample.

We can reject two other hypotheses about how short selling impacts the likelihood of a forced turnover. According to one alternative hypothesis, the effect of short selling on forced turnovers could be caused by an increase in the informativeness of stock prices. However, controlling for a variety of different stock performance measures does not eliminate the predictive power of short interest for forced turnover. Additionally, the negative relation between announcement returns and short interest suggests that the negative information on CEO quality was not known to the market before. Thus, while we cannot exclude that an effect on prices may also influence the turnover decision, short interest is informative beyond what can be captured by the stock price. Moreover, lifting short selling restrictions only significantly increases the sensitivity of forced turnovers to the level of short interest and not to prices.

Another alternative hypothesis is that short sellers are not informed about CEO quality but manipulate the stock price to induce the board to undertake a shareholder-value-decreasing decision by firing the CEO. Goldstein and Guembel (2008) show that short sellers have the incentive to manipulate prices to distort investment decisions and profit from the resulting decline in firm value. While at first glance the negative announcement returns are in line with this argument, the long-run stock price and operating performance contradict the hypothesis. While firms with high short interest perform significantly worse before the turnover, there are no differences in calendar-time abnormal returns or operating performance in the years after the turnover.

Three papers are most closely related to ours. Karpoff and Lou (2010) find that short sellers detect firms with financial misrepresentation over one year before the misconduct becomes public information. In addition, the authors discover that short sellers' trades not only predict financial misconduct but play a role in uncovering this information for the public. Thus, the results of the paper imply that short sellers' actions have a real impact on the firm in addition to having certain information. Grullon, Michenaud, and Weston (2015) examine the effect of Regulation SHO on the investment behavior of firms. They find that particularly small firms experience a drop in share prices and a corresponding decrease in investments. Our results suggest that a change in resource allocation must not stem from a change in the informativeness of prices but rather that short interest serves as a signal directly. De Angelis, Grullon, and Michenaud (2017) examine how

Regulation SHO shaped CEO compensation contracts. They interpret their findings such that boards adapt CEOs' compensation contracts to accommodate the increased downside risk of their equity holdings due to bear raids. We add to their findings by showing that short selling also increases CEOs' risk of being dismissed.

3.2 Related research

Our paper relates to two strings of the literature on short selling. First, the paper complements research on whether short sellers can identify overvalued stock. A number of papers find that short interest and short volume predict future negative returns (Senchack and Starks, 1993; Asquith, Pathak, and Ritter, 2005; Boehmer, Jones, and Zhang, 2008; Desai, Ramesh, Thiagarajan, and Balachandran, 2002; Cohen, Diether, and Malloy, 2007). Moreover, short sellers increase their positions before certain types of negative information become public. For example, Christophe, Ferri, and Angel (2004) report informed short sales in the 5 days before negative earnings surprises and Christophe, Ferri, and Hsieh (2010) in advance of analyst downgrades. However, short sellers' investment horizons seem to also extend over longer periods of time, such as several months or even years. Extant studies find short selling increases for up to 18 months before the release of important firm news, such as earnings restatements (Desai, Krishnamurthy, and Kumar, 2006), the revelation of financial misconduct (Karpoff and Lou, 2010), analyst forecast revisions (Akbas, Boehmer, Erturk, and Sorescu, 2017), and unfavourable public news in the media (Akbas, Boehmer, Erturk, and Sorescu, 2017). Importantly, the information provided by short interest is incremental to the information contained in regular sales (Boehmer, Jones, and Zhang, 2008). We add to this literature by providing evidence that short interest also contains incremental information about managerial quality.

The second string discusses the effects of short selling constraints on market efficiency as well as real corporate decisions. Diamond and Verrecchia (1987) show that constraining short selling has negative effects on market efficiency because it slows down the price discovery process. Several empirical papers find evidence in support of this result (Nagel, 2005; Saffi and Sigurdsson, 2011; Beber and Pagano, 2013; Baruch, Panayides, and Venkataraman, 2017). Results on the effects of restrictions on short selling on real corporate decisions are more mixed. A couple of papers come to the conclusion that some restrictions on short selling are necessary to hinder the downward manipulation of prices (Goldstein and Guembel, 2008; Khanna and Mathews, 2012; Brunnermeier and Oehmke, 2014). Opposed to this literature are recent papers that find that an increased threat of short selling, created by Regulation SHO or a larger availability of lendable shares, provides an external monitoring mechanism, such that managers engage in less earnings management (Massa, Zhang, and Zhang, 2015; Fang, Huang, and Karpoff, 2016) and innovate more (He and Tian, 2015). Our study adds to the literature on the real effects of short selling by showing that the threat of short selling increases the probability of CEO turnover.

Our paper also relates to the literature on firm performance and CEO turnover. This literature has mostly focused on whether stock returns and accounting variables such as ROA predict turnovers and in how far the predictive power varies along corporate governance dimensions.[8] Although the sensitivity of CEO turnover to these measures does increases with stronger governance, the general finding is that the effects of performance measures on forced turnover are very small (Jenter and Lewellen, 2017). This weak relation is most commonly attributed to CEO entrenchment (Taylor, 2010; Hermalin and Weisbach, 1998). Our study contributes to this literature by presenting another capital market signal that contains incremental information about the CEO. Thus, the relation between stock returns and forced turnovers may also be smaller than expected because some information in the market is not contained in stock returns. Using the, to the best of our knowledge, the largest sample of announcement returns to CEO turnovers to date, we find short interest is concentrated before those turnover decisions that are based on private information (based on the reasoning of Hermalin and Weisbach (1998) and Warner, Watts, and Wruck (1988)). We also follow the call by Adams, Hermalin, and Weisbach (2010) and control for firm-specific heterogeneity using firm fixed effects. Moreover, most studies on the relation between CEO turnover and firm performance measures only show correlations, whereas we use a natural experiment to have an exogenous shock to short interest.

[8]See Weisbach (1988), Warner, Watts, and Wruck (1988), Denis and Denis (1995), Yermack (1996), Denis, Denis, and Sarin (1997), Huson, Parrino, and Starks (2002), Goyal and Park (2002), Adams and Funk (2009), Kaplan and Minton (2012), and Jenter and Kanaan (2015).

3.3 Sample, data, and variable definitions

3.3.1 Sample construction

Data are compiled from several sources. Our initial sample consists of CEO data from Standard and Poor's (S&P) ExecuComp database, covering all firms in the S&P 1500 index. The sample period is 1993 to 2015. We observe a turnover for each fiscal year in which the person classified as CEO changes. We exclude CEOs who were in office for less than 12 months.

Data on whether the turnover was forced or voluntary as well as the exact announcement date was provided to us by Jenter and Kanaan (2015) and Peters and Wagner (2014) for the sample period from 1993 to 2009 and hand-collected from newspaper articles found in LexisNexis for the sample period from 2010 to 2015. All turnovers are classified according to the classification scheme in Parrino (1997): A turnover is forced if the press reports that the CEO is fired, forced out, retires, or resigns due to policy differences or pressure. If the press does not report any of these reasons and the CEO is above 59 years old, the turnover is voluntary. All turnovers of CEOs under 60 years old are reviewed further. If the press reports death, poor health, or the acceptance of another position as the reason for departure, the turnover is classified as voluntary. If the CEO is younger than 60 years old and the press reports none of the above reasons, then the turnover is classified as forced. The departure is also classified as forced if CEO age is below 60 and the turnover was not announced at least six months in advance. This detailed classification scheme accounts for the fact that CEOs are rarely openly fired. The data excludes turnovers related to mergers and spin-offs.

Data on short interest comes from the "Supplemental Short Interest File" in Compustat. Short interest depicts the open short positions in a particular stock on the 15th of each calendar month or the last business day before the 15th if the 15th is not a business day, divided by the number of shares outstanding at the end of the previous month. We classify firms into industries using the Fama and French 48 industry classification. We exclude all firms in the category "Other."[9] To control for heterogeneity in short interest across industries, we use industry-adjusted short interest in our analyses, which is the difference between monthly raw short interest and the median monthly short interest in the same industry, if not indicated otherwise.

Data on firm characteristics come from the annual CRSP/Compustat Merged Database

[9]Additionally excluding financial firms from our sample does not change our results.

and stock return information from the CRSP monthly stock files. Following Jenter and Kanaan (2015), we decompose a firm's stock performance into a systematic component, reflecting the industry performance, and an idiosyncratic component by regressing the firm's cumulative stock return over the last 12 months on the average value-weighted industry return over the same period. We exclude each sample firm from its own industry benchmark. Data on the number of analysts following the firm, as well as data on analyst dispersion, come from I/B/E/S. Data on the VIX index is provided by the Chicago Board Options Exchange. Data on director independence comes from the ISS (formerly RiskMetrics) directors database. We drop any observations for which any of this information is missing. Our final sample consists of 31,862 firm-years. When defining our variables, we aggregate monthly data over the last 12 months before a CEO turnover if there was a CEO turnover in the fiscal year or over the last 12 months before the fiscal year end if there was no CEO turnover in the fiscal year. Annual data is taken from the previous fiscal year-end.

For our main analysis in Section 3.5, we focus on the period when Regulation SHO was active and the years immediately before and after the regulation, i.e. from 2000 to 2010. The following paragraph explains the construction of this sample in more detail. For all other analyses, we use the entire sample period from 1993 to 2015. The Appendix contains detailed definitions of all variables.

To construct the sample for our Regulation SHO analysis, we start with a list of tickers of all Russell 3000 index firms as of June 25, 2004. We follow Litvak and Black (2017) and sort these firms into a large firm and a small firm sample according to their index membership: Firms in the Russell1000 index are classified as large firms, and firms in the Russell2000 index are categorized as small firms. This separation is necessary since the firms in each index received different treatments in terms of the lifting of short sale constraints through the SEC.[10] To identify the pilot firms in these samples, we merge the datasets with the ticker list of Category A Pilot Securities that can be obtained from the SEC.[11] We compare the resulting datasets with the summary file of updates to pilot securities provided by the SEC to exclude all securities that were exempted from the pilot program due to business combinations, permanent delistings, or name changes before it started.[12] The remaining Russell1000 and Russell2000 firms that are not classified as

[10]See Question B.1 in the following document: `https://www.sec.gov/spotlight/shopilot.htm`.

[11]The list is available under the following link: `https://www.sec.gov/spotlight/shopilot/currentpilota41305.txt`.

[12]The summary file is available under the following link: `https://www.sec.gov/spotlight/`

Category A Pilot Securities form our control groups in each of the two samples. The originated data sets are then merged with our CEO turnover data set.

3.3.2 Descriptive statistics

Table 3.1 Panel A shows the frequencies of forced and voluntary turnovers in our sample as well as the related raw short interest and stock returns over the previous twelve months. The complete sample consists of 31,862 firm-year observations with an average monthly raw short interest of 3.9%. The average yearly stock return is 1.75%. The sample comprises 730 firm-years with at least one forced turnover and 2,074 firm-years with at least one voluntary turnover. These years make up 2.29% and 6.51% of all firm-years, respectively. When comparing short interest across firm-years, we find the highest mean [median] short interest occurs before forced turnovers (5.1% [2.9%]). Compared to forced turnovers, short interest is significantly lower before voluntary turnovers (3.4% [1.8%]) and when the CEO is retained (3.9% [2.3%]). Short interest does not differ statistically between the latter two cases. For firms to have a similar level of short interest before voluntary and no turnovers is in line with our understanding of voluntary turnovers being unrelated to performance. We find a similar pattern for the average cumulative stock return, such that stock returns are significantly lower in the years before forced turnovers than in all other firm-years.

[Insert Table 3.1 about here]

Panel B presents summary statistics for our main variable of interest as well as for our control variables. Overall, the mean industry-adjusted short interest is 2.2% with a standard deviation of 4%. Since our sample is restricted to firms in Execucomp, the firms in our sample are relatively large with a median value of $1.5 billion in assets. The distribution is skewed to the right with a much larger mean of $12.9 billion in assets. We, therefore, take the log of assets as a control variable. With 10.75 analysts following the average firm, analyst coverage is relatively high, as would be expected for large companies. The average firm has a CEO who is 55.75 years old, has been in office for 7.91 years, and owns 2% of the shares outstanding.

`shopilot/currentpilotc41305.txt`.

3.4 Can short sellers identify bad CEOs?

In this section, we examine whether short sellers can identify firms with poor CEO quality before a turnover event takes place. We first analyze short interest in the months before and after a turnover. To understand whether short positions are informative, we relate short interest to turnover announcement returns as well as to long-term measures of post-turnover performance. Last, we check whether short interest is a predictor of forced turnover.

3.4.1 Short interest around CEO turnovers

We first look at the development of short interest around forced and voluntary turnovers. In Figure 3.1 we show short interest starting 36 months before and ending 36 months after forced and voluntary turnovers. Short interest increases over our sample period and average levels differ considerably across firms. Therefore, to control for this heterogeneity not related to turnovers, we plot the residuals from a regression of raw short interest on firm and month fixed effects.

[Insert Figure 3.1 about here]

Residual short interest is higher in firms with forced turnovers than in firms with voluntary turnovers from around 35 months before a forced turnover until 36 months after. Specifically, we find a steady incline in short interest leading up to the forced turnover in month 0. The increase is steepest from around 17 to 3 months before the dismissal. There is another small increase just after the announcement. This could be due to remaining uncertainty regarding the replacement of the CEO. The average residual short interest declines again to around the original level from 3 years before the announcements. For firms with voluntary turnovers, we do not find a peak at the turnover month. Instead, short interest remains mostly stable[13] over the 36 pre-turnover and post-turnover months. Thus, short sellers increase their short positions in firms in which a forced turnover will take place and dissolve them again afterward.

[13] Short interest in firms with voluntary turnovers remain mostly stable except for an increase between months -21 and -15 and a slow decline afterward. The values for voluntary turnovers may be biased towards the values for forced turnovers, since some forced turnovers may be falsely classified as voluntary turnovers.

3.4.2 The informational advantage of short sellers

Figure 3.1 shows that short sellers continually increase their short positions over 3 years before a forced CEO turnover and then decrease them again. This could mean that short sellers are informed about the bad quality of the CEO before the CEO is fired. Depending on when share prices adapt to this information, it will impact the investment strategy of the short seller. To test the proposition that short sellers know about the (bad) quality of the CEO before the market and profit from this information, we analyze announcement returns to CEO turnovers and relate these to the level of short interest. In addition, we also analyze the long-term post-turnover stock and operating performance of firms with high and low preceding short interest.

There are no clear theoretical predictions about the announcement effects of forced and voluntary turnovers. Assuming the market was perfectly informed about the dismissed CEO's ability and a different CEO can indeed provide more value to the firm, the announcement of a turnover should result in positive abnormal returns. However, if the market was not perfectly informed about the CEO's previous performance, the announcement of a forced CEO turnover can reveal new information to the market. Under these circumstances, the firm value should drop on the news of CEO dismissal. In line with the latter argument, Parrino, Sias, and Starks (2003) hypothesize that some better-informed institutional investors will sell their shares before a forced turnover in anticipation of negative abnormal returns. Warner, Watts, and Wruck (1988) call the two possible effects the "real" and the "informational" component, suggesting that both may occur simultaneously leading to positive, negative, or no abnormal returns depending on which effect outweighs. Hermalin and Weisbach (1998) have a similar argument, according to which they expect stock price reactions to be negative if the CEO is fired based on private information, and positive, if based on public information. Additionally, Dedman and Lin (2002) mention that forced CEO turnovers could lead to succession problems, also resulting in negative abnormal returns. Fittingly, empirical evidence is mixed and strongly depends on the usage of specific subsamples.[14] No prior study includes the most recent 15 years in their sample, with the latest study ending in 2002. Moreover, sample sizes are sometimes rather small due to a focus on specific subsamples of firms. Our sample of 2,022 voluntary and 726 forced turnovers spanning from 1993 to 2015 is to the

[14]See Chang, Dasgupta, and Hilary (2010), Dedman and Lin (2002), Denis and Denis (1995), Hayes and Schaefer (1999), Huson, Parrino, and Starks (2002), Khanna and Poulsen (1995), and Warner, Watts, and Wruck (1988).

best of our knowledge the largest sample of announcement returns to CEO turnovers to date.

Table 3.2 Panel A reports average three-day (-1,1) cumulative abnormal returns for our sample of voluntary and forced turnovers. We use this event window to be able to measure the complete value effect of the announcement of a turnover without including too much noise.[15] Abnormal returns are calculated using the Carhart four-factor model. Overall, we find significantly positive returns of 0.36% as a response to voluntary turnovers and significantly negative returns of -1.63% as a response to forced turnovers. The former suggests that the "real" component outweighs the "informational" component in our sample of voluntary turnovers. A voluntary turnover may come as good news to shareholders even for CEOs with good performance if they have been in office for a long time. In our sample, the CEOs involved in voluntary turnovers on average have a longer tenure than the CEOs in forced turnovers. Over time, a growing proportion of the CEO-firm match surplus accrues to the CEO and not to the shareholders, deteriorating the rents to the shareholders (Jenter and Anderson, 2017; Harris and Holmstrom, 1982). By contrast, the "informational" component of the turnover announcement outweighs the "real" component in our sample of forced turnovers. Thus, forced turnovers reveal negative information about past managerial decisions.

[Insert Table 3.2 about here]

Next, we split all turnovers into high and low short interest subsamples depending on whether the average monthly industry-adjusted short interest in the year before the turnover was below or above the median value in the same year over all turnover observations. For voluntary turnovers, the mean CARs within the high and low short interest subsamples are economically very similar and statistically not significantly different. For forced turnovers, the economic difference between the mean CARs within the low and high short interest subsamples is much larger (-0.7% vs. -2.4%) and statistically significant ($p = 0.053$). It appears that there is more negative information revealed around the announcement of a forced turnover when it is preceded by high short interest. Whereas the informational component does not outweigh the real component in the low short interest sample, it does so in the high short interest sample: The mean CAR in the high short interest sample is significantly negative at the one percent level.

[15] In untabulated results, we find significant abnormal returns only on the day of the announcement and the day after and none on the other days surrounding the announcement, suggesting that there is little or no information leakage before the announcement and that information is priced in completely during this window.

In Table 3.2 Panel B, we turn to a more nuanced analysis of short interest and announcement returns by controlling for a set of firm and CEO characteristics as well as industry and year fixed effects in columns (2) and (3), respectively. Similar to other studies such as Demerjian, Lev, and MacVay (2012) or Dedman and Lin (2002), non-turnover-related variables have little or no effect on the CARs. Consequently, including controls and industry and year fixed effects has barely any effect on the size and significance of the three coefficients of interest for *Short Interest*, *Forced*, and *Short Interest* $\times$ *Forced*. The results are in line with the preceding univariate analysis: First, the level of short interest has no significant effect on the announcement returns of voluntary turnovers. Second, holding other factors constant, forced turnovers with short interest at the industry mean have lower announcement returns than voluntary turnovers. Third, the interaction between forced turnover and short interest is negative and highly significant. The higher the industry-adjusted short interest, the lower are the announcement returns for forced turnovers. This impact is also economically significant: In column (3), a one-standard-deviation increase in industry-adjusted short interest decreases the cumulative abnormal returns in response to forced turnovers additionally by 1.3 percentage points. In summary, we interpret the findings such that investors hold larger short positions in firms for which more negative information is revealed upon the announcement of a forced turnover. The missing relation between short selling and announcement returns for voluntary turnovers supports our interpretation that the negative relation for forced turnovers is not mechanically caused by the price impact of short selling. Moreover, the negative CARs mean that short sellers profit from shorting firms for which they anticipate a forced turnover to happen.

Another explanation for our results could be that higher short interest leads to bad turnover decisions, i.e., the dismissal of an actually good CEO. To explore this hypothesis further, we look at long-term post-turnover operating and stock performance. Table 3.3 shows calendar time portfolio returns for portfolios of firms with forced and voluntary turnovers for up to three years following a turnover. Portfolios are rebalanced monthly. We leave out the month of the turnover in the first year to capture the performance without the announcement effect. We split the portfolios according to low and high pre-turnover levels of industry-adjusted short interest, and drop all months in which there were only high or low short interest observations in the portfolios. Jensen's alphas are calculated by regressing the portfolio excess returns on a Carhart four-factor model. Panel A reports Jensen's alphas for value-weighted and equal-weighted portfolios of forced turnovers. Returns for the low short interest portfolios are slightly positive in the first and second years following a forced turnover for both value-weighted and equal-weighted portfolios. Returns for the high short interest portfolio are only robustly positive for both portfolio weighting schemes in the first year after the turnover. However, when comparing low and high short interest portfolios, we do not find any robust differences in returns. For comparison, we also report returns for portfolios of voluntary turnovers in Panel B. Returns are similar in size. Again, there is no consistent pattern of difference between returns following turnovers preceded by high or low short interest. In summary, we find no performance differences between turnovers that were preceded by high and low short interest and thus find no evidence that high short interest leads to worse turnover decisions.

[Insert Table 3.3 about here]

To examine post-turnover operating performance, in Table 3.4, we also look at the change in firms' ROA after a turnover. We define the year in which a turnover occurred as year zero. To avoid confounding effects from further turnovers, we exclude turnovers that are preceded or followed by another turnover in the previous and subsequent three years. The performance in each year is defined as its fiscal year end value. We then calculate the change between year -1 and year 0, 1, 2, and 3. To control for within-industry and year heterogeneity as well as other factors, we calculate abnormal Δ ROA as the residuals from a regression of the changes in ROA on a number of control variables and industry and year fixed effects. In Panel A, we report the average of these residuals in our sample of forced CEO turnovers. Overall, we find a significant performance decrease from the year before to the year of a forced turnover and from the year before to the year after the turnover. However, there is no significant difference in the decrease between the high and the low short interest subsamples.

[Insert Table 3.4 about here]

In the second and third years after a forced turnover, firms seem to recover from their low performance such that there is no significant difference in performance compared to the pre-turnover year. These results are comparable to previous findings by Jenter and Anderson (2017) for exogenous turnovers. Even though the authors also document significant announcement returns in their turnover sample, they find no long-term performance effects. Moreover, there are no significant differences between the average residual performance change of turnovers for the high and low short interest subsamples. Again, we also report results for voluntary turnovers in Panel B for comparison. As to be expected, there is no performance decrease around voluntary turnovers and also no difference between the high and low short interest subsamples.

In sum, higher short interest is associated with more negative announcement returns, but the long-term performance of firms after a forced turnover does not differ between firms whose turnover was preceded by high levels of short interest and firms whose turnover was preceded by low levels of short interest. Thus, short sellers seem to be better informed than the market about the quality of past managerial decisions, possessing value-relevant (negative) information concerning the management of the firm. At the same time, the post-turnover performance of firms with higher short interest is not different from that of firms with lower short interest, indicating that short sellers do not induce bad turnover decisions.

3.4.3 Short interest as a predictor of forced turnover

The evidence presented in Section 3.4.1 and Section 3.4.2 indicates that short sellers are informed about CEO quality or the firm-CEO-match months before the information is revealed to the public during a turnover announcement. However, this evidence comes from firms that ex-post experienced a CEO turnover and thus does not answer the question of whether short sellers predict a forced turnover in general. We explore this issue by analyzing whether short interest predicts forced CEO turnover.

We estimate the following OLS regression model of forced turnover for our complete sample of firms:

$$Forced_{it} = \beta_0 + \beta_1 \text{Short Interest}_{it} + \beta_2 \text{Performance Measures}_{it} + \beta_3 \text{Controls}_{it} + \epsilon_{it} \tag{3.1}$$

$Forced_{it}$ is a dummy variable that equals 1 if the CEO was dismissed during the fiscal year, and 0 otherwise. Even though the binary dependent variable and time-to-failure structure of our analysis would arguably call for a probit, logit, or proportional hazard model, we will opt for a linear model throughout this paper. In most of our subsequent analyses of forced turnover, we are most interested in the interaction effects. Due to the non-linear nature of probit or hazard models, the interaction effects cannot be readily interpreted using these models (Ai and Norton, 2003; Greene, 2010). Moreover, estimates from linear models are usually a very good approximation of the actual effect around the center of the distribution. To the extent that the Probit and Cox models are applicable, we get qualitatively similar results.

The relationship between stock returns and CEO turnover is already well established.[16] Since short interest is at the same time related to stock returns (Diether, Lee, and Werner, 2009b; Boehmer, Jones, and Zhang, 2008), the relation between short selling and CEO turnover could fully be reflected by the already well-documented CEO turnover-stock return relation. To find out whether short interest is informative beyond stock returns, we control for idiosyncratic and industry stock returns. We also include ROA and book-to-market as other *Performance Measures* publicly available before the turnover. These variables are also known to be related to higher levels of short interest (Dechow, Hutton, Meulbroek, and Sloan, 2001). To account for uncertainty and the public information present in the market, we also include the dispersion in analyst forecasts, the number of analysts following a firm, and the CBOE Volatility Index (VIX) as controls. Furthermore, as is common in the CEO turnover literature, we use a dummy for whether the CEO is older than 63 to account for likely retirements and another dummy for CEOs with a high amount of equity ownership (more than 5%) to account for the alignment of manager and shareholder interests, as well as tenure. Last, we add firm and year fixed effects to comply with the call of Adams, Hermalin, and Weisbach (2010) to control for firm-specific heterogeneity and time trends in CEO-turnover analyses.

Table 3.5, Panel A reports the coefficients for equation 3.1. In line with our results in sections 3.4.1 and 3.4.2, short interest has a large and statistically significant predictive power for forced turnover both with and without controls and firm, industry, and year fixed effects. In the most restrictive specification in column (4) with year and firm fixed effects, a one standard deviation increase in short interest is associated with an increase in the probability of forced turnover by 0.5 percentage points. Compared with the unconditional probability of a forced turnover of 2.3%, this constitutes a 22% increase.[17]

[16] See for example Weisbach (1988), Warner, Watts, and Wruck (1988), Denis and Denis (1995), Yermack (1996), Denis, Denis, and Sarin (1997), Huson, Parrino, and Starks (2002), Goyal and Park (2002), Kaplan and Minton (2012), and Jenter and Kanaan (2015).

[17] Only 1.3 percent of the predicted values fall outside the unit interval, suggesting that the linear probability model does not lead to large misspecifications. Moreover, we also find significantly positive associations of short interest with forced turnover when using probit or Cox hazard models, showing that our results are not an artifact of an arguably not completely suitable model. Economic effect sizes are also similar: A one standard deviation increase in short interest from the mean is associated with a 15% (14%) increase in the probability (hazard) of forced turnover for the probit (Cox) model. We report the

[Insert Table 3.5 about here]

To rule out that non-linear effects of stock returns or different time periods are driving the above relation between short interest and CEO turnover, in Panel B, we test whether the effect subsists using different models. In column (1), additionally to *Idiosyncratic Return (t-12,t-1)* and *Industry Return (t-12,t-1)* measured contemporaneously to short interest (i.e., over one year before the turnover), we also include their one and two-year lags measured from months -24 to -13 as well as -36 to -25. This slightly increases the size and significance of the coefficient on short interest. In column (2), we control for non-linear effects of returns by including squared terms of both return variables. In column (3), we use a linear spline regression for *Idiosyncratic Return (t-12,t-1)* by including linear splines for each of the five quintiles of the return variable in the model. These non-linear controls slightly decrease the size and significance of the coefficient on short interest. However, short interest still significantly predicts forced turnovers even when controlling for linear and non-linear stock and industry returns as well as firm fixed effects.

Yet, even though we deploy firm fixed effects, we cannot rule out reverse causality in our model. Hence, while short interest predicts CEO turnover, we have so far not addressed causality. In the next section, we will adopt Regulation SHO as a natural experiment to examine a potential causal effect of short selling on CEO turnover.

3.5 Does short selling trigger CEO turnover: evidence from a natural experiment

In Section 3.4 we provide evidence that short sellers have information about management quality and that their short positions predict forced CEO turnover. However, we do not know whether short selling also leads to forced turnovers. SEC's Rule 202T of Regulation SHO suspended short selling restrictions for a random sample of firms. In this section, we will use this regulation as a natural experiment to explore whether short selling can lead to forced turnovers.

In the 1930s, the Securities and Exchange Commission (SEC) defined Rule 10-a1, which stated that short sales can only occur at an uptick or a zero uptick (zero-plus tick) on all national exchanges. This meant that stocks could only be sold short above the last trade price or at the last trade price if this price was higher than the most recent different

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results for the Probit and Cox models in Table B.1 in the Appendix.

trade price. The rule was meant to prevent a downward spiral of prices. Nasdaq had applied its own price test since 1994, called the "bid test": Traders other than market makers had to sell short at a price one penny above the bid if a bid was a downtick from the previous tick. On August 1, 2006, when Nasdaq became a national exchange, it also implemented the uptick rule.

In July 2004, the SEC adopted Regulation SHO, containing Rule 202T, which allowed the SEC to establish a program to examine the "effectiveness and necessity" of price tests. The program exempted one-third of stocks in the Russell 3000 index from price tests. The exemption applied to both the uptick rule and the Nasdaq bid test. We call these stocks "pilot stocks". The SEC chose every third stock on each exchange (NYSE, Nasdaq and AMEX) ranked by average daily dollar volume over the previous year to be a pilot stock.[18] The program went into effect on May 2, 2005 and was scheduled to end after one year on April 28, 2006, but was extended until August 6, 2007.

Although Regulation SHO initially looks like a truly random experiment, Litvak and Black (2017) uncover that after the initial randomization, but before the treatment period, the SEC suspended the uptick rule for the largest one-third of the original control firms after regular trading hours. Thus, the SEC created a non-random partially treated subsample.[19] This deviation from strict randomization has so far not been taken into account in previous studies. To circumvent the non-random treatment problem, we run two separate analyses as suggested by Litvak and Black (2017): The small firm experiment (with fully treated firms and full control firms) and the large firm experiment (with fully treated versus partially treated firms).[20] Price tests were suspended for fully treated firms at any point in time. Price tests were also suspended from 4:15 pm until the opening of the consolidated tape on the next day for partially treated firms. Full control firms' price tests were not suspended while the consolidated tape was open.[21]

3.5.1 Methodology

We use Regulation SHO as an exogenous shock to the possibility to short sell pilot firms during the period between May 2005 and August 2007. We first deploy a standard difference-in-difference (thereafter, DiD) methodology to assess the effect of this shock on

[18]See `https://www.sec.gov/rules/other/34-50104.htm#P56_14071`

[19]See `https://www.sec.gov/spotlight/shopilot.htm`

[20]Section 3.3.1 provides a detailed description of the construction of the data sets.

[21]The SEC ordered to lift price tests for category C firms from "the close of the consolidated tape until the open of the consolidated tape the next day" (see `https://www.sec.gov/spotlight/shopilot.htm`).

forced turnover. The methodology compares the change in forced turnover from before to after the treatment in the treated group with the change in forced turnover in the untreated group. Doing so controls for differences between the two groups as well as for differences across time, thus allowing us to estimate a treatment effect. In a second step, we follow Edmans, Heinle, and Huang (2016) and use a modified DiD approach to analyze the change in the sensitivity of forced turnover to short-interest.

Our sample period starts in 2001 and ends in January 2010, since the SEC adopted an alternative uptick rule in February 2010. We divide the sample period into three subperiods. The period from January 2001 to the announcement of the program in July 2004 is labeled "Pre." The treatment period includes the time between when the experiment became effective in May 2005 and the end of the experiment in August 2007. We label the treatment period "During." After August 2007, the price tests were suspended for all firms. We include the period between September 2007 and January 2010 as a placebo test and label this period "Post." Similar to Fang, Huang, and Karpoff (2016), we leave out observations falling into the time between the announcement and the actual start of the program. We consider a firm-year to be in a certain period if the majority of the firm-year, i.e. at least 6 months, was within that period.[22]

We estimate the following model, both for the small firm and the large firm sample:

$$\begin{aligned} Forced_{it} = \beta_0 + \beta_1 \text{Pilot}_i + \beta_2 \text{During}_t + \beta_3 \text{During}_t \times \text{Pilot}_i + \beta_4 \text{Post}_t \\ + \beta_5 \text{Post}_t \times \text{Pilot}_i + \beta_6 \text{Controls}_{it} + \epsilon_{it} \end{aligned} \quad (3.2)$$

Again, $Forced_{it}$ is a dummy variable that equals 1 if the CEO was dismissed during the fiscal-year, and 0 otherwise. $Pilot_i$ is an indicator that equals 1 if the firm was selected to be in the pilot group by the SEC. $During_t$ and $Post_t$ are indicator variables equal to 1 if the firm-year falls into the During or the Post period, respectively. $Controls_{it}$ is a vector of firm and CEO control variables that could be correlated with both short interest and CEO turnover. The Pre period functions as the baseline period.

The DiD coefficient β_3 captures the treatment effect and is our main coefficient of interest. β_1 shows the difference between the two groups in the Pre period while β_2 captures the change in the probability of forced turnover from the Pre to the During period for control firms, thus capturing a time trend in CEO turnover. By lifting the short selling constraints for all firms in August 2007, the SEC effectively ran a second

[22] Our results are robust to varying this period from 3 to 9 months.

experiment, where the control firms become the treated firms. β_4 represents the change in forced turnover from the Pre to the Post period for control firms. β_5 serves as a our placebo test. It captures whether forced CEO turnover changed differently for pilot and control firms from the Pre to the Post period. We do not expect β_5 to be significant since both groups are now treated equally by the SEC (i.e. have no short selling restrictions applied).

To test the effectiveness of the randomization, we compare pilot and control firms within the small firm and the large firm sample immediately before the announcement of Regulation SHO using data from the fiscal years ending in 2003. Table 3.6 Panel A reports descriptive statistics for the pilot and control firms in the small firm sample. Average company size in terms of assets amounts to $ 1.1 billion. There is no significant difference in means in terms of assets or any of the other firm or CEO characteristics. Panel B states the descriptive statistics for pilot and control firms in the large firm sample. The average firm in the large firm sample is naturally much larger than in the small firm sample. Also, there is a significant size difference between the pilot and the control group when looking at the t-statistic of the mean comparison test. However, the Wilcoxon signed rank test does not show a significant difference. The difference in means is driven by two outliers within the control group that are almost twice as large as the largest treatment group firm in terms of assets. When removing these two outliers, the difference is no longer significant. There is also a marginally significant difference in CEO ownership. Overall, there seem to be no large differences between the treatment and the control firms in each sample. Nonetheless, we control for these firm and CEO characteristics in our analyses.

[Insert Table 3.6 about here]

3.5.2 The effects of the experiment on forced CEO turnover

Our first analysis examines how the removal of short selling constraints affects the CEO turnover probability of pilot firms. Table 3.7 shows the results of regression equation 3.2. Panel A reports the results for the small firm experiment and Panel B for the large firm experiment. The model in column (1) contains only the DiD coefficients. In column (2), we add firm and CEO controls. Column (3) additionally includes industry fixed effects to control for unobservable differences across industries. Time trends are captured by our time period dummies *Pre*, *During*, and *Post*. We find no evidence that the removal of the short sale constraints had any effect on the turnover probability in the small firm sample: β_3 is not significant in any model in Panel A. We find a marginally significant effect for our placebo coefficient β_5 in the first and second columns, but it is no longer significant when including industry fixed effects in column (3). The control variables behave as expected. As in Jenter and Kanaan (2015), we find a significantly negative relation between turnover and both idiosyncratic and industry stock returns. The other performance measures, *ROA* and *BTM*, are also significant and carry the expected signs: Better performance is associated with a smaller probability of being fired and vice versa. We also find very similar results to Jenter and Kanaan (2015) with respect to the CEO controls with the exception of CEO tenure, which is not significant in our split samples. We also find a positively significant relationship of forced turnover with the average number of *Analysts Following* and *Analyst Dispersion*.

Panel B of Table 3.7 shows the results for the large firm experiment. In contrast to the small firm experiment, the coefficient β_3 is positive and significant at the 1% level after including controls and industry fixed effects. The economic impact is large: The size of β_3 implies that the probability of forced turnover is 2.7 percentage points higher for pilot firms compared to control firms in the During compared to the Pre period. This matches 16.7% of the standard deviation of forced turnover (0.159) in the pooled sample. The fact that the DiD coefficient remains almost the same when adding controls and industry fixed effects suggests that the treatment was indeed randomly allocated. This significant interaction effect implies that lifting short selling restrictions was associated with an increase in the probability of forced turnover. Again, β_5 functions as a placebo test and is not significant in any specification as expected. The control variables behave very similarly as in the small firm experiment with the exception of *ROA* and *Analyst Dispersion*, which show the expected signs but are not significant. Overall, the large firm experiment provides consistent evidence that Regulation SHO led to an increase in the probability of forced turnover. This provides evidence that short selling leads to CEO turnover.

[Insert Table 3.7 about here]

3.5.3 Changes in the informativeness of short interest

So far, we find a significant increase in CEO turnover associated with a relaxation of short selling restrictions. However, existing studies examining the effects of Regulation SHO on short interest have not been able to report a significant change in short interest through the treatment in the first months after the adoption of the regulation (Securities and Exchange Commission, 2007; Diether, Lee, and Werner, 2009a; Alexander and Peterson, 2008). Likewise, we also do not observe a significant difference in short interest between pilot and controls firms in our sample. As Figure 3.2 shows, short interest levels move similarly for pilot and control firms during our entire sample period within the large and small firm samples, respectively. Statistical tests of the differences in levels and changes of short interest between pilot and control firms also deliver insignificant results.

[Insert Table 3.2 about here]

Since we do not find an impact of Regulation SHO on short interest levels, in this section we aim to understand where the increase in CEO turnover we find in Table 3.7 is coming from. The model by Diamond and Verrecchia (1987) implies two opposing predictions for the effect of the regulation on the informational content of short interest depending on whether the uptick rule had a predominantly prohibiting or restricting effect. If the prohibiting effect dominates, their model predicts an overall reduction of information content especially when there is bad news. If the restricting effect dominates, their model predicts that the information content in each period will improve. With respect to our setting, the sensitivity of forced turnovers to short interest should increase if the prohibition effect dominates and decrease in case the restriction effect dominates. In the third scenario, we do not find any change in the short interest-forced turnover sensitivity. This could be the case either if Regulation SHO is a “weak event”, meaning that Regulation SHO does not significantly affect the amount of information contained in short sales, or if it has an effect on the informational content of short interest, but this information does not influence turnover decisions.

To analyze the change in the sensitivity to short interest, we modify the standard DiD approach similar to Edmans, Jayaraman, and Schneemeier (2017). In this analysis, we are not interested in a change in the level of forced turnover, but in a change in the slope coefficient of short interest. Our main specification for this analysis is given below:

$$\begin{aligned}
\text{Forced}_{it} = \; & \beta_0 + \beta_1 \text{Pilot}_i + \beta_2 \text{During}_t + \beta_3 \text{During}_t \times \text{Pilot}_i \\
& + \beta_4 \text{Short Interest}_{it} + \beta_5 \text{Short Interest}_{it} \times \text{Pilot}_i \\
& + \beta_6 \text{Short Interest}_{it} \times \text{During}_t + \beta_7 \text{Short Interest}_{it} \times \text{During}_t \times \text{Pilot}_i \\
& + \beta_8 \text{Post}_t + \beta_9 \text{Post}_t \times \text{Pilot}_i \\
& + \beta_{10} \text{Post}_t \times \text{Pilot}_i + \beta_{11} \text{Short Interest}_{it} \times \text{Post}_t \times \text{Pilot}_i \\
& + \beta_{18} \text{Controls}_{it} + \epsilon_{it} \qquad (3.3)
\end{aligned}$$

As before, the coefficient β_3 captures the treatment effect of Regulation SHO on the level of forced CEO turnover. The two dummy variables $Pilot_i$ and $During_t$ capture the between-group and across-time differences in CEO turnover, such that β_3 captures only the change in forced CEO turnover over and above any difference in forced CEO turnover across time and between pilot and control firms. To control for the differences in turnover-short interest sensitivity across time and between pilot and control firms, we add the interactions $Short\ Interest_{it} \times\ During_t$ and $Short\ Interest_{it} \times Pilot_i$. The coefficient β_7 is our main coefficient of interest and captures the change in CEO turnover-short interest sensitivity as a result of Regulation SHO. Based on our previous findings, we hypothesize that an increase in the information contained in short interest will increase the sensitivity of the CEO turnover decision to short interest and, therefore, $\beta_7 \neq 0$.

According to the model by Diamond and Verrecchia (1987), short selling restrictions reduce the adjustment speed of security prices to bad news. Hence, Regulation SHO may have also or instead made stock prices more informative. To disentangle whether the effect of the regulation was due to changes in the information contained in short sales or in returns, we also include interactions between $Idiosyncratic\ Return_{it}$ and the treatment and time period coefficients. If the increase in forced turnover is due to stock prices being more informative, we would expect a negative and significant coefficient on the interaction $Idiosyncratic\ Return_{it} \times\ During_t \times\ Pilot_t$.

Table 3.8 Panel A (B) shows the results of the sensitivity analysis for the small (large) firm experiment. In each panel, column (1) contains only the DiD coefficients and the triple interactions. Column (2) adds all control variables also used in Table 3.7 (not reported). Column (3) adds industry fixed effects. Our main variable of interest is the triple interaction $Short\ Interest_{it} \times\ During_t \times\ Pilot_i$. In the large firm sample, we find that Regulation SHO leads to an increased sensitivity of forced turnover to short interest. The coefficient is positive and highly significant in all specifications of the large firm experiment. Although the coefficient in the small firm sample is also positive, it is not significant. This non-result in the small firm sample mirrors the findings from the DiD analysis in Section 3.5.2.

[Insert Table 3.8 about here]

Again, the coefficient on $\textit{Short Interest}_{it} \times \textit{Post}_t \times \textit{Pilot}_i$ serves as a placebo test. As expected, the coefficient is not statistically significant in any specification. Also, we do not find any significant change in the sensitivity of forced turnover to idiosyncratic stock returns. This result is in line with De Angelis, Grullon, and Michenaud (2017), who also do not find a change in stock price informativeness between 2003 and 2005 through the announcement and implementation of Regulation SHO. Thus, our result on the increased informativeness of short interest is not driven by a change in the informativeness of stock returns.

3.6 Through which channel(s) does short selling trigger turnover?

So far, we show that short interest is informative about CEO turnover. Moreover, less restricted short selling leads to a higher probability of CEO turnover and this may be due to a higher informational content in short interest. In this section, we ask *how* the information contained in short interest triggers forced turnovers. We examine two possible channel(s): the board of directors and shareholder activism.

3.6.1 Cross-sectional differences in the boards of directors

In this section, we analyze whether the board of directors uses the information in short interest directly. We exploit the cross-sectional heterogeneity between boards, assuming that if boards use the information in short interest directly, certain characteristics will lead them to react more stronger compared to other boards. In particular, we hypothesize that boards with better monitoring abilities or less entrenchment as well as boards with a higher need for information will show a higher sensitivity to short interest. The effect on the sensitivity of having more diverse director opinions is less clear theoretically. We estimate the following OLS regression model of forced turnover for our complete sample of firms using a set of different variables to proxy for each of the above characteristics:

$$\begin{aligned}\text{Forced}_{it} = \alpha_s + \alpha_t + \beta_1\text{Short Interest}_{it} + \beta_2\text{Moderator}_{it} \times \text{Short Interest}_{it} \\ + \beta_3\text{Performance Measures}_{it} + \beta_4\text{Moderator}_{it} \times \text{Performance Measures}_{it} \\ + \beta_5\text{Controls}_{it} + \epsilon_{it} \quad (3.4)\end{aligned}$$

$Moderator_{it}$ stands for a dummy variable that is equal to one if the value of the proxy is above the median value of all firms within the same year and zero otherwise. To measure the effect of each proxy on the turnover-short interest sensitivity, we also interact the moderator variables with our measure of short interest. We additionally include interactions with the other performance measures, our standard set of control variables, and industry (α_s) and year (α_t) fixed effects to allow for a cross-sectional comparison.

Table 3.9 reports our results. Panel A shows regressions testing the monitoring hypothesis. We use board independence, co-opted boards, director share ownership, and CEO pay slice as proxies for the level of entrenchment. We hypothesize that the sensitivity will increase with better monitoring abilities of the board and decrease the more entrenched the CEO is. Therefore, we expect a positive coefficient on the interaction term in column (1) and negative coefficients in columns (2) to (4). The signs of the interaction terms of short interest with the moderator variable are all as expected. However, none of the coefficients are statistically significant.

[Insert Table 3.9 about here]

Panel B shows interactions of proxies for the informedness of the board. We hypothesize that boards that have less information about the ability of the CEO will show a higher sensitivity to outside information such as short interest. The more busy directors a board has, the less inside information it will be able to gather about the ability of the CEO. We, therefore, expect the interaction of short interest with busy boards in column (1) to be positive. Assuming Bayesian learning, new information about a CEO's ability is more valuable at the beginning of a CEO's tenure. Hence, we expect the interaction with CEO tenure in column (2) to be negative. Last, we assume that boards with more financial expertise, proxied for by the fraction of directors defined as financial experts by SOX, have lower costs of processing and understanding information from financial markets (Minton, Taillard, and Williamson, 2014). Accordingly, we assume a positive interaction term for financial expertise in column (3). As in Panel A, all three coefficients have the expected signs but are not statistically significant.

Last, we analyze the influence of the diversity of opinion in Panel C. We use two proxies for diversity of opinion: board diversity and size. The influence of diversity of opinion on CEO turnover is neither theoretically nor empirically clear. A larger and/or more diverse board may have lower social cohesion, leading to higher coordination costs as well as more free-riding or inertia (Adams, Hermalin, and Weisbach, 2010). For example, Yermack (1996) finds that smaller boards are more likely to have a CEO turnover after bad stock performance. On the other hand, a larger and/or more diverse board may also bring more different perspectives and, therefore, more information to the firm, improving its monitoring abilities (Boone, Casares Field, Karpoff, and Raheja, 2007; Coles, Daniel, and Naveen, 2008; Knyazeva, Knyazeva, and Raheja, 2013). To measure board diversity, we follow Bernile, Bhagwat, and Yonker (2018) and construct an index based on the percentage of female directors, the standard deviation of directors' age, the average number of directorships, director ethnicity, directors' financial expertise, and directors' education. Appendix B.1 contains a detailed definition of the variable. The coefficient of the interaction of board diversity with short interest in column (1) is positive but not significant. We find some (marginally) significant interaction effects with other performance variables, however, they are not conclusive. Whereas there is slight evidence that diverse boards are more sensitive to idiosyncratic stock returns in their CEO dismissal decisions, the effect of ROA is weakened. The coefficient of the interaction of board size with short interest in column (2) is negative but not significant.

Summing up, we do not find any significant effects with regard to any board characteristics even though their interaction terms carry the expected signs. This non-result could be due to measurement problems or due to the fact that board characteristics do not play a role with respect to whether the CEO is dismissed on the cause of short selling or not.

3.6.2 Activist shareholders as catalysts

From past literature, we know that shareholder activism is an important governance mechanism leading to governance interventions in target firms (Brav, Jiang, and Kim, 2015; Becht, Franks, Mayer, and Rossi, 2009), including CEO turnover (Brav, Jiang, Partnoy, and Thomas, 2008). In turn, there is theoretical and empirical evidence that institutional selling can trigger shareholder activism (Attari, Banerjee, and Noe, 2006;

Gantchev and Jotikasthira, 2018). We, therefore, hypothesize that short selling influences forced turnover by triggering activism.

Similar to Gantchev and Jotikasthira (2018), we first test whether the probability of becoming an activist target increases in short selling activity. We do so by estimating the following linear probability model of activist targeting:

$$\text{Activism}_{it} = \alpha_i + \alpha_t + \beta_1 \text{Short Interest}_{it} + \beta_2 \text{Controls}_{it} + \epsilon_{it} \tag{3.5}$$

The dependent variable $Activism_{it}$ is equal to one if the company was an activism target at least once in the fiscal year and zero otherwise. We define a company as an activism target if an activist filed a 13D filing for the first time for this company in that year. Our main explanatory variable $Short\ Interest_{it}$ is the average industry-adjusted short interest over the fiscal year. Detailed variable definitions can be found in the Appendix. We control for different dimensions known to influence activist targeting: firm performance measures (stock return, book-to-market, ROA, and sales growth), as well as firm size and uncertainty measures (stock liquidity, analysts following, and analyst dispersion, and VIX). We include firm and year fixed effects in all regressions.

Table 3.10 reports the results on the impact of short selling on becoming an activist target. Column (1) shows a positive correlation between short interest and shareholder activism. When adding control variables in column (2), the coefficient on short interest increases both statistically and economically. A one standard deviation increase in industry-adjusted short interest is associated with an increase in the likelihood of becoming a target by 0.5 percentage points or 7.7% of the unconditional probability. The coefficients of all control variables have the expected sign and are similar in size to those reported by Gantchev and Jotikasthira (2018). In column (3), we add two firm policy measures, *Leverage* and *R&D*, to our set of control variables. This considerably decreases our sample size to about half the original sample due to poor data availability in these variables. The relationship between short interest and activism remains almost unchanged.

[Insert Table 3.10 about here]

In the next step, we analyze whether activism provides a channel through which short interest leads to forced turnover. The information from short selling could be transmitted to the board via activists or short selling could lead activists to pressure the board to dismiss the CEO. In both cases, the relationship between short selling and forced turnover should be stronger when there is activism.

We estimate the following OLS regression model of forced turnover for our complete sample of turnover and non-turnover firm-years:

$$\begin{aligned}\text{Forced}_{it} = \alpha_i + \alpha_t + \beta_1 \text{Short Interest}_{it} + \beta_2 \text{Activism}_{it} + \beta_3 \text{Short Interest} \times \text{Activism}_{it} \\ + \beta_4 \text{Performance Measures}_{it} + \beta_5 \text{Controls}_{it} + \epsilon_{it} \quad (3.6)\end{aligned}$$

We present the results of this analysis in Table 3.11. Column (1) only includes the base effects of *Short Interest* and *Activism*, while column (2) additionally includes their interaction as described by equation 3.6. The positive coefficient on activism in column (1) reflects the well-known predictive relation between activism and CEO turnover (Brav, Jiang, Partnoy, and Thomas, 2008; Del Guercio, Seery, and Woidtke, 2008). Being targeted at least once increases the probability of a forced turnover relative to its unconditional probability by 53.8% or by 8.2% of its standard deviation. Adding activism to the equation does not decrease the size or significance of the positive coefficient on short interest compared to Table 3.5.

[Insert Table 3.11 about here]

If activism acts as a channel through which short interest affects CEO turnover, we expect an activist campaign will increase the predictive power of short interest. We thus expect a positive coefficient on the interaction term in column (2). Indeed, the coefficient of the interaction term of *Short Interest* × *Activism* is positive and highly significant. This result implies that activist campaigns amplify the effect of short interest on forced turnovers: A one standard deviation increase in *Short Interest* increases the probability of forced turnover by 1.4 percentage points in the presence of activism compared to an increase of 0.4 percentage points in the presence of no activism. The effect in the presence of activism constitutes an over 60% increase in the unconditional probability of forced turnover. We thus find evidence in line that short interest influences forced turnover through shareholder activism.

To analyze whether activism is also a channel for the effect of Regulation SHO on CEO turnover, we plot the average number of activism months between 2001 and 2009 for the pilot and control groups in the small and large firm samples in Figure 3.3. In line with previous literature according to which smaller firms are targeted more often by activists

(Brav, 2009), we find a higher average number of firm-months per year in which activism occurs in the small firm sample.

[Insert Figure 3.3 about here]

There is no significant difference in the occurrence of shareholder activism between pilot and control firms in the small firm sample during our sample period. In the large firm sample, pilot and control firms have approximately parallel trends between 2001 and 2003. Yet, in the year after the announcement of Regulation SHO, pilot firms experience an increase in activism reaching its peak in the During period. At the same time, the likelihood of activism only slightly increases for the control firms. In fact, the increase in activism for pilot firms is significant, and, more importantly, significantly larger than for control firms.[23] We suggest that the missing influence on the channel in the small firm sample could be a reason why we do not find an influence of short interest on forced turnovers here. However, we leave further analyses about the effects of Regulation SHO on shareholder activism to future research.

3.7 Conclusion

We examine the real effects of short selling in forced CEO turnovers. We argue that short sellers possess negative information on the CEO-firm match and that they trade on this information. Short sellers can profit from their position either when firm value declines on account of bad management or when negative information is revealed at a turnover announcement. Furthermore, we argue that shareholders or the board can use the information in short interest in the decision to retain or fire the CEO. Short interest may, thus, not only predict forced turnover but also trigger it. It is not clear whether the board reacts to short interest directly or whether the information is carried to the board through activist shareholders.

Our empirical results suggest that short sellers have information on CEO quality and can predict forced turnovers. We observe that short interest steadily increases in the months before a turnover and decreases afterward. We find that the turnover announcement returns in our sample are negative on average, implying that the degree of the CEO's poor performance was not previously known to the market. Further, the amount

[23]See section B.3 in the Appendix for regression results.

of short interest in the year prior to a forced turnover is negatively related to the announcement returns. Therefore, short sellers seem to be present, especially in those cases where the market was particularly surprised about the CEO's poor performance. At the same time, the turnovers do not seem to be bad decisions since both stock and operating performance recovers in the years after a turnover. Moreover, firms whose forced turnovers were preceded by a high level of short interest do not show any performance differences from other firms after the turnover, suggesting that these firms are neither worse firms in general nor that the turnovers preceded by more short interest are worse decisions. Furthermore, short interest predicts forced turnover and this predictive power goes beyond what can be predicted through stock prices or various other performance measures. We also find that an exogenous shock to short sale restrictions increases forced turnovers in large firms. This increase seems to be due not to an actual increase in short interest but possibly to an increased informativeness of short interest. Furthermore, we identify shareholder activism as a channel through which short interest influences the turnover decision: Short interest predicts shareholder activism and the positive relation of short interest and forced turnover grows stronger with the level of activism. We only find inconclusive evidence that boards with less entrenched CEOs, boards with a higher need for information, or boards with less diversity of opinion have an increased sensitivity to short interest.

More broadly, our results provide evidence consistent with recent theoretical and empirical literature about the real effects of financial markets. We find evidence supporting both theories on the disciplinary effects of the threat of short selling as well as on information provision by financial markets. Several papers empirically connect the threat of short selling to corporate governance outcomes. Our paper provides a logical basis for their results in that we find evidence in favor of the threat of short selling being a credible one. Another string of literature going back to Hayek (1945) and summarized in Bond, Edmans, and Goldstein (2012), purports the real effects of financial markets as an information provider. Indeed, our study offers evidence in line with short interest being informative for the CEO turnover decision of a firm. Our results therefore also have implications for the public policy debate on posing restrictions on short selling. Whereas public opinion is often opposed to short selling, the practice may actually help in the decision to identify and remove bad CEOs. Restricting short selling may therefore have adverse effects on shareholder value and lead to an inefficient allocation of CEOs.

3.8 Figures Chapter 3

Figure 3.1: Short interest around CEO turnovers

This figure shows the average monthly short interest (demeaned and detrended) around CEO turnover months for voluntary and forced turnovers.

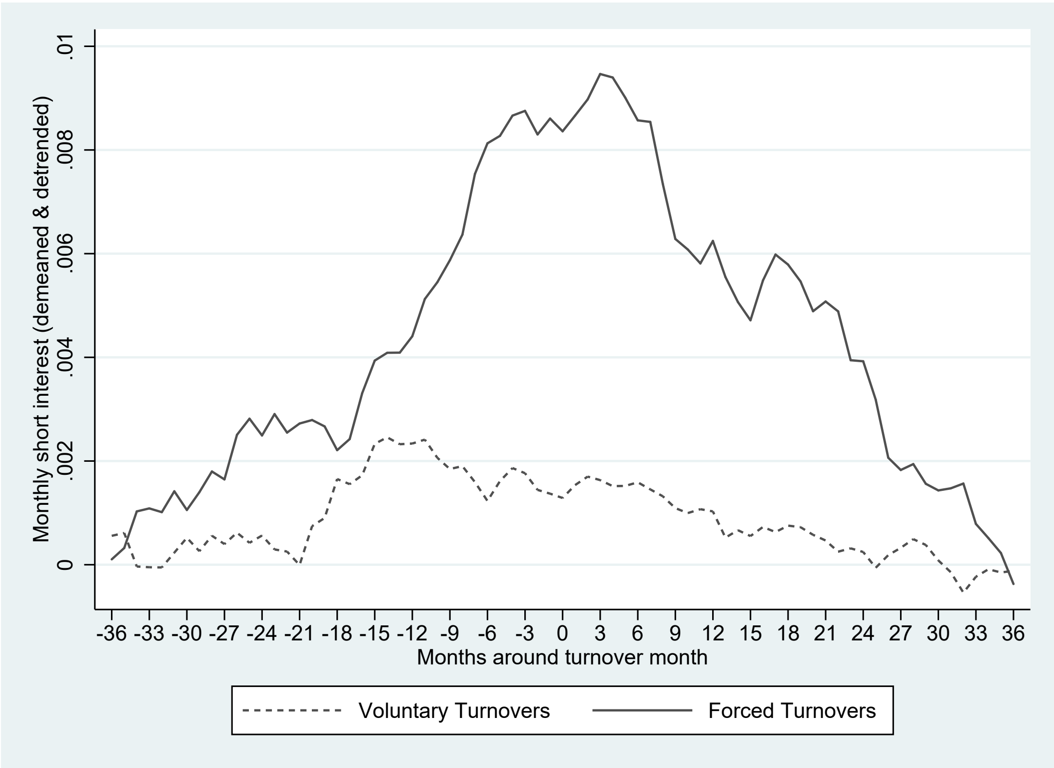


Figure 3.2: Short interest development for pilot and control firms

This figure shows the average monthly short interest for pilot and control firms in the small firm and the large firm experiment. Vertical lines mark the beginning and the end of the treatment period.

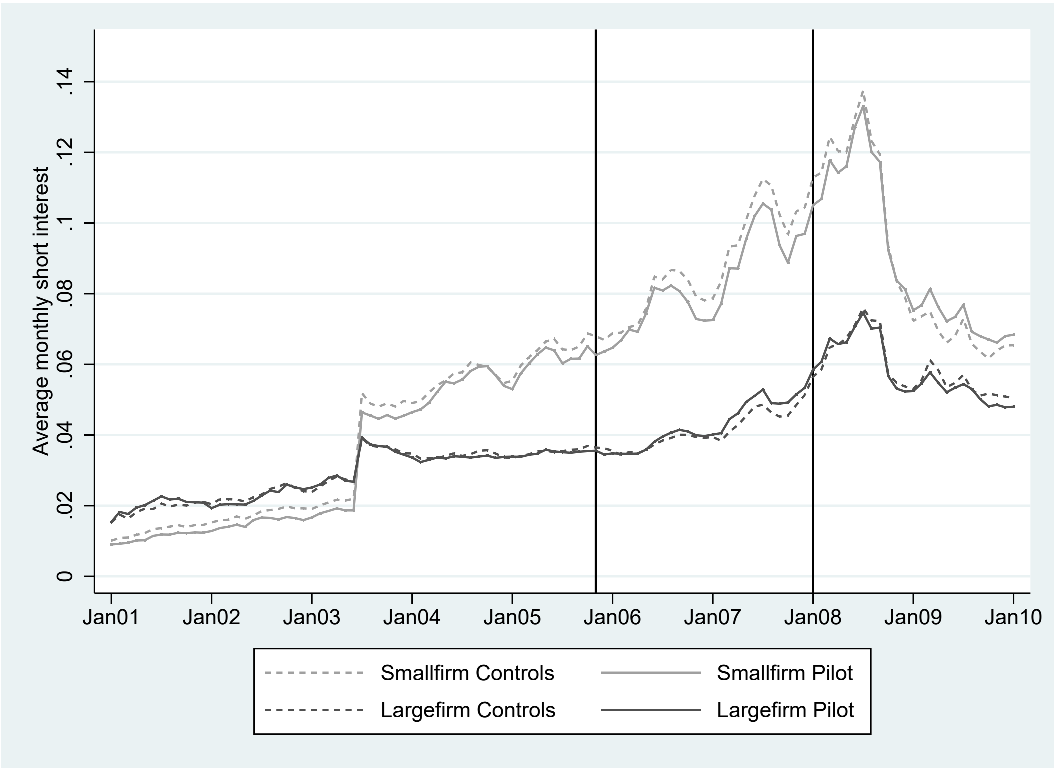
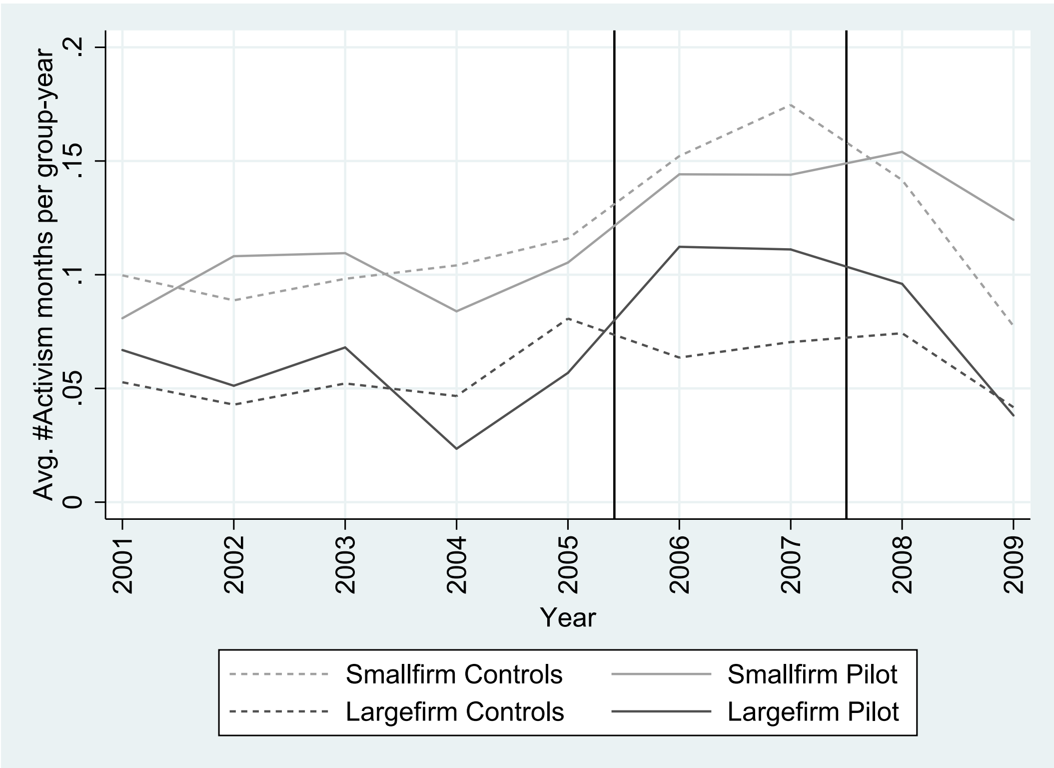


Figure 3.3: Activism in pilot and control firms

This figure shows the average number of activism firm-months per year for each group of pilot and control firms in the small firm and the large firm experiment. An activism month is defined as a firm-month in which the firm was targeted by a new activist. Vertical lines mark the beginning and the end of the treatment period.



3.9 Tables Chapter 3

Table 3.1: Descriptive statistics

This table reports descriptive statistics for our sample of US firms in the S&P1500 index from 1993 to 2015. Panel A shows frequencies of CEO turnover decision outcomes as well as average [median] short interest and stock returns in the 12 months before each outcome. Panel B shows summary statistics for the main variables used in our regression analyses.

Panel A: Turnover distributions				
	Frequency	% of firm-years	Average [median] raw short interest	Average [median] cumulative stock return
Firm-Years	31,862	100.00	0.039	0.175
			[0.022]	[0.107]
CEO is retained	29,058	91.20	0.039	0.187
			[0.023]	[0.116]
CEO Turnovers	2,804	8.80	0.038	0.050
			[0.020]	[0.010]
Forced CEO Turnovers	730	2.29	0.051	-0.140
			[0.029]	[-0.156]
Voluntary CEO Turnovers	2,074	6.51	0.034	0.117
			[0.018]	[0.068]

Panel B: Summary statistics				
	Mean	Median	SD	N
Short Interest	0.02	0.01	0.04	31,862
Idiosyncratic Return	-0.00	-0.06	0.56	31,862
Industry Return	0.18	0.17	0.22	31,862
BTM	0.50	0.44	0.36	31,862
ROA	0.06	0.03	0.12	31,862
Assets	12,880.74	1,549.75	77,179.43	31,862
Analysts Following	10.75	9.00	7.17	31,862
Analyst Dispersion	0.13	0.03	0.33	31,862
VIX	20.31	20.78	6.39	31,862
Activism	0.07	0.00	0.25	31,862
Amihud (log)	-20.04	-20.08	2.09	31,854
Sales Growth	1.28	1.09	20.85	31,843
Leverage	0.35	0.33	0.72	27,658
R&D	0.06	0.03	0.08	17,046
CEO Age	55.75	56.00	7.32	31,862
Share Ownership (%)	0.02	0.00	0.06	31,862
Tenure	7.91	5.83	7.37	31,862

Table 3.2: CARs, short interest and turnover type

This table shows cumulative abnormal returns (CARs) around the announcement of voluntary and forced CEO turnovers.
Panel A reports the average CARs over time window [-1,1] for voluntary (column (1)) and forced (column (2)) CEO turnovers. The first row contains the full sample of voluntary or forced turnovers, while the second (third) row includes only observations for which the mean industry-adjusted short interest over the previous 12 months was low (high), i.e., below (above) the median in the same year. The fourth row reports the difference in average CARs between the low and high short interest samples.
Panel B shows the results of a regression of CAR[-1,1] on average industry-adjusted 12-month short interest before the turnover, a dummy variable for the type of turnover (voluntary vs. forced), the interaction of the two variables and a set of control variables. Control variables are measured as they are available, i.e., either at the end of the prior fiscal year (financial statement variables) or over the 12 months before the turnover. Column (3) additionally includes year and industry fixed effects (FE). *t*-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix B.1.

Panel A: CARs after high and low short interest

	CAR[-1,1]	
	Voluntary Turnovers (N = 2069)	Forced Turnovers (N = 727)
Full sample	0.0033***	-0.0163***
	(2.84)	(-3.87)
Low Short Interest	0.0025	-0.0077
	(1.56)	(-1.40)
High Short Interest	0.0042**	-0.0240***
	(2.47)	(-3.83)
High-Low	0.0016	-0.0163*
	(0.70)	(-1.94)

Table 3.2: CARs, short interest and turnover type cont'd

Panel B: CARs and short interest - Multivariate regressions			
Dependent Variable: CAR[-1,1]	(1)	(2)	(3)
Short Interest	0.0158	0.0164	0.0261
	(0.37)	(0.36)	(0.55)
Forced	-0.0093*	-0.0105**	-0.0100**
	(-1.90)	(-2.14)	(-1.98)
Short Interest × Forced	-0.3612***	-0.3623***	-0.3557***
	(-2.98)	(-3.02)	(-2.94)
Idiosyncratic Return		-0.0072**	-0.0077***
		(-2.57)	(-2.71)
Industry Return		0.0068	0.0057
		(1.07)	(0.75)
ROA		-0.0252*	-0.0285*
		(-1.70)	(-1.70)
BTM		0.0055	0.0057
		(1.00)	(0.95)
Assets (log)		-0.0007	-0.0001
		(-0.54)	(-0.05)
Analysts Following		0.0003	0.0002
		(1.22)	(0.77)
Analyst Dispersion		-0.0012	-0.0020
		(-0.21)	(-0.35)
VIX		-0.0004*	-0.0015*
		(-1.85)	(-1.69)
Retirement Age		0.0014	0.0008
		(0.54)	(0.31)
High Ownership		0.0005	0.0002
		(0.08)	(0.03)
Tenure		0.0001	0.0001
		(0.67)	(0.50)
Constant	0.0029**	0.0082	
	(2.20)	(0.80)	
R^2	0.026	0.031	0.036
Observations	2,796	2,796	2,795
Industry FE	N	N	Y
Year FE	N	N	Y

Table 3.3: Calendar time portfolio returns after CEO turnovers

This table shows the monthly Jensen's alphas of calendar time portfolios after forced (Panel A) and voluntary (Panel B) CEO turnovers. Columns (1) to (3) ((4) to (6)) report returns for equal-weighted (value-weighted) portfolios. Columns 1 and 4 (2 and 5, 3 and 6) include post-turnover months from 2 months to 12 months (from 13 months to 24 months, from 25 months to 36 months) after the announcement month. Low (High) Short Interest is a dummy variable that takes the value 1 if the mean industry-adjusted short interest over the previous 12 months was low (high), i.e., below (above) the median in the same year. *t*-statistics are provided in parentheses. Standard errors are robust to heteroskedasticity. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix B.1.

Panel A - Forced Turnovers						
	Equal Weighted Portfolios			Value Weighted Portfolios		
	(1)	(2)	(3)	(4)	(5)	(6)
Jensen's Alpha (monthly)	$\alpha_{m+2,m+12}$	$\alpha_{m+13,m+24}$	$\alpha_{m+25,m+36}$	$\alpha_{m+2,m+12}$	$\alpha_{m+13,m+24}$	$\alpha_{m+25,m+36}$
Low Short Interest	0.0107***	0.0081***	0.0027	0.0088**	0.0076**	0.0069*
	(3.45)	(3.07)	(1.15)	(2.05)	(2.18)	(1.88)
High Short Interest	0.0063**	-0.0003	0.0024	0.0085**	-0.0005	0.0079**
	(2.02)	(-0.10)	(0.90)	(2.09)	(-0.13)	(2.03)
High-Low	-0.0044	-0.0083**	-0.0004	-0.0004	-0.0082	0.0010
	(-1.01)	(-2.17)	(-0.11)	(-0.06)	(-1.48)	(0.19)
R^2	0.712	0.674	0.693	0.442	0.398	0.507
Observations	269	263	246	269	263	246

Panel B - Voluntary Turnovers						
	Equal Weighted Portfolios			Value Weighted Portfolios		
	(1)	(2)	(3)	(4)	(5)	(6)
Jensen's Alpha (monthly)	$\alpha_{m+2,m+12}$	$\alpha_{m+13,m+24}$	$\alpha_{m+25,m+36}$	$\alpha_{m+2,m+12}$	$\alpha_{m+13,m+24}$	$\alpha_{m+25,m+36}$
Low Short Interest	0.0063***	0.0051***	0.0055***	0.0041	0.0069***	0.0049**
	(4.66)	(3.78)	(3.39)	(1.56)	(3.06)	(2.46)
High Short Interest	0.0014	0.0025**	0.0043***	0.0049***	0.0021	0.0065***
	(0.95)	(2.05)	(3.21)	(2.77)	(1.24)	(3.75)
High-Low	-0.0050**	-0.0026	-0.0012	0.0007	-0.0048*	0.0015
	(-2.52)	(-1.40)	(-0.55)	(0.23)	(-1.70)	(0.58)
R^2	0.839	0.870	0.859	0.752	0.770	0.777
Observations	270	264	251	270	264	251

Table 3.4: Operating performance after CEO turnovers

This table shows abnormal changes in industry-adjusted ROA around forced (Panel A) and voluntary (Panel B) CEO turnovers. Turnovers are excluded if there was another turnover in the three previous or subsequent fiscal years. Abnormal change in industry-adjusted ROA is defined as the residuals of a regression of the change in industry-adjusted ROA on a set of firm control variables. Low (High) Short Interest is a dummy variable that takes the value 1 if the mean industry-adjusted short interest over the previous 12 months was low (high), i.e., below (above) the median in the same year. *t*-statistics are provided in parentheses. Standard errors are robust to heteroskedasticity. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix B.1.

Panel A - Forced Turnovers				
	Δ ROA[-1,0]	Δ ROA[-1,1]	Δ ROA[-1,2]	Δ ROA[-1,3]
Full sample	-0.0097**	-0.0080*	-0.0083	-0.0085
	(-2.37)	(-1.66)	(-1.37)	(-0.94)
Low Short Interest	-0.0100	-0.0050	-0.0053	-0.0091
	(-1.52)	(-0.71)	(-0.57)	(-0.73)
High Short Interest	-0.0094*	-0.0104	-0.0108	-0.0079
	(-1.82)	(-1.57)	(-1.36)	(-0.62)
High-Low	0.0005	-0.0054	-0.0055	0.0012
	(0.06)	(-0.56)	(-0.45)	(0.07)
Observations	378	353	302	252
Panel B - Voluntary Turnovers				
	Δ ROA[-1,0]	Δ ROA[-1,1]	Δ ROA[-1,2]	Δ ROA[-1,3]
Full sample	0.0025	0.0021	0.0020	0.0019
	(1.27)	(1.00)	(0.82)	(0.65)
Low Short Interest	0.0039	0.0024	0.0009	0.0003
	(1.37)	(0.78)	(0.25)	(0.08)
High Short Interest	0.0010	0.0017	0.0031	0.0035
	(0.36)	(0.62)	(0.94)	(0.85)
High-Low	-0.0030	-0.0007	0.0022	0.0032
	(-0.75)	(-0.17)	(0.46)	(0.54)
Observations	1,459	1,368	1,263	1,131

Table 3.5: Short interest and CEO turnover

This table shows the results of linear probability models of forced CEO turnover. In column (1) of Panel A, we regress a dummy variable for forced turnover on our measure of short interest. Column (2) includes a set of control variables, column (3) additionally includes year and industry fixed effects (FE), and column (4) includes year and firm fixed effects. In Panel B, we repeat the regression from Panel A, column (4) with varying measures of returns as control variables. Column (1) of Panel B includes additional lags of the idiosyncratic and industry return variables, column (2) includes squared terms of these variables, and column (3) adds splines for each quintile of the idiosyncratic return variable. *t*-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix B.1.

Panel A: Short interest as predictor of CEO turnovers

Dependent Variable: Forced	(1)	(2)	(3)	(4)
Short Interest	0.1477***	0.1068***	0.1019***	0.1201***
	(5.43)	(4.04)	(3.74)	(3.26)
Idiosyncratic Return		-0.0225***	-0.0226***	-0.0216***
		(-11.64)	(-11.75)	(-10.76)
ROA		-0.0338***	-0.0523***	-0.0710***
		(-3.98)	(-5.56)	(-5.24)
BTM		0.0174***	0.0196***	0.0343***
		(4.47)	(4.80)	(5.96)
Industry Return		-0.0036	-0.0104*	-0.0126**
		(-0.83)	(-1.94)	(-2.30)
Assets (log)		-0.0019**	-0.0003	0.0060**
		(-2.42)	(-0.32)	(2.25)
Analysts Following		0.0005***	0.0003	-0.0001
		(2.86)	(1.60)	(-0.23)
Analyst Dispersion		0.0099***	0.0095***	-0.0020
		(3.01)	(2.85)	(-0.49)
VIX		0.0005***	0.0001	0.0002
		(3.55)	(0.21)	(0.29)
Retirement Age		-0.0153***	-0.0143***	-0.0241***
		(-9.58)	(-8.81)	(-9.08)
High Ownership		-0.0118***	-0.0129***	-0.0179***
		(-6.29)	(-6.46)	(-3.82)
Tenure		-0.0003***	-0.0003***	0.0015***
		(-3.21)	(-2.89)	(7.17)
Constant	0.0196***	0.0184***		
	(20.54)	(3.04)		
R^2	0.001	0.016	0.021	0.029
Observations	31,866	31,866	31,866	31,729
Year FE	N	N	Y	Y
Industry FE	N	N	Y	N
Firm FE	N	N	N	Y

Table 3.5: Short interest and CEO turnover cont'd

Panel B: Robustness tests			
Dependent Variable: Forced	(1)	(2)	(3)
Short Interest	0.1299***	0.1126***	0.0897**
	(3.33)	(3.08)	(2.48)
Idiosyncratic Return (t-12,t-1)	-0.0235***	-0.0351***	
	(-10.27)	(-12.74)	
Idiosyncratic Return (t-24,t-13)	-0.0049***		
	(-2.86)		
Idiosyncratic Return (t-36,t-25)	0.0016		
	(0.65)		
Industry Return (t-12,t-1)	-0.0109*	-0.0283***	-0.0352***
	(-1.84)	(-3.26)	(-6.32)
Industry Return (t-24,t-13)	0.0061		
	(0.91)		
Industry Return (t-36,t-25)	0.0039		
	(0.66)		
Squared Idiosyncratic Return (t-12,-1)		0.0039***	
		(7.12)	
Squared Industry Return (t-12,t-1)		0.0138*	
		(1.74)	
Idiosyncratic Return Q1			-0.1113***
			(-6.99)
Idiosyncratic Return Q2			-0.0858***
			(-3.82)
Idiosyncratic Return Q3			-0.0319
			(-1.45)
Idiosyncratic Return Q4			-0.0134
			(-1.03)
Idiosyncratic Return Q5			0.0003
			(0.17)
R^2	0.037	0.033	0.038
Observations	29,535	31,729	31,729
Controls	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y

Table 3.6: Summary statistics for Regulation SHO firms

This table shows summary statistics of the treatment and the control groups for the small firm sample (Panel A) and large firm sample (Panel B) in the Regulation SHO experiment. All variables are measured in the fiscal year ending in 2003. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix B.1. For reasons of readability, the following variables are abbreviated in the table: Idiosyncratic Return (Idio.Return), Analysts Following (Following), Analyst Dispersion (Dispersion).

Panel A: Small Firm Sample

	Treatment Group				Control Group			
	N	Mean	Median	SD	N	Mean	Median	SD
Short Interest	235	0.02	0.01	0.04	454	0.03	0.01	0.04
Idio. Return	231	0.16	0.01	0.83	440	0.24	0.05	0.89
Industry Return	231	0.20	0.22	0.19	440	0.19	0.22	0.17
ROA	235	0.13	0.12	0.10	454	0.13	0.12	0.15
BTM	235	0.53	0.50	0.29	454	0.50	0.46	0.34
Assets	235	1,145.36	697.24	1,780.26	454	1,142.29	572.88	1,972.37
Following	232	5.56	5.00	3.76	452	5.93	5.17	3.80
Dispersion	223	0.19	0.04	0.44	442	0.21	0.04	0.60
CEO Age	235	55.71	56.00	7.65	454	54.91	55.00	7.32
Ownership	235	0.03	0.01	0.08	454	0.02	0.00	0.06
Tenure	235	8.13	5.17	8.03	454	7.26	4.92	6.56

Differences between Treatment and Control Firms

	Diff.	T-stat	Wilcoxon z-stat
Short Interest	0.00	1.46	1.82
Idio. Return	0.08	1.12	1.49
Industry Return	-0.01	-0.43	-0.79
ROA	0.00	0.41	-0.25
BTM	-0.03	-1.03	-1.73
Assets	-3.07	-0.02	-1.46
Following	0.36	1.19	1.29
Dispersion	0.02	0.53	1.75
CEO Age	-0.80	-1.33	-1.30
Ownership	-0.00	-0.85	-1.46
Tenure	-0.87	-1.44	-0.58

Table 3.6: Summary statistics for Regulation SHO firms cont'd

Panel B: Large Firm Sample

	Treatment Group				Control Group			
	N	Mean	Median	SD	N	Mean	Median	SD
Short Interest	252	0.03	0.02	0.03	493	0.02	0.02	0.03
Idio. Return	249	0.13	-0.03	0.73	487	0.07	-0.00	0.39
Industry Return	249	0.19	0.22	0.17	487	0.19	0.22	0.18
ROA	252	0.16	0.15	0.12	493	0.15	0.14	0.12
BTM	252	0.43	0.39	0.29	493	0.41	0.35	0.28
Assets	252	17,284.85	4,588.21	50,665.08	493	30,447.37	4,640.10	110,199.59
Following	252	13.32	12.13	7.05	493	13.29	12.42	6.64
Dispersion	251	0.08	0.02	0.21	492	0.09	0.02	0.29
CEO Age	252	56.67	57.00	6.95	493	55.80	56.00	7.04
Ownership	252	0.02	0.00	0.04	493	0.01	0.00	0.04
Tenure	252	8.06	5.92	7.83	493	7.32	5.25	6.65

Differences between Treatment and Control firms

	Diff.	T-stat	Wilcoxon z-stat
Short Interest	-0.00	-0.76	-0.80
Idio. Return	-0.07	-1.33	0.26
Industry Return	0.00	0.03	-0.32
ROA	-0.01	-0.62	-1.39
BTM	-0.01	-0.60	-0.24
Assets	13,162.52	2.23**	0.16
Following	-0.04	-0.07	0.26
Dispersion	0.01	0.59	-0.22
CEO Age	-0.87	-1.61	-1.71
Ownership	-0.01	-1.83*	-0.05
Tenure	-0.75	-1.29	-0.83

Table 3.7: Regulation SHO: DiD models

This table shows the results of linear probability models of forced CEO turnover in the Regulation SHO period. Panel A (B) reports the results for our small firm (large firm) sample. We regress a dummy variable for forced turnover on difference-in-difference variables for the treatment group and period. Column (2) includes a set of control variables. Column (3) additionally includes industry fixed effects (FE). t-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix B.1.

Table 3.7: Regulation SHO: DiD models cont'd

Panel A: Small Firm Sample			
Dependent Variable: Forced	(1)	(2)	(3)
Pilot	-0.0012	0.0005	-0.0004
	(-0.15)	(0.07)	(-0.06)
During	-0.0011	0.0034	0.0038
	(-0.17)	(0.28)	(0.31)
During × Pilot	-0.0081	-0.0074	-0.0077
	(-0.78)	(-0.72)	(-0.74)
Post	-0.0079	-0.0188**	-0.0197**
	(-1.25)	(-2.25)	(-2.34)
Post × Pilot	0.0202*	0.0197*	0.0193
	(1.65)	(1.66)	(1.61)
Idiosyncratic Return		-0.0197***	-0.0196***
		(-4.87)	(-4.76)
Industry Return		-0.0353***	-0.0308***
		(-3.38)	(-2.95)
ROA		-0.0821***	-0.1010***
		(-3.67)	(-4.34)
BTM		0.0302***	0.0278***
		(3.18)	(2.92)
Assets (log)		-0.0053**	-0.0013
		(-2.08)	(-0.40)
Analysts Following		0.0023***	0.0019**
		(3.40)	(2.53)
Analyst Dispersion		0.0175**	0.0155*
		(2.18)	(1.86)
VIX		0.0002	0.0004
		(0.23)	(0.37)
Retirement Age		-0.0182***	-0.0164***
		(-4.65)	(-3.99)
High Ownership		-0.0108*	-0.0096*
		(-1.92)	(-1.67)
Tenure		-0.0002	-0.0003
		(-0.72)	(-1.11)
Constant	0.0281***	0.0379	
	(6.24)	(1.30)	
R^2	0.000	0.023	0.024
Observations	5,307	5,307	5,307
Industry FE	N	N	Y

Table 3.7: Regulation SHO: DiD models cont'd

Panel B: Large Firm Sample			
Dependent Variable: Forced	(1)	(2)	(3)
Pilot	-0.0084	-0.0090	-0.0078
	(-1.37)	(-1.51)	(-1.27)
During	-0.0054	-0.0263**	-0.0247**
	(-0.99)	(-2.11)	(-1.99)
During × Pilot	0.0263**	0.0273***	0.0266***
	(2.57)	(2.70)	(2.63)
Post	0.0052	0.0022	0.0007
	(0.76)	(0.21)	(0.07)
Post × Pilot	0.0163	0.0165	0.0167
	(1.31)	(1.37)	(1.39)
Idiosyncratic Return		-0.0316***	-0.0315***
		(-3.99)	(-3.99)
Industry Return		-0.0433***	-0.0410***
		(-4.31)	(-3.92)
ROA		-0.0069	-0.0378
		(-0.36)	(-1.58)
BTM		0.0433***	0.0449***
		(3.65)	(3.58)
Assets (log)		0.0003	0.0008
		(0.15)	(0.33)
Analysts Following		0.0012***	0.0012**
		(2.85)	(2.40)
Analyst Dispersion		0.0156	0.0155
		(1.52)	(1.50)
VIX		-0.0018*	-0.0016*
		(-1.78)	(-1.65)
Retirement Age		-0.0144***	-0.0138***
		(-3.06)	(-2.86)
High Ownership		-0.0057	-0.0086
		(-1.01)	(-1.43)
Tenure		-0.0002	-0.0002
		(-0.87)	(-0.62)
Constant	0.0243***	0.0417	
	(5.88)	(1.37)	
R^2	0.001	0.023	0.025
Observations	5,538	5,538	5,538
Industry FE	N	N	Y

Table 3.8: Regulation SHO: Sensitivity models

This table shows the results of linear probability models of forced CEO turnover in the Regulation SHO period. Panel A (B) reports the results for our small firm (large firm) sample. We regress a dummy variable for forced turnover on our measure of short interest, difference-in-difference variables for the treatment group and period, and their interactions. Column (2) includes a set of control variables. Column (3) additionally includes industry fixed effects (FE). t-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix B.1.

Table 3.8: Regulation SHO: Sensitivity models cont'd

Panel A: Small Firm Sample			
Dependent Variable: Forced CEO Turnover	(1)	(2)	(3)
Pilot	0.0044	0.0064	0.0055
	(0.50)	(0.75)	(0.67)
During	-0.0014	0.0074	0.0074
	(-0.16)	(0.53)	(0.52)
During × Pilot	-0.0205	-0.0179	-0.0177
	(-1.55)	(-1.36)	(-1.34)
Post	-0.0034	-0.0098	-0.0117
	(-0.39)	(-0.90)	(-1.07)
Post × Pilot	0.0262	0.0274	0.0269
	(1.47)	(1.57)	(1.53)
Short Interest	0.3896*	0.4111**	0.3775*
	(1.92)	(2.10)	(1.91)
Short Interest × Pilot	-0.2883	-0.2616	-0.2543
	(-1.07)	(-0.99)	(-0.98)
Short Interest × During	-0.3178	-0.3427	-0.3141
	(-1.33)	(-1.48)	(-1.35)
Short Interest × During × Pilot	0.4714	0.3864	0.3757
	(1.36)	(1.15)	(1.12)
Short Interest × Post	-0.3733*	-0.4260*	-0.3832*
	(-1.67)	(-1.94)	(-1.73)
Short Interest × Post × Pilot	0.0345	-0.0128	-0.0145
	(0.10)	(-0.04)	(-0.04)
Idiosyncratic Return	-0.0161**	-0.0176**	-0.0174**
	(-2.24)	(-2.37)	(-2.33)
Idiosyncratic Return × Pilot	-0.0031	-0.0045	-0.0048
	(-0.30)	(-0.43)	(-0.47)
Idiosyncratic Return × During	-0.0189	-0.0175	-0.0183
	(-1.38)	(-1.29)	(-1.35)
Idiosyncratic Return × During × Pilot	0.0070	0.0133	0.0161
	(0.37)	(0.71)	(0.86)
Idiosyncratic Return × Post	0.0108	0.0119	0.0114
	(1.37)	(1.46)	(1.40)
Idiosyncratic Return × Post × Pilot	-0.0468**	-0.0444**	-0.0436**
	(-2.29)	(-2.26)	(-2.19)
Constant	0.0226***	0.0336	
	(4.10)	(1.14)	
R^2	0.009	0.026	0.027
Observations	5,307	5,307	5,307
Controls	N	Y	Y
Industry FE	N	N	Y

Table 3.8: Regulation SHO: Sensitivity models cont'd

Panel B: Large Firm Sample			
Dependent Variable: Forced CEO Turnover	(1)	(2)	(3)
Pilot	-0.0036	-0.0050	-0.0050
	(-0.44)	(-0.63)	(-0.61)
During	-0.0026	-0.0238*	-0.0217
	(-0.38)	(-1.74)	(-1.59)
During × Pilot	0.0120	0.0145	0.0144
	(1.08)	(1.31)	(1.29)
Post	-0.0016	0.0018	0.0006
	(-0.21)	(0.17)	(0.06)
Post × Pilot	0.0076	0.0086	0.0100
	(0.63)	(0.72)	(0.83)
Short Interest	0.2167	0.2123	0.2445
	(1.06)	(1.06)	(1.18)
Short Interest × Pilot	-0.2908	-0.2259	-0.1800
	(-1.23)	(-0.96)	(-0.75)
Short Interest × During	-0.4656**	-0.4592**	-0.4794**
	(-2.16)	(-2.15)	(-2.19)
Short Interest × During × Pilot	1.0362***	0.9965***	0.9833***
	(2.86)	(2.75)	(2.68)
Short Interest × Post	0.1493	0.0876	0.0529
	(0.57)	(0.34)	(0.20)
Short Interest × Post × Pilot	0.4578	0.3808	0.3353
	(1.25)	(1.04)	(0.91)
Idiosyncratic Return	-0.0367**	-0.0361**	-0.0363**
	(-2.56)	(-2.45)	(-2.45)
Idiosyncratic Return × Pilot	0.0140	0.0158	0.0145
	(0.78)	(0.85)	(0.78)
Idiosyncratic Return × During	-0.0063	-0.0079	-0.0069
	(-0.31)	(-0.39)	(-0.34)
Idiosyncratic Return × During × Pilot	-0.0262	-0.0268	-0.0265
	(-0.56)	(-0.57)	(-0.56)
Idiosyncratic Return × Post	0.0215	0.0221	0.0221
	(1.10)	(1.11)	(1.10)
Idiosyncratic Return × Post × Pilot	-0.0616**	-0.0640**	-0.0595*
	(-1.97)	(-2.06)	(-1.93)
Constant	0.0221***	0.0355	
	(3.94)	(1.14)	
R^2	0.015	0.028	0.030
Observations	5,538	5,538	5,538
Controls	N	Y	Y
Industry FE	N	N	Y

Table 3.9: Cross-sectional analysis

This table shows the results of linear probability models of forced CEO turnover. We regress a dummy variable for forced turnover on our measure of short interest, moderator variables for board characteristics (indicated in the column header), and their interactions. Except for *CEO Tenure*, the moderator variables are represented by a dummy that takes the value 1 if the moderator variable is above the median value within the same year, and 0 otherwise. *CEO Tenure* takes the value 1 if the CEO's tenure is above the sample median, and 0 otherwise. We split the board characteristics into three categories: Panel A reports models for board monitoring and CEO entrenchment, Panel B reports models for the boards' need and use of information, and Panel C reports models for the boards' diversity of opinion. All columns include year and industry fixed effects (FE). t-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix B.1.

Panel A: Monitoring / Entrenchment				
Moderator variable	Independence	Co-Opted	Share Ownership	Payslice
	(1)	(2)	(3)	(4)
Short Interest	0.0758**	0.1893***	0.1531***	0.1196***
	(1.98)	(3.34)	(3.07)	(2.73)
Moderator	-0.0121***	-0.0077	0.0073	-0.0099**
	(-2.62)	(-1.14)	(1.49)	(-2.10)
Moderator X Short Interest	0.0698	-0.0367	-0.0732	-0.0497
	(1.18)	(-0.50)	(-1.21)	(-0.90)
ROA	-0.0517***	-0.0587***	-0.0399**	-0.0583***
	(-3.66)	(-2.72)	(-2.56)	(-4.12)
Moderator X ROA	0.0092	-0.0067	-0.0148	0.0015
	(0.50)	(-0.26)	(-0.83)	(0.09)
BTM	0.0098*	0.0197**	0.0284***	0.0180***
	(1.79)	(2.54)	(4.41)	(3.03)
Moderator X BTM	0.0162**	0.0156	-0.0234***	0.0005
	(2.04)	(1.43)	(-2.96)	(0.07)
Idiosyncratic Return	-0.0242***	-0.0537***	-0.0379***	-0.0280***
	(-9.17)	(-9.72)	(-8.89)	(-8.97)
Moderator X Idiosyncratic Return	-0.0036	0.0223***	0.0203***	0.0082**
	(-0.70)	(2.75)	(4.08)	(2.13)
Industry Return	-0.0070	-0.0063	-0.0074	-0.0014
	(-1.03)	(-0.63)	(-1.02)	(-0.17)
Moderator X Industry Return	0.0067	-0.0067	0.0070	-0.0173*
	(0.72)	(-0.57)	(0.74)	(-1.89)
Controls	Y	Y	Y	Y
R^2	0.020	0.029	0.022	0.025
Observations	24,308	18,677	24,308	29,779
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y

Table 3.9: Cross-sectional analysis cont'd

Panel B: Informed Directors			
Moderator variable	Busy (1)	CEO Tenure (2)	Financial Expertise (3)
Short Interest	0.1046***	0.1419***	0.0982**
	(3.24)	(3.37)	(2.00)
Moderator	0.0031	-0.0087**	-0.0000
	(0.50)	(-1.97)	(-0.00)
Moderator X Short Interest	0.0220	-0.0759	0.0016
	(0.28)	(-1.45)	(0.02)
ROA	-0.0488***	-0.0651***	-0.0276
	(-3.87)	(-4.92)	(-1.27)
Moderator X ROA	0.0107	0.0256	0.0027
	(0.45)	(1.62)	(0.10)
BTM	0.0189***	0.0164***	0.0128
	(3.76)	(3.20)	(1.64)
Moderator X BTM	-0.0054	0.0067	0.0068
	(-0.52)	(0.92)	(0.61)
Idiosyncratic Return	-0.0235***	-0.0277***	-0.0095
	(-8.89)	(-9.28)	(-1.51)
Moderator X Idiosyncratic Return	-0.0130**	0.0106***	-0.0251***
	(-2.08)	(2.87)	(-2.92)
Industry Return	-0.0021	-0.0096	-0.0174
	(-0.35)	(-1.29)	(-1.44)
Moderator X Industry Return	-0.0108	-0.0016	0.0014
	(-0.94)	(-0.20)	(0.12)
Controls	Y	Y	Y
R^2	0.020	0.021	0.013
Observations	24,308	31,862	11,145
Year FE	Y	Y	Y
Industry FE	Y	Y	Y

Table 3.9: Cross-sectional analysis cont'd

Panel C: Diversity of Opinion		
Moderator variable	Diversity (1)	Size (2)
Short Interest	0.0944*	0.1128***
	(1.85)	(3.04)
Moderator	-0.0073	0.0001
	(-1.03)	(0.01)
Moderator X Short Interest	0.0469	-0.0083
	(0.63)	(-0.14)
ROA	-0.0484**	-0.0522***
	(-2.08)	(-4.00)
Moderator X ROA	0.0590**	0.0197
	(1.97)	(0.98)
BTM	0.0124	0.0173***
	(1.52)	(2.89)
Moderator X BTM	0.0123	0.0011
	(1.06)	(0.13)
Idiosyncratic Return	-0.0155**	-0.0234***
	(-2.51)	(-8.17)
Moderator X Idiosyncratic Return	-0.0154*	-0.0102*
	(-1.79)	(-1.83)
Industry Return	-0.0189	0.0073
	(-1.56)	(1.07)
Moderator X Industry Return	-0.0007	-0.0350***
	(-0.06)	(-3.88)
Controls	Y	Y
R^2	0.012	0.021
Observations	10,353	24,308
Year FE	Y	Y
Industry FE	Y	Y

Table 3.10: Determinants of the probability of activism

This table shows the results of linear probability models of activism. We regress a dummy variable for activism on our measure of short interest. Column (2) includes a set of control variables. Column (3) further extends this set of variables, reducing our sample size by half. All columns include year and firm fixed effects (FE). t-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix B.1.

Dependent Variable: Activism	(1)	(2)	(3)
Short Interest	0.0935*	0.1475***	0.1471**
	(1.74)	(2.74)	(1.98)
Idiosyncratic Return		0.0014	0.0042
		(0.45)	(0.98)
Industry Return		-0.0135*	-0.0256***
		(-1.83)	(-2.69)
ROA		-0.1264***	-0.1307***
		(-6.30)	(-5.16)
BTM		0.0149*	0.0274**
		(1.84)	(2.24)
Assets (log)		-0.0085**	-0.0130**
		(-1.97)	(-1.99)
Analysts Following		-0.0018***	-0.0010
		(-3.65)	(-1.39)
Analyst Dispersion		0.0254***	0.0264***
		(4.05)	(2.87)
VIX		-0.0017*	-0.0021*
		(-1.95)	(-1.93)
Amihud (log)		0.0047*	0.0047
		(1.78)	(1.36)
Sales Growth		0.0000	0.0000
		(0.14)	(0.46)
Leverage			0.0123*
			(1.70)
R&D			0.0698
			(1.26)
R^2	0.072	0.079	0.086
Observations	37,165	37,165	17,781
Year FE	Y	Y	Y
Firm FE	Y	Y	Y

Table 3.11: CEO turnover sensitivity and shareholder activists

This table shows the results of linear probability models of forced CEO turnover. In column (1), we regress a dummy variable for forced turnover on our measure of short interest and a dummy for activism. In column (2), we additionally include the interaction of the two variables. All columns contain a set of control variables and year and firm fixed effects (FE). t-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix B.1.

Dependent Variable: Forced	(1)	(2)
Short Interest	0.1182***	0.0960***
	(3.22)	(2.63)
Activism	0.0123***	0.0046
	(2.75)	(0.94)
Activism × Short Interest		0.2825**
		(2.06)
Idiosyncratic Return	-0.0216***	-0.0216***
	(-10.76)	(-10.73)
Industry Return	-0.0125**	-0.0123**
	(-2.30)	(-2.27)
ROA	-0.0694***	-0.0690***
	(-5.13)	(-5.11)
BTM	0.0339***	0.0339***
	(5.91)	(5.91)
Assets (log)	0.0061**	0.0060**
	(2.31)	(2.25)
Analysts Following	-0.0001	-0.0001
	(-0.17)	(-0.17)
Analyst Dispersion	-0.0022	-0.0024
	(-0.53)	(-0.57)
VIX	0.0002	0.0002
	(0.32)	(0.33)
Retirement Age	-0.0240***	-0.0240***
	(-9.02)	(-9.03)
High Ownership	-0.0183***	-0.0183***
	(-3.88)	(-3.90)
Tenure	0.0015***	0.0016***
	(7.18)	(7.20)
R^2	0.030	0.030
Observations	31,725	31,725
Year FE	Y	Y
Firm FE	Y	Y

Chapter 4

The impact of role models on women's self-selection into competitive environments

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4.1 Introduction

Although several countries have introduced gender quotas to promote a higher representation of women in top management positions, the fraction of female top managers is still very low (Adams and Kirchmaier, 2016). One suggested reason why women are under-represented in top management positions is that they are reluctant to compete against others (Gneezy, Niederle, and Rustichini, 2003a; Niederle and Vesterlund, 2007;

Bertrand, 2011).[1] Individuals' willingness to compete is important in the context of reaching leadership positions, because high-profile, high-earning occupations usually take place in highly competitive settings (Bertrand, 2011). Prior studies show that gender differences in the willingness to compete indeed affect women's career choices and their performance in competitive workplaces (Kamas and Preston, 2012), and can help explain the persistent differences in career outcomes and wages between men and women (Sutter and Gätzle-Rützler, 2014; Buser, Niederle, and Oosterbeek, 2014; Buser, Peter, and Wolter, 2017).

In line with the view that top management positions, which are usually characterized by tough competition among managers, are less attractive for women, Flory, Leibbrandt, and List (2015) find that women are less likely to apply for jobs with a competitive compensation scheme, eventually self-selecting in other segments of the labor market. A number of experimental studies confirm this result by showing that women prefer less competitive environments, especially when having to compete against men, and that their performance suffers in competitive environments.[2]

Given that the gender gap in the willingness to compete is reversed in matrilineal societies (Gneezy, Leonard, and List, 2009), women's reluctance to compete in patriarchal societies seems to be at least partially driven by their social environment and upbringing. Specifically, stereotypes may distort women's believes regarding their performance in tournaments (Bordalo, Coffman, Gennaioli, and Shleifer, 2016). If patriarchal societies produce stereotypes regarding certain tasks, according to which women are expected to underperform, the fear of confirming this stereotype is one explanation for women's lower self-confidence regarding the task and, if the task involves competition, their lower willingness to compete (Bordalo, Coffman, Gennaioli, and Shleifer, 2019).

If women's social environment and their upbringing contributes to their lower willingness to compete, "soft" policies that make the choice to compete less threatening to women may help undo the impact of negative prescriptive stereotypes, that may otherwise shape women's preference for competition (Betrand, 2018). In this paper, we investigate whether the availability of competitive female role models influences women's choice to compete. Past research has shown that role models can have a short- and long-term impact on stereotype threat. For example, several studies find that in-group role mod-

[1] Other reasons for the low fraction of women in leadership positions include limited access to information networks, incompatibility of working inflexible hours and childcare, cultural and social obstacles like stereotypes, etc. For an overview, see Ely and Rhode (2010); Koenig, Eagly, Mitchell, and Ristikari (2011); Bertrand (2011).

[2] An overview of this literature is provided by Niederle and Vesterlund (2011) and Niederle (2015).

els can increase performance in situations where stereotype threat is present (Marx and Roman, 2002; Stout, Dasgupta, Hunsinger, and McManus, 2011). Bettinger and Long (2005) show a strong impact of female faculty as role models on female students' choice of mathematical subjects. Similarly, Beaman, Duflo, Pande, and Topalova (2012) provide causal evidence that gender differences in career aspirations and educational attainment decrease if adolescents live in villages which are randomly selected to have a female leader, and Adams, Barber, and Odean (2018) show that STEM mothers increase the likelihood that their daughters become CFA Institute members. In a similar vein, Alan and Ertac (2019) show that the gender gap in the willingness to compete disappears when children are exposed to a worldview that emphasizes the role of effort in achievement and encourages perseverance. Taken together, these findings suggest that the availability of female role models may encourage more women to compete.

To test whether female role models indeed increase women's willingness to compete, we conduct an experiment with a 3 (female role model, male role model, no role model) x 2 (subject gender) between-subject design. The experiment consists of two main parts: In the first part, subjects are randomly assigned to watch a video with either a neutral landscape, a female competitive role model, or a male competitive role model. The second part is based on the experimental design of Niederle and Vesterlund (2007), where subjects have to add up as many five two-digit numbers as possible in a short period of time. They are exposed to both, a piece-rate and tournament compensation scheme first, and then choose which scheme should be applied to the next round.

We first examine whether our experimental design allows us to replicate the results of Niederle and Vesterlund (2007). We confirm their main result by showing that, in our neutral condition without any role models, women are significantly less likely to chose the tournament compensation scheme than men.

The core of our experiment are the female and male role model conditions, in which we show subjects a video of a competitive woman or man, respectively. We indeed find that showing female and male role models to subjects has an impact on their willingness to compete. Specifically, female subjects' willingness to compete increases in the female role model condition. As a result, the gender difference in tournament entry decreases markedly and turns insignificant. By contrast, in the male role model condition, female subjects' willingness to compete decreases even further, and the gender gap in tournament entry gets more pronounced than in the neutral condition.

In the next step, we analyze the impact of performance on subjects' willingness to compete: We find that better performing men are generally more likely to enter the tournament than worse performing men. In contrast, we find no such impact of performance on tournament entry for women as long as they do not observe a female role model. However, the impact of female role models on female subjects' tournament entry decision is strongest for the best performing women, i.e., mainly well performing women are encouraged by a female role model to enter the tournament. This result is in line with Carrell, Page, and West (2010), who show that female professors have the largest impact on the performance and college majors of female students with high prior math ability. Also consistent with their results, we do not find a significant impact of female role models on the worst performing women.

To examine in more detail the channels through which the role mode effect works, we elicit whether and to what extent subjects are affected by stereotype threat. Specifically, they are asked whether they agree to the statement that men are more skilled at solving math-related problems than women. Although gender differences in actual mathematical skills are insignificant for most countries (and among our subject population), there are often stereotypes that women lack mathematical ability (Else-Quest, Hyde, and Linn, 2010; Guiso, Monte, Sapienza, and Zingales, 2008). These stereotypes can lead to distorted believes and thus negatively affect women's willingness to compete (Bordalo, Coffman, Gennaioli, and Shleifer, 2016). Our results show that female role models reduce stereotypes on gender differences in mathematical skills among both, female and male subjects.

In a contemporaneous paper, Schier (2020) finds a positive role model effect of female, as well as male role models on women's willingness to compete. Thus, our results are similar to those in Schier (2020) for female role models, while we find opposite results for male role models. This may be due to differences in the experimental design of the two papers. To induce a role model effect, Schier (2020) informs subjects that a woman or a man from a previous round in the experiment favored the tournament. This information is provided immediately before subjects choose their compensation scheme in round 3. One concern with this approach is that this information could be interpreted as a direct recommendation on what to choose in round 3. In line with this view, de Quidt, Haushofer, and Roth (2018) provide evidence that women respond more strongly to demand treatments than men. This may explain why Schier (2020) finds a positive role model effect for both, female and male role models, on female subjects' choice to enter the tournament. To mitigate such experimenter demand effects in our experiment, we separated the experiment into two different parts, which was also communicated to participants. First, they watched a video about a famous and competitive person and answered several questions about this person. Then, the second part of the experiment started with no explicit link to the first part. Starting the second part of the experiment without information how it is linked to the first part should at least mitigate experimenter demand effects and may explain why we find that female role models increase female subjects' willingness to compete, while male role models decrease female subjects' willingness to compete.

Our paper informs the policy debate on how the fraction of women in leadership positions can be increased. They suggest that increasing the availability and visibility of female role models may be a "soft policy" to break down gender stereotypes that make women believe that they are less skilled than men (Adams and Funk, 2012). Eventually, counter-stereotypical female role models may nudge other (highly qualified) women to enter a competitive career and aim for a top management position.

4.2 Experimental procedure and replication of baseline results

4.2.1 Experimental design

Our experiment is conducted on Amazon's Mechanical Turk (AMT) platform. All instructions are provided to subjects in written form on their screens. We programmed the experiment using Sosci Survey (Leiner, 2015) and used their server to collect the data.[3]

To test our hypotheses, we use a 3 (female role model, male role model, no role model) x 2 (subject gender) between-subject design. At the beginning of the experiment, subjects are randomly assigned to watch one of five videos, four of them containing either a female or a male role model, and one containing an Australian landscape without any human element like as voices or people. Since mental capacities or visual influences may impact subsequent decisions, we wanted all three conditions (female role model, male role model, and no role model) to be as similar as possible, and showed subjects in the neutral condition a video as well. We chose a video of a landscape to make sure that it would not be activating in any way as this may change risk behavior (Andrade, Odean, and

[3]For more information on this tool, see https://www.soscisurvey.de/.

Lin, 2015).[4] Subjects were told that they would be shown a video and that they would subsequently have to answer questions about the video. Each video lasted around three minutes. Subjects could not pause or rewind.

After the first part was finished, subjects were automatically forwarded to the second part of the experiment, which closely follows the design of Niederle and Vesterlund (2007). We provide an overview of the experiment in section C.4 of the Appendix. In the first three rounds, subjects have to solve the same task of adding up as many randomly generated sets of five two-digit numbers in three minutes as possible. Subjects are informed about their absolute performance after each round, but not about their relative performance compared to the other subjects.

In the first "piece rate round", subjects are paid for their performance with a non-competitive piece-rate scheme of 50 cents for each correct answer.[5] In the second round, only the best performing subject with the highest number of correct answers in a group of four is paid and receives $4 for each correct answer.[6] As in Niederle and Vesterlund (2007), subjects are informed that each group consists of two men and two women who are randomly assigned to the groups.

Round three is the main round of the experiment, in which subjects decide whether they want to apply the piece rate compensation scheme of round 1 or the tournament compensation scheme of round 2, before solving the next addition task. We call this round "Choice 1". In the fourth round, subjects do not have to perform any calculations anymore and are only asked which compensation scheme they want to be applied to their past performance in the first, i.e., piece rate, round. We call this round "Choice 2". Thus, Choice 2 differs from Choice 1 because subjects no longer need to actually perform under a competition. Niederle and Vesterlund (2007) use this setup to differentiate the actual act of performing under competition from other gender differences, for example in risk aversion and overconfidence, which may also be causing a gender gap in tournament

[4]The video was created by Selmesfilm. It can be accessed here: https://www.youtube.com/watch?v=FJPwPqvZaUI.

[5]We report all instructions and questions subjects received in the experiment in Online Appendix C.5.

[6]In Niederle and Vesterlund (2007), a risk neutral subject with a 25 percent chance of winning the tournament would have the same expected payoff from the tournament as from the piece rate, i.e., subjects received $2 for each correct answer in the tournament. We increased the payment in the tournament in order to increase the incentives for choosing the tournament. In contrast to a lab experiment, subjects could not see each other while working on AMT and also cannot calculate their bonus payments on their own. Thus, the perceived risk of the tournament compared to the piece-rate is higher. We provided subjects with higher rewards in the "tournament round" to compensate for taking this risk.

entry.

In Niederle and Vesterlund (2007), subjects are not allowed to use a calculator to solve the addition tasks. However, since our experiment is not conducted in a laboratory, but each subject takes part in the experiment remotely, we have no possibility to enforce this rule and thus explicitly allow the use of calculators. Subjects have a strong incentive to use calculators to increase their performance-based compensation. Forbidding a calculator without the means to enforce this rule would induce several unobservable factors that may impact the decision to compete and that may also be correlated with gender, mainly the propensity to cheat (Gino, Krupka, and Weber, 2013), and trust in other subjects (Croson and Gneezy, 2009).

At the end of the experiment, after all choices regarding tournament entry are made, we elicit subjects' perceived performance and their stereotype threat. First, we ask them to estimate their relative performance rank in the piece rate round which we use as a proxy for their self-estimated math competence. They are paid \$1 for each correct guess. Further, we ask subjects to what extent they agree to the stereotypical statement that "Men are more skilled at solving math-related problems". Answers are given on a 7-point Likert scale ranging from "very untrue" to "very true".

After the experiment ended, subjects' performance-based compensation is determined based on one of the four rounds that is randomly chosen. Thus, subjects cannot use their decision in one round to hedge against the outcome of another round. Subjects are paid a participation fee of \$5 and an additional performance-based fee averaging \$10.89. We neither mention that the goal of our experiment is to investigate gender differences in tournament entry in the recruitment process of participants nor in the description of the task. All questions related to perceived performance or gender stereotypes are asked in the end of the experiment, when no more decisions regarding tournament participation have to be made, but before participants are informed about their payout.

4.2.2 Details on using Amazon Mechanical Turk

We conduct our experiment on Amazon's Mechanical Turk (AMT) platform. We chose to run the experiment on this platform rather than in the laboratory because the number of observations needed for statistical power in a 3 x 2 between subjects design is large. Furthermore, we wanted the sample to consist of U.S. participants to make our results comparable to the previous literature (e.g., Niederle and Vesterlund, 2007). The experiment was conducted in three sessions on Nov 15^th 2016, Nov 21^th 2016, and May 5^th

2017. Our regressions therefore include session fixed effects to account for any unobserved differences between these sessions.

Two issues are important to note when using AMT. First, AMT workers might not take their task serious and just produce noise. We try to mitigate such concerns by selecting only workers with an approval rate above 95 percent, i.e., workers that have been rated to be highly reliable on previous tasks. Furthermore, we drop participants with a missing values score ("MISSREL") of more than two. The missing values score is a quality indicator generated by the Sosci platform to help identify survey participants who just click through the task and likely do not work on it seriously. Questions that are rarely answered (e.g., voluntary text questions) are mostly irrelevant for this score, questions that most participants have answered weight worse. The linear weighting factor for a question/item is the number of answers given to this question/item divided by how often the question/item has been asked.

Second, AMT workers are not physically exposed to a tournament situation as they only obtain information about their group online but are not sitting with other group members in the same room (as would be the case in a laboratory). We think that this would only work against us finding gender differences in tournament entry, because the environment that AMT workers are in should be less intimidating for women, make stereotype threats less salient and thus might actually encourage more women to participate in a tournament compared to a laboratory environment.

4.2.3 Summary statistics

Table 4.1 shows summary statistics of the variables collected from all subjects in our experiment, as well as differences between female and male subjects.

Our final sample consists of 668 observations. There are 48% female and 52% male subjects in our experiment (Panel A).

With respect to performance, we find that the average number of correctly answered addition problems is 11.83 in the piece rate round, 13.12 in the tournament round, and 13.74 in the Choice 1 round. The increase in performance is likely to be due to learning effects and an increase in performance caused by the competitive compensation scheme applied to later rounds. There is no significant difference in piece rate performance between female and male subjects, but male subjects perform slightly better in the tournament (Table 4.1, Panel B), with 13.4 correct answers, compared to 12.6 correct answers for women.

Overall, 21% of participants chose the tournament compensation scheme in Choice 1 (Panel A). Only 16.5% of female subjects entered the tournament, while 27.5% of male subjects chose the tournament (Panel B). This difference is highly statistically significant (t-stat: -3.92).

On average, on a scale from 1 (best) to 4 (worst), subjects estimate their performance rank to be around 2. However, female subjects are less confident and estimate their performance rank to be significantly lower than male subjects (2.36 vs. 2.11, which is highly significant with a t-stat of 4.16). At the same time, they agree significantly less to the stereotype question whether men are better at solving math-related problems.

In the third session of our experiment, we added a question on how important knowledge in math is to subjects. Most subjects indicated that it is important for them to be good in math (average score of 3.77 on a scale ranging from zero (not important) to six (very important)), with no significant gender difference (Panel B).

4.2.4 Tournament entry without role models

In this section, we examine whether our experimental design delivers the same baseline result as in Niederle and Vesterlund (2007).

In Panel A of Table 4.2, we replicate Table I in Niederle and Vesterlund (2007) and report the mean past performance characteristics of subjects by choice of compensation scheme. As in Niederle and Vesterlund (2007), we find that there is no performance difference between female subjects who do and do not enter the tournament. In contrast, male subjects who chose the tournament perform significantly better than male subjects who chose the piece rate compensation in Choice 1. The difference is statistically significant for all three performance measures.

In Panel B of Table 4.2, we replicate Table II in Niederle and Vesterlund (2007). Specifically, we run logit regressions where the dependent variable is equal to one if a subject chooses the tournament compensation scheme in the third round of the experiment, and zero otherwise. As Niederle and Vesterlund (2007), we include subjects' performance in the tournament round as well as the performance difference between the tournament round and the piece rate round as a proxy for learning effects.

Column (1) shows odds ratios from logit regressions. They indicate that women are only half as likely as men to enter the tournament in the neutral condition. This difference is statistically significant at the 10% level. Controlling for subjects' tournament performance in column (2) and subjects' performance difference between the tournament and piece rate compensation scheme (column (3)) does not alter this finding. Female subjects are still only half as likely to enter the tournament than male subjects.

We conclude that our experimental design is suitable to replicate the main results of Niederle and Vesterlund (2007). This is important as we can now compare the impact of role models on the willingness to compete to a baseline effect that is derived from an already established experimental framework.

4.3 Role models and the willingness to compete

4.3.1 Validation of role model choice

We start by identifying potential female and male role models to be included in our experiment. For our treatment to work, the individuals we present in our videos need to be perceived as role models for competitiveness. In a pretest which is described in detail in Meier (2017), we searched and collected twelve videos of female and male individuals that we thought could serve as role models. They are listed in Appendix Table C.2.

These videos were then evaluated by a large pool of AMT workers (different from the subject pool in our experiment) who answered a survey on whether they perceived these individuals as role models for competitiveness. All of the potential role models are successfully working in competitive environments and are interviewed about their career path. In the videos, they stress their willingness to engage in competitive behavior in order to be successful, and how much they enjoy to compete. Role models' perceived competitiveness is measured using the four items on competitive motivation from the Motivational Trait Questionnaire from Heggestad and Kanfer (2000). We report the exact questions in Section C.5 of the Appendix. Subjects gave their answer to all items on 7-point Likert scales.

According to the literature, role model behavior is more likely to be imitated if the role model is perceived as likeable, if her behavior is rewarded, and if she is similar to the observer (Bandura, 1986). To examine whether likeability, perceived success, and similarity predict whether a person is seen as a role model, we run ordered probit regressions where the dependent variable is subjects' answer to the question whether the person seen in the video could be a role model. Answers were given on a 7 point Likert scale ranging from 0(=very untrue) to 6(=very true). As independent variables, we include subjects' ratings on whether they thought the person in the video was likeable, successful, competitive, and caring. We proxy for similarity between role model and subject by including a gender dummy.

Results in Panel A of Table 4.3 show that perceived likeability and the extent to which a person is seen as caring positively predicts whether she is seen as a role model. This result holds for both, female and male role models. However, being perceived as competitive has a negative impact on the eligibility of female role models (column (1)), but it has no such impact for male role models (column (2)). Furthermore, female subjects are less likely to accept a male person as potential role model (column (2)).

Based on the psychological literature (e.g., Bandura, 1986), a perfect role model in our context should be perceived as competitive and successful, at the same time very likeable, and also similar to the subject. However, the above findings show that it is quite hard to identify suitable female role models for our experiment, as counter-stereotypical behavior such as competitiveness seems to lower women's attractiveness as a role model. Out of the twelve potential role models, we identified two male and female role models each, that were perceived as competitive and displayed equal levels of likeability and role model potential. These role models are from two different competitive fields, sports and business. One male and one female role model are famous tennis players: Serena Williams and Roger Federer. Both of them had worldwide success for a number of years and became famous for winning an extraordinary number of tennis grand slam tournaments. The other two role models are successful business people: Marc Cuban and Nour Al Nuaimi. Marc Cuban, an American business man, became famous for his role as investor in "Shark Tank", an ABC reality television series. The show is about aspiring entrepreneur-contestants making business presentations and competing for funding. Nour Al Nuaimi is a private equity and venture capital investor, who is interviewed about her career aspirations and the enjoyment of competing.[7]

Panels B and C of Table 4.3 display female and male subjects' mean ratings for competitiveness, likeability, similarity, success and care for the female and male role models used in this paper. Results in column (1) show that both, female and male role models, are perceived to be equally competitive by female subjects. In contrast, male subjects perceive male role models to be significantly more competitive than female role models. In column (2), we compare the likeability ratings of our role models. Results show that, relative to midpoint three of the scale, female and male role models are perceived to be likeable. However, both female and male subjects perceive female role models to be slightly more likeable. Female and male role models' are perceived by all subjects to be

[7]We provide clean verbatim transcripts of all videos in section C.6 of the Appendix, available on our personal websites (e.g., https://www.bwl.uni-mannheim.de/niessen-ruenzi/forschung/).

comparable in terms of their success and whether they are caring or not (columns (4) and (5).

Overall, we are confident that male and female role models in our experiment do not differ on important dimensions that may confound our main results.

4.3.2 Tournament entry in role model conditions

We now investigate our main research question whether exposing female subjects to competitive role models changes their propensity to participate in tournaments. Table 4.4 reports odds ratios from logit models where the dependent variable is equal to one if a subject chooses the tournament compensation scheme in Choice 1, and zero otherwise. We use the same model specifications as in Panel A of Table 4.2 and subsequently add additional control variables that we elicited in our experiment.

Panel A of Table 4.4 displays tournament entry decisions for subjects who are shown a male role model (i.e., Marc Cuban or Roger Federer). In this condition, the coefficient on the female subject dummy is highly statistically significant. Specifically, the odds for a male subject to chose the tournament is 2.5 times larger than the odds for a female subject to choose the tournament. This difference is statistically significant at the 1% level for all specifications. Thus, compared to the neutral condition without role models (see Panel A of Table 4.2), male role models increase the gender gap in tournament entry even further. A possible reason is that male role models activate stereotype threat, which may intimidate female subjects and further decrease their willingness to compete.[8] Regarding the impact of the control variables, we find that subjects' tournament performance significantly increases the probability to enter the tournament (columns (2) and (3)). Adding subjects' age and education as control variables as well as including session fixed effects does not change this result (column (3)).

Panel B of Table 4.4 presents results for subjects who are shown a female role model (i.e., Nour Al Nuaimi or Serena Williams). In this condition, the gender gap in the propensity to enter the tournament disappears to a large extent. Marginal effects suggest that male subjects are still 1.5 times more likely to enter the tournament than female subjects, but this difference is not statistically significant anymore. We find that this effect is driven by female subjects entering the tournament more frequently: While 19.9% of female subjects

[8]In line with such an intimidating effect, in the tournament condition, female subjects solve significantly fewer math problems correctly than male subjects if they have seen a male role model (difference: -0.956, t-stat: -1.76). We do not observe a significant gender difference in performance in the piece-rate compensation scheme of the male role model treatment (difference: -0.547, t-stat: 1.10).

enter the tournament if they saw a female role model, only 14.1% do so if they saw either a male role model or the neutral video. In contrast, the fraction of men entering the tournament is almost the same independent of whether they saw a female role model or not (27.4% vs. 27.5%). Presenting a competitive female role model to female subjects thus indeed seems to encourage more women to enter the tournament.

Finally, we pool all observations and interact our female role model dummy with an indicator for female subjects (Panel C of Table 4.4). In column (1), we use the same set of control variables as in Niederle and Vesterlund (2007). Consistent with the patterns observed in Panels A and B, we find that female subjects are significantly less likely to enter the tournament than male subjects, but that the effect is mitigated to a large extent if they are exposed to a female role model. This result holds if we control for subjects' age and education (column (2)).

In column (3), we additionally control for subjects' perceived importance of math as a proxy for how serious they take this task, their perceived performance as a proxy for their confidence, and the time they needed to make their choice as a proxy for whether the decision was made rather spontaneously or thought through. Note that the sample size reduces significantly, since we only elicited the importance of math in one out of three experimental sessions. Thus, results in column (3) are based on one experimental session only. Results show that female subjects are still significantly less likely to choose the tournament than male subject, but that the effect is mitigated if they were exposed to a female role model.[9]

4.4 Which female subjects react most?

Increased tournament entry rates of female subjects are not necessarily socially optimal. Efficiency losses can occur both, when high performing women refrain from entering the tournament even though they would have good chances of winning, but also when low performing women enter the tournament even though they have little chances of winning. In our experiment, the best performing women (defined as those belonging to the top performance quartile) should enter the tournament, as they have a high chance (i.e.,

[9]In Appendix Table C.3, we additionally control for subjects' Choice 2, where they decide ex-post whether a piece-rate or a tournament compensation scheme should be applied to their performance in the first round. Niederle and Vesterlund (2007) use Choice 2 to examine whether gender differences in tournament entry are due to weaker preferences of female subjects to perform in a competition, or due gender differences in risk aversion or overconfidence. We still find that male subjects are more likely to enter the tournament than female subjects and that female role models mitigate the effect.

65%) of winning. They earn on average 8.67$ in the piece rate compensation scheme, while they receive on average 50$ if they win the tournament. Thus, their expected tournament payoff is 32.50$, which is nearly four times as large as their payoff under the piece-rate condition.[10]

Female role models would be an efficient instrument to achieve a socially optimal tournament entry rate, if they encourage the best performing women to enter the tournament, while they have no such effect on underperforming women. We now examine whether this is the case.

4.4.1 The impact of role models on high vs. low performing women

Previous literature in psychology suggests that high and low performing women might indeed react differently to female role models. According to Marx and Roman (2002), women with a high math competence may be most subject to stereotype threat and thus profit most from role models, which buffer this threat. For women with low math competence, subtyping may impede the impact of role models on their willingness to compete. According to the concept of subtyping, members of a group may view an individual that dis-confirms stereotypes of that group as being an exception from the rule and place them in a separate category (Richards and Hewstone (2001), Ziegler and Stoeger (2008)), i.e., low performing women will be less likely to see successful women as role models and thus will not be encouraged by them. Moreover, a lack of perceived attainability may lead subjects to become intimidated by dissimilar role models such that they cannot benefit as much from the role model as subjects with higher perceived attainability (Marx and Ko, 2012; Lockwood and Kunda, 1997).

In Table 4.5, we report odds ratios from logit regressions run separately for subjects in the highest and lowest performance quartiles, respectively. We use two alternative performance measures. In Panels A and B, high and low performers are defined based on their actual performance in the piece rate round. In Panels C and D, high and low performers are defined based on their own perception on how they think they performed in the piece rate round. The latter measure could also be interpreted as a proxy for subjects' self-confidence regarding performing well in the calculation task.

[10]Of course, the standard deviation of payoffs in the tournament condition is much higher. However, to rationalize a decision of the best performing females to choose the piece-rate would require implausibly high levels of risk aversion.

In column (1), the sample is restricted to female subjects only, while column (2) presents results for male subjects only. Results in column (3) are based on both, female and male subjects. We use the same set of control variables as before.

Results in column (1) of Panel A show that observing a female role model has a significantly positive effect on female subjects' propensity to enter the tournament in the highest performance quartile. Specifically, female subjects who are shown a female role model are 3.8 times more likely to enter the tournament, than female subjects who are shown no role model or a male role model. This finding is in line with Breda, Grenet, Monnet, and Effenterre (2018), who show that an in-class intervention of a female role model increases the probability of applying to a science major in college, particularly for high-achieving female students.

By contrast, results in column (2) of Panel A show that being shown a female role model does not impact the tournament entry decision for the best performing men. This result is similar to Carrell, Page, and West (2010), who show that professor gender does not impact male students' performance or selection of future courses. One potential reason for male subjects not reacting to role models may be that they do not face a stereotype threat discouraging them from competing.[11] When pooling together both, male and female subjects in column (3), we find that female subjects are again significantly less likely to enter the tournament. However, this effect is mitigated if a female subject is shown a female role model.

Results for the best performing women are very similar if we sort subjects into performance quartiles based on their perceived performance in the piece rate round (Panel C). Being exposed to a female role model seems to have a particularly strong effect on female subjects who think that they are good in solving math related problems in the piece rate condition. This again points at a potential stereotype threat that reduces women's willingness to compete, although their actual and perceived performance would qualify them to participate the tournament.

Results in Panels B and D show coefficient estimates for subjects in the lowest actual or perceived performance quartiles, respectively. For this group, there are no significant role model effects, neither for female nor for male subjects.

[11] We also perform a probit regression for male subjects with a dummy for the male role model and do not find a significant result (marginal effect: 0.118, t-stat: 1.23).

4.5 Do female models reduce stereotype threat?

According to Steele and Aronson (1995), an individual exposed to stereotype threat feels at risk of confirming a negative preconception about his or her group. This may lead to a distortion of beliefs about own abilities (Bordalo, Coffman, Gennaioli, and Shleifer, 2019). Ultimately, stereotypes can even lead to changes in behavior, such as actual worse performance (Spencer, Steele, and Quinn, 1999). In our case, the widespread stereotype that women are worse at math than men (Guiso, Monte, Sapienza, and Zingales, 2008) may cause female subjects to estimate their performance to be lower even though this is actually not the case (see Table 3.6, Panel B). As a result, they may experience higher anxiety when facing a tournament entry decision and thus decide not to compete.

Marx and Roman (2002) suggests that in-group counter-stereotypical role models can buffer the individual against stereotype threat, i.e., women who compete successfully against men increase women's math performance (Marx and Roman, 2002). Therefore, we now test whether female role models in our experiment reduce female subjects' stereotype threat.

In column (1) of Table 4.6, we report results from an ordered probit regression. The sample is restricted to female subjects only. The dependent variable is subjects' perceived stereotype threat. It reflects the extent to which subjects agree to the statement that men are better at solving math-related problems, ranging on a scale from 0 (very untrue) to 6 (very true). That is, a higher value indicates a stronger stereotype threat. We find that female subjects' stereotype threat is indeed significantly reduced if they were exposed to a female role model. Female role models may thus indeed serve as counter-stereotypes that buffer our female subjects against the negative impact of stereotype threat on their willingness to compete.

In column (2) of Table 4.6, we test whether this is indeed the case. Specifically, we regress female subjects' choice to enter the tournament on a dummy for whether they have seen a female role model, our measure of stereotype threat, the interaction of these variables, and our standard set of control variables. For women who did not see a female role model, stereotype threat significantly decreases their willingness to compete. However, the negative impact of stereotype threat on tournament entry is mitigated for female subjects exposed to a female role model.

4.6 Discussion and conclusion

There is broad evidence in the literature that, compared to men, women are more likely to shy away from competing with others. This effect has been suggested as one possible reason why there are only few women in top management positions or other leadership positions. Many efforts have been undertaken by governments to increase the fraction of women in these positions with the aim of establishing gender equality.

We suggest a new mechanism that helps encouraging women to self-select in competitive environments and trust more in their own abilities: Exposing them to female role models, i.e., successful women who express their preference for competition and their aspiration to belong to the best. These counter-stereotypical role models encourage their female observers to view competition more positively and eventually self-select into competitive environments - a necessary condition to climb up the career ladder and reach top management positions. The effects we document are particularly strong among the best performing women, for whom it is typically most beneficial to enter competitions. Female role models seem to reduce the negative influence of gender stereotypes on women's willingness to compete by increasing women's self-confidence and alleviating the impact of negative stereotype threats.

Increasing women's willingness to compete by nudging them with female role models may not be socially optimal if women prefer not to compete and, as a consequence, competing means disutility. However, if women's preference not to compete is the result of nurture rather than nature, raising awareness about gender stereotypes and providing counter-stereotypical examples may not only increase women's willingness to compete, but also their utility.

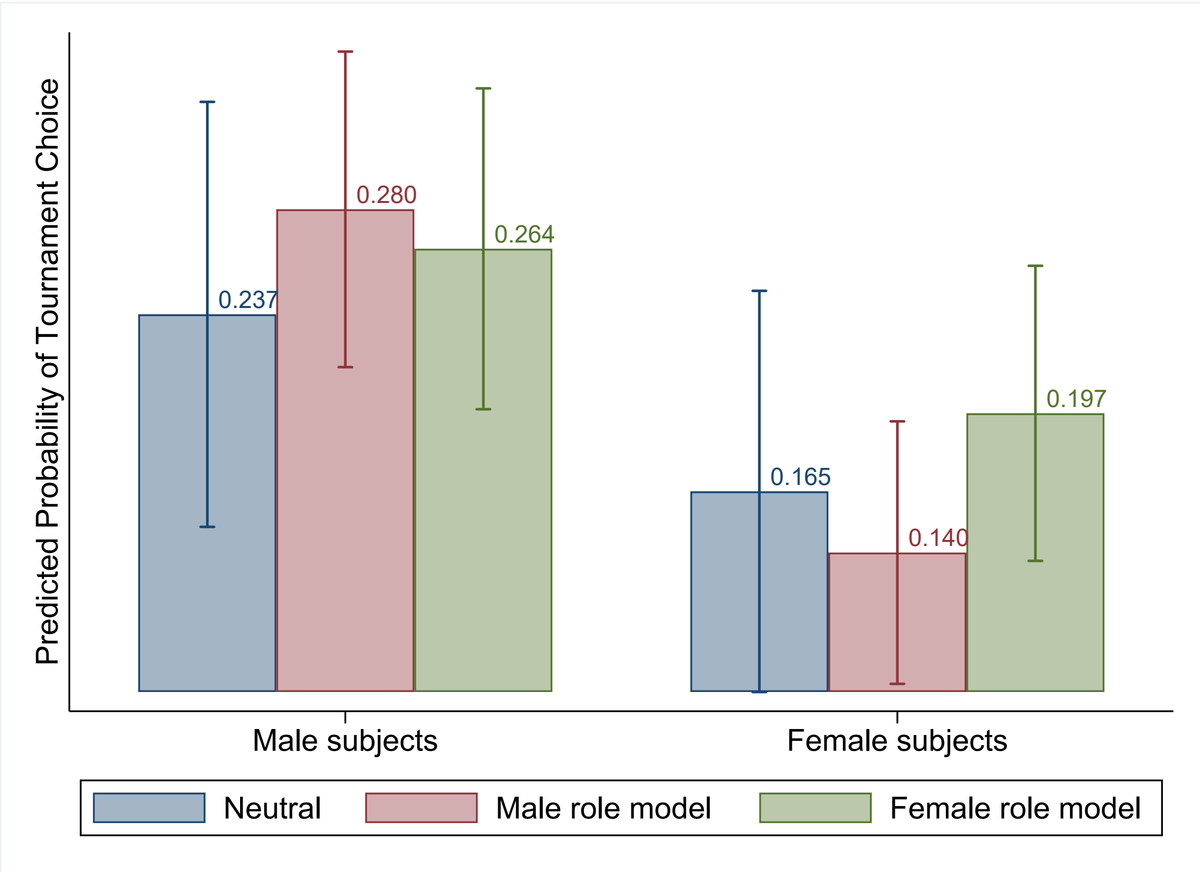
Our findings show that even a short-term intervention of introducing a female role model has an impact on women's subsequent behavior. The cost of providing such role models seem to be rather low as the underlying incentives to compete do not have to be changed. Successful and competitive women just need to become more visible. If counter-stereotypical role models are persistently available, attitudes towards competing women are likely to change and stereotypes are weakened (Bohnet, 2016).

Can gender quotas lead to a provision of such role models? In principle, yes, but only if the quota is constructed very carefully to make sure that no underqualified women are hired for or promoted to top positions and then eventually underperform. Otherwise, these women could be seen as a negative role models, which might discourage other women from entering career competitions even more.

4.7 Figures Chapter 4

Figure 4.1: Tournament entry by role model condition

This figure shows tournament entry rates of female and male participants in each role model condition (male, female, and neutral). Predicted entry rates and 95% confidence intervals are obtained from estimating logit regressions for each role model condition (neutral, male, female), separately. The tournament-entry decision of Choice 1 is the dependent variable (1 for tournament and 0 for piece rate). We include the same set of control variables as in column (2) of Table 4.4.



4.8 Tables Chapter 4

Table 4.1: Summary statistics

Panel A of table shows summary statistics (mean, standard deviation (sd), median (p50), 1st percentile (p1), 99th percentile (p99), and the number of observations (N)) for all subjects in our experiment. Panel B reports means for all male subjects (column (1)), means for all female subjects (column (2)), differences in means between male and female subjects (column (3)), and p-values based on two-sided t-tests (column (4)). All variables are defined in detail in Appendix C.1

Panel A: Whole sample						
	mean (1)	p50 (2)	sd (3)	p25 (4)	p75 (5)	N (6)
Female subject	0.483	0	0.500	0	1	838
Subject age	4.668	4	2.186	3	6	838
College education	0.377	0	0.485	0	1	838
Piece rate performance	11.59	11	4.506	9	14	838
Tournament performance	12.94	13	4.915	10	16	838
Performance Choice 1	13.62	13	5.056	10	16	838
Tournament-piece rate	1.374	1	2.086	0	2	838
Choice 1	0.220	0	0.414	0	0	838
Choice 2	0.153	0	0.360	0	0	838
Perceived performance	2.230	2	0.875	2	3	838
Stereotype threat	1.674	1	1.752	0	3	838

Panel B: Gender differences				
	mean male (1)	mean female (2)	diff. m-f (3)	p-value (4)
Subject age	4.413	4.941	-0.527	0.000
College education	0.393	0.360	0.0321	0.338
Piece rate performance	11.81	11.35	0.458	0.139
Tournament performance	13.23	12.62	0.609	0.071
Choice 1 performance	13.94	13.28	0.664	0.056
Tournament-piece rate	1.457	1.284	0.173	0.230
Choice 1	0.275	0.160	0.114	0.000
Choice 2	0.194	0.109	0.0854	0.000
Guessed piece rate rank	2.102	2.368	-0.266	0.000
Stereotype threat	1.947	1.383	0.564	0.000

Table 4.2: Tournament entry in neutral condition

Panel A of this table shows average math scores of female and male subjects conditional on the compensation scheme that they have chosen in Choice 1. Differences between subjects choosing the piece rate vs. tournament compensation scheme in Choice 1 are computed for each of the performance measures (columns (1) to (3)). Panel B of this table shows average marginal effects from logit regressions. The tournament-entry decision of Choice 1 is the dependent variable (1 for tournament and 0 for piece rate). z-statistics based on robust standard errors are reported in parentheses. All variables are defined in detail in Appendix C.1. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Performance by choice of compensation scheme			
		Average performance	
	Piece rate round	Tournament round	Tournament-piece rate
	(1)	(2)	(3)
Choice 1 of female subjects			
Piece rate	11.24	12.49	1.24
Tournament	11.68	13.33	1.43
Difference	0.44	0.84	0.19
Choice 1 of male subjects			
Piece rate	11.35	12.71	1.33
Tournament	12.83	14.49	1.91
Difference	1.48***	1.78***	0.58*

Panel B: Logit regressions of tournament entry			
	(1)	(2)	(3)
Female subject	–0.108*	–0.110*	–0.111*
	(–1.75)	(–1.77)	(–1.77)
Tournament performance		0.009	0.008
		(1.48)	(1.15)
Tournament-piece rate			0.003
			(0.23)
Pseudo R^2	0.018	0.033	0.033
Observations	163	161	160

Table 4.3: Finding suitable role models

This table shows subjects' evaluations of role models for female (Panel A) and male subjects (Panel B), separately. Mean ratings for competitiveness and likeability of the role model are provided in columns (1) and (2), respectively. Mean ratings for role model's perceived success is provided in (column (3), and mean ratings for whether a role model is perceived to be caring are displayed in column (4). Moreover, the table shows the difference in ratings between the male and female role models, and the corresponding p-values. All variables are defined in detail in Appendix C.1. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Female subjects (N=405)				
	Competitive (1)	Likeable (2)	Successful (3)	Caring (4)
Male role models	4.62	4.96	6.52	5.79
Female role models	4.59	5.15	6.65	5.87
Difference (m-f role models)	0.03	-0.19	-0.13	-0.08
p-value	0.82	0.09	0.12	0.54

Panel B: Male subjects (N=433)				
	Competitive (1)	Likeable (2)	Successful (3)	Caring (4)
Male role models	4.86	4.74	6.42	5.46
Female role models	4.43	4.97	6.48	5.62
Difference (m-f role models)	0.43	-0.23	-0.06	-0.14
p-value	0.00	0.04	0.46	0.22

Table 4.4: Tournament entry in role model conditions

Panels A and B of this table show average marignal effects from logit regressions. The tournament-entry decision of Choice 1 is the dependent variable (1 for tournament and 0 for piece rate). Panel A (B) shows average marginal effects estimated for subjects who saw a male (female) role model. Panel C shows results from a linear probability regression of the tournament-entry decision on the interaction of subjects' gender and a dummy variable indicating if the role model was female. z-statistics based on robust standard errors are reported in parentheses. Missrel indicates whether the sample only includes observations with a missing value score of one or less. Panel D shows the odds of choosing the tournament for female and male subjects conditional on whether they saw a female role model, or were in the male or neutral condition. All variables are defined in detail in Appendix C.1. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Male role model condition			
	(1)	(2)	(3)
Female subject	–0.147***	–0.140***	–0.162***
	(–3.39)	(–3.28)	(–3.38)
Tournament performance		0.008	0.016***
		(1.58)	(3.15)
Tournament-piece rate		0.006	0.008
		(0.53)	(0.66)
College education		-0.033	–0.064
		(-0.69)	(–1.19)
Subject age		-0.008	0.007
		(-0.66)	(0.51)
Session FE	No	No	Yes
Missrel <= 1	No	No	Yes
Pseudo R^2	0.031	0.056	0.118
Observations	343	341	247

Table 4.4: Tournament entry in role model conditions cont'd

Panel B: Female role model condition			
	(1)	(2)	(3)
Female subject	–0.075	–0.067	–0.033
	(–1.65)	(–1.48)	(–0.63)
Tournament performance		0.004	0.006
		(0.78)	(0.88)
Tournament-piece rate		0.001	–0.017
		(0.05)	(–1.08)
College education		0.069	0.070
		(1.49)	(1.33)
Subject age		–0.020*	–0.011
		(–1.68)	(–0.82)
Session FE	No	No	Yes
Missrel <= 1	No	No	Yes
Pseudo R^2	0.007	0.025	0.038
Observations	341	337	239

Table 4.4: Tournament entry in role model conditions cont'd

Panel C: All conditions (neutral, male, female)			
	(1)	(2)	(3)
Female subject × Female role model	0.059	0.058	0.112*
	(1.01)	(0.99)	(1.70)
Female subject	–0.134***	–0.124***	–0.140***
	(–3.78)	(–3.49)	(–3.51)
Female model	–0.001	–0.011	–0.032
	(–0.03)	(–0.24)	(–0.65)
Tournament		0.007*	0.014***
		(1.71)	(3.64)
Tournament-piece rate			–0.000
			(–0.00)
College education		–0.004	–0.013
		(–0.13)	(–0.39)
Subject age		–0.018***	–0.005
		(–2.74)	(–0.72)
Session FE	No	No	Yes
Missrel <= 1	No	No	Yes
Adj. R^2	0.057	0.061	0.141
Observations	847	838	582

Panel D: Expected odds of tournament entry			
	Margin	Std. error	z-stat
	(1)	(2)	(3)
male subject & male or neutral condition	0.3901	0.067	5.78
male subject & female role model	0.3179	0.072	4.39
female subject & male or neutral condition	0.1139	0.030	3.76
female subject & female role model	0.2437	0.059	4.12
Pseudo R^2	0.058		
Observations	582		

Table 4.5: Impact of role models on tournament entry conditional on performance

This table shows coefficients from a linear probability models. The dependent variable is tournament entry, which is equal to one if a subject chooses the tournament compensation scheme in Choice 1, and zero otherwise. In columns (1) and (2) (columns (3) and (4)), the sample is restricted to all female subjects in the highest (lowest) performance quartile. We include the same control variables as in Table 4.4. t-statistics based on robust standard errors are reported in parentheses. Missrel indicates whether only subjects with a missing values score of one or less are included in the regression. All variables are defined in detail in Appendix C.1. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	High performer		Low performer	
	(1)	(2)	(3)	(4)
Female subject × Female role model	0.237*	0.337**	–0.008	0.030
	(1.76)	(2.13)	(–0.08)	(0.32)
Female subject	–0.208**	–0.259**	–0.083	–0.118*
	(–2.31)	(–2.35)	(–1.39)	(–1.91)
Female model	–0.117	–0.188*	–0.017	–0.035
	(–1.24)	(–1.75)	(–0.24)	(–0.44)
Tournament	0.024**	0.019	–0.019	0.005
	(2.09)	(1.50)	(–1.52)	(0.31)
Tournament-piece rate	–0.014	–0.008	0.027*	0.008
	(–0.64)	(–0.34)	(1.87)	(0.52)
College education	–0.039	–0.039	–0.004	–0.056
	(–0.57)	(–0.47)	(–0.07)	(–0.97)
Subject age	0.014	0.038	–0.029***	–0.017*
	(0.52)	(1.12)	(–3.18)	(–1.70)
Session FE	No	Yes	No	Yes
Missrel<=1	No	Yes	No	Yes
Adj. R^2	0.039	0.044	0.051	0.022
Observations	177	131	260	177

Table 4.6: Gender stereotypes and perceived performance

Results in this table are based on ordered logit regressions. The sample is restricted to female subjects. In columns (1) and (2), the dependent variable is subjects' agreement to a gender stereotype question. Agreement to the statement "Men are more skilled at solving math-related problems." is measured on a seven-point Likert scale, ranging from 0 = "Very untrue" to 6 = "Very true". In columns (3) and (4), the dependent variable is subjects' perceived performance in the piece-rate round ranging from 1 (best) to 4 (worst). We include the same set of control variables as in Table 4.4. z-statistics based on robust standard errors are reported in parentheses. All variables are defined in detail in Appendix C.1. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	Gender stereotype		Perceived performance	
	(1)	(2)	(3)	(4)
Female subject × Female role model	0.020	–0.076	–0.228	0.049
	(0.07)	(–0.24)	(–0.86)	(0.15)
Female model	–0.454**	–0.473**	0.029	–0.123
	(–2.50)	(–2.21)	(0.15)	(–0.53)
Female subject	–0.567***	–0.649***	0.656***	0.482**
	(–3.69)	(–3.51)	(3.83)	(2.36)
Tournament	–0.028*	0.001	–0.127***	–0.146***
	(–1.81)	(0.04)	(–6.89)	(–6.14)
Tournament-piece rate	0.028	0.023	0.314***	0.363***
	(0.79)	(0.54)	(7.96)	(6.90)
College education	–0.008	0.036	–0.022	0.022
	(–0.06)	(0.23)	(–0.16)	(0.13)
Subject age	–0.068**	–0.007	0.068**	0.013
	(–2.15)	(–0.19)	(2.19)	(0.37)
Pseudo R^2	0.015	0.018	0.066	0.075
Observations	838	584	838	584

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Appendix A

Appendix for Chapter 2

A.1 Variable description

This table defines all variables used in the empirical analysis. Any variable referring to the firms in an institutional investor's portfolio always refers only to those holdings made available through 13F. I use the following abbreviations for the data sources (in alphabetical order):

- Bushee: Institutional Investor Classification Data (1981 – 2018) as provided by Brian Bushee on his website https://accounting-faculty.wharton.upenn.edu/bushee/ and downloaded on 21.02.2019
- Compustat: Compustat Annual updates
- CRSP: CRSP's stocks database
- Execucomp: Compustat's Execucomp database on executive compensation
- KPSS: Patent data used in Kogan, Papanikolaou, Seru, and Stoffman (2017), downloaded from Dimitris Papanikolaou's website at https://iu.app.box.com/v/patents downloaded on 07.09.2020
- TR: Thomson Reuters's 13F filings database

Variable name	Description	Source
Institutional level data		

Variable name	Description	Source
Investor age	Age of the institutional investor in quarter q measured as the number of quarters since it first appears in the Thomson Reuters 13F filings.	TR
Firms in portfolio	The number of individual stocks an institution holds in quarter q.	TR
Portfolio concentration	Normalized Herfindahl-Hirschman Index = (hhi - 1/N)/(1-1/N), where hhi is the sum of portfolio weights of firms held by an institution squared and N is the number of firms in an investor's portfolio.	TR, CRSP
MV portfolio	Average market value of the portfolio (sum of MV stake) of an institution i in quarter q.	TR, CRSP
Is blockholder	Fraction of portfolio firms in which the institution is a blockholder, i.e., holds at least 5% of shares outstanding.	
Dedicated	Dummy variable equal to 1 if the institution is classified as a "dedicated" investor according to Bushee (1998) and 0 otherwise.	Bushee
Quasi-indexer	Dummy variable equal to 1 if the institution is classified as a "quasi-indexer" according to Bushee (1998) and 0 otherwise.	Bushee
Transient	Dummy variable equal to 1 if an institutional investor is classified as a "transient" investor according to Bushee (1998) and 0 otherwise.	Bushee
IO	Percent of shares outstanding in portfolio firm owned by institutional investors averaged per institutional investor	TR, CRSP
% shares owned	Percent of shares outstanding of firm j owned by institution i in quarter q.	TR, CRSP
% owned by blockholders	Percent of shares outstanding of portfolio firm owned by a blockholder.	

Variable name	Description	Source
MV stake	Average market value of shares held in firms in quarter q.	TR, CRSP
Firm age	Average age of firms held by institution i in quarter q in years measured as the current date minus the date when the firm first appeared in CRSP.	TR, CRSP
Volatility (q-8, q-1)	Average volatility of firms held by institution i in quarter q measured as the standard deviation of monthly returns over the past 2 years.	TR, CRSP
Share turnover (q-1)	Average share turnover of firms held by institution i in quarter q, where share turnover is volume/shares outstanding, measured for the previous quarter.	TR, CRSP
Momentum (q)	Average percentage return earned in the current quarter of firms held by institution i in quarter q.	TR, CRSP
Momentum (q-3, q-1)	Average percentage return earned in the previous three quarters of firms held by institution i in quarter q.	TR, CRSP
Firm level data		
Failure tolerance	Measures the amount of time and resources a firm's institutional investors, on average, invested in firms with CEOs who failed in the past 5 years (from year t - 4 to year t).	TR, Execucomp
Failure tolerance (non-aggregated)	Measures the amount of time and resources an institutional investor invested in firms with CEOs who failed in the past 5 years (from year t - 4 to year t).	TR, Execucomp
IO	Percent of shares outstanding owned by institutional investors.	TR, CRSP

Variable name	Description	Source
Failure tolerance (10y)	Measures the amount of time and resources a firm's institutional investors, on average, invested in firms with CEOs who failed in the past 10 years (from year t - 9 to year t).	TR, Execucomp
Failure tolerance (LI)	Measures the amount of time and resources a firm's largest institutional investors in firms with CEOs who failed in the past 5 years (from year t - 4 to year t).	TR, Execucomp
R&D stock	Cumulative sum of past R&D expenditures (XRD). I follow Hall, Jaffe, and Trajtenberg (2005) and calculate R&D stock as $G_t = R_t + (1 - \delta)G_{t-1}$, where R is the R&D expenditure in year t and $\delta = 0.15$, the depreciation rate. I interpolate missing values of R&D.	Compustat
K/L	Capital-to-labor ratio, where capital is property, plants, and equipment (PPE), and labor is the number of employees.	Compustat
Sales	Sales (item: sale), measured at the end of the previous fiscal year.	Compustat
Assets	Total assets.	Compustat
Firm age	The number of years since a firm's first stock return appears in CRSP.	CRSP
ROA	Return on assets = (Operating income before depreciation (item: oibdp)/ Total assets (item: at) at the end of the previous fiscal year).	Compustat
Tobin's Q	Market-to-book ratio is calculated as the market value of equity plus the book value of assets minus the book value of equity minus the balance sheet deferred taxes divided by the book value of assets.	Compustat

Variable name	Description	Source
Patents	The number of eventually granted patents in the fiscal year in which their application was filed, winsorized at the 99th percentile.	KPSS
Citations	The citation-weighted number of eventually granted patents in the fiscal year in which their application was filed, winsorized at the 99th percentile. I weight each patent with the number of forward citations it received divided by the average number of forward citations received by patents filed in the same year as the patent. See Kogan, Papanikolaou, Seru, and Stoffman (2017), equation (9).	KPSS
Market value	The yearly sum of ξ, the estimated economic value of a patent, as defined in equation (3) of Kogan, Papanikolaou, Seru, and Stoffman (2017), in millions of dollars (nominal), with $\bar{\pi} = \frac{1}{0.44}$ and $\delta = 1 - e^{-0.0146}$, that is, the total dollar value of innovation due to patents filed in year t to firm j.	KPSS

A.2 Descriptive statistics

This Appendix contains detailed supplementary information on descriptive statistics of my main independent variable.

Figure A.1 illustrates the development of both the percentage of forced turnovers in the firms held by the institutions in my sample as well as the average $Failure\ tolerance$ of institutions by quarter averaged per year. I use year fixed effects in all models to control for the observed time trends. Table A.1 shows mean and median values of $Failurtolerance$ by year. In line with the literature (Kaplan and Minton, 2012; Huson, Parrino, and Starks, 2001), the table shows a consistent increase in the number of institutions I observe per year.

Figure A.1: Forced turnovers and Failure tolerance

This figure shows forced turnovers and $Failure\ tolerance$ (NA) over the years 1992 to 2017. The left axis depicts the average fraction of institution-firm-quarters per year with forced turnovers averaged on the institutional-quarter level. The right axis shows the average number of quarters out of 5 years institutions invested in a forced-out CEO.

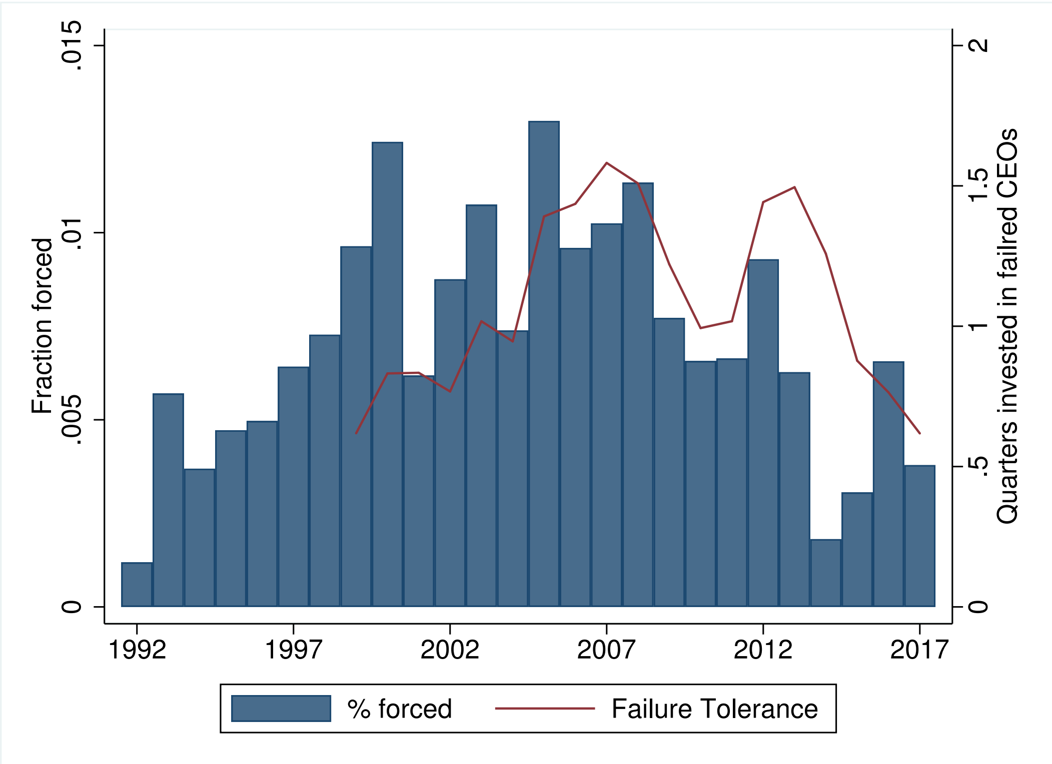

Table A.1: Average Failure tolerance per year

This table reports mean and median *Failure tolerance* (NA) of institutional investors by year. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix A.1.

Year	N	Mean	Median
1999	3,581	0.619	0.538
2000	3,799	0.832	0.76
2001	4,110	0.834	0.769
2002	4,550	0.768	0.691
2003	5,029	1.018	0.937
2004	5,435	0.946	0.859
2005	5,898	1.391	1.350
2006	6,236	1.437	1.390
2007	6,448	1.584	1.566
2008	6,695	1.513	1.489
2009	7,096	1.227	1.190
2010	7,654	0.997	0.967
2011	8,110	1.018	0.969
2012	8,620	1.443	1.387
2013	9,047	1.496	1.425
2014	9,212	1.259	1.185
2015	9,465	0.877	0.806
2016	9,748	0.764	0.644
2017	9,900	0.618	0.471

Appendix B

Appendix for Chapter 3

B.1 Variable description

This table briefly defines all variables used in the empirical analysis. In the variable descriptions, t refers to either the month of a turnover announcement if there was a CEO turnover in the fiscal year or the month of the fiscal year end if there was no CEO turnover in the fiscal year.

Variable name	Description	Source
Δ ROA[-1,1]	Abnormal change in ROA from the fiscal year before to the fiscal year after a CEO turnover. The abnormal change is calculated as the residuals of a regression of the change in ROA on the following variables from the turnover year: Idiosyncratic Return, Industry Return, BTM, ROA, Assets (log), Analysts Following, Analyst Dispersion, VIX, Retirement Age, High Ownership, Tenure and year and industry fixed effects.	Compustat, CRSP, Execucomp, I/B/E/S Summary History
Activism	A dummy variable that takes on the value 1 if an activist filed an initial 13D filing in the past 12 months, and 0 otherwise. A 13D filing is defined to be "initial," if it is the first 13D filing filed for a subject company by an investor.	SEC EDGAR

Variable name	Description	Source
Amihud (log)	Log of the yearly average of daily Amihud ratio, which is measured as the absolute daily return, divided by the daily trading volume in dollars (items: [abs(ret)/ prc $\times$ vol], adjusted for delistings and stock splits).	CRSP
Analyst Dispersion	Monthly standard deviation (item: stdev) of 1-year earnings forecasts divided by the absolute value of mean earnings estimate (item: meanest), averaged over months t-1 to t-12.	I/B/E/S Summary History
Analyst Following	Monthly number of analysts following (item: numest) for 1-year earnings forecasts, averaged over months t-1 to t-12.	I/B/E/S Summary History
Assets	Total assets (item: at) at the end of the previous fiscal year.	Compustat Fundamentals Annual
Assets (log)	Log of total assets (item: at) at the end of the previous fiscal year.	Compustat Fundamentals Annual
BTM	Book-to-market ratio = Book value of common equity(item: ceq) /Market value of common equity (item: csho $\times$ prcc_f) at the end of the previous fiscal year.	Compustat Fundamentals Annual
Busy	A dummy variable that takes the value 1 if the fraction of busy directors on the board is larger than the median value in the same year, and 0 otherwise. Busy directors are defined as directors holding 3 or more directorships at other firms.	Institutional Shareholder Services

Variable name	Description	Source
CAR [-1,1]	The sum of abnormal returns over the time window d-1 to d+1, where d refers to the announcement date of a CEO turnover and abnormal returns are measured relative to the market model.	CRSP
CEO Age	Age of the incumbent CEO at the end of the previous fiscal year.	Execucomp + hand-collected data
CEO Tenure	A dummy variable that takes the value 1 if the tenure of the CEO is larger than the sample median, and 0 otherwise.	Execucomp
Co-Opted	A dummy variable that takes the value 1 if the fraction of independent directors elected to the board after the CEO started her tenure is larger than the median value in the same year, and 0 otherwise. We follow Coles, Daniel, and Naveen (2014) and use the co-opted fraction of the previous fiscal year if the annual meeting date is after the CEO turnover announcement date. For non-turnover years, we use the average of the co-opted fraction from the previous and the current fiscal year.	Data from Coles, Daniel, and Naveen (2014)

Variable name	Description	Source
Diversity	A dummy variable that takes the value 1 if the diversity of the board is larger than the median value in the same year, and 0 otherwise. To determine diversity, we follow Bernile, Bhagwat, and Yonker (2018) and use the percentage of female directors (pct_fem), the standard deviation of directors' age (age_sd), the average number of other directorships (avg_other), director ethnicity (hhi_ethnicity), directors' financial expertise (hhi_fin), and directors' education (hhi_edu) for the diversity index: Div = pct_fem + age_sd + avg_other - hhi_ethnicity - hhi_fin - hhi_edu.	Institutional Shareholder Services, BoardEx
Financial Expertise	A dummy variable that takes the value 1 if the fraction of directors defined to be financial experts (acc. to SOX) is larger than the median value in the same year, and 0 otherwise.	Institutional Shareholder Services
Forced	A dummy variable that takes on the value 1 if a CEO turnover is classified as forced (according to the classification by Parrino (1997)), and 0 otherwise.	Execucomp, LexisNexis
High Ownership	A dummy variable that takes on the value 1 if the CEO's equity ownership (item: shrown_excl_opts) in % of shares outstanding (item: shrout) is larger than 5%, and 0 otherwise.	Execucomp, CRSP
Idiosyncratic Return	Cumulative idiosyncratic return over 12 months, calculated as the residuals from a regression of the 12-month cumulative holding period return (item: ret) on the 12-month cumulative value-weighted industry holding period return (in the same FF48 industry. For further details see Jenter and Kanaan (2015).	CRSP

Variable name	Description	Source
Idiosyncratic Return Q1	Linear spline of the variable *Idiosyncratic Return* for the lowest of five quintiles	Own calculation
Independence	A dummy variable that takes the value 1 if the fraction of independent directors (item: classification = "I") on the board is larger than the median value in the same year.	Institutional Shareholder Services
Industry Return	Average cumulative industry return over 12 months, calculated as the predicted values from a regression of the 12-month cumulative holding period return (item: ret) on the 12-month cumulative value-weighted industry holding period return in the same FF48 industry. For further details see Jenter and Kanaan (2015).	CRSP
Jensen's alpha $\alpha_{m+2,m+12}$	Alpha of regressions of equal- and value-weighted monthly calendar portfolios of stocks over the 2 to 12 months after a forced or voluntary CEO turnover on the monthly Fama-French (excess market return, SMB, HML) and momentum (UMD) factors (methodology closely related to Mitchell and Stafford (2000)).	CRSP, Kenneth R. French's homepage
Leverage	Book leverage (items: (dltt+dlc)/(dltt+dlc+pstkl-txditc+ceq)) at the end of the previous fiscal year.	Compustat
Ownership	% of shares outstanding owned by the CEO at the end of the previous fiscal year.	Execucomp
Payslice	A dummy variable that takes the value 1 if the CEO pay slice is larger than the median value in the same year, and 0 otherwise. Payslice is defined as the fraction of the total compensation (tdc1) of the 5 top executives of the firm earned by the CEO.	Execucomp

Variable name	Description	Source
Pilot	A dummy variable that takes on the value 1 if the firm was classified as a Category A Pilot Security firm by the SEC as part of Regulation SHO, and 0 otherwise.	FTSE Russel 3000 constituents in 2004, SEC list of pilot firms of Regulation SHO
Pre	Dummy variable that takes on the value 1 in the period from January 2001 to June 2004 (and 0 otherwise)	
During	Dummy variable that takes on the value 1 in the period from November 2005 to January 2008 (and 0 otherwise)	
Post	Dummy variable that takes on the value 1 in the period from February 2008 to January 2010 (and 0 otherwise)	
R&D	R&D over assets (items: xrd/at) at the end of the previous fiscal year.	Compustat
Retirement Age	A dummy variable that takes on the value 1 if the CEO is over 63 years old (item: age), and 0 otherwise.	Execucomp
ROA	Return on assets = (Operating income before depreciation (item: oibdp)/Total assets (item: at) at the end of the previous fiscal year) minus median ROA in the same FF48 industry.	Compustat Fundamentals Annual
Sales Growth	Annual change in sales, i.e. current sales/last year's sales (item: sale), measured at the end of the previous fiscal year.	Compustat

Variable name	Description	Source
Share Ownership	A dummy variable that takes the value 1 if the fraction of shares outstanding owned by the directors is larger than the median value in the same year, and 0 otherwise.	Institutional Shareholder Services
Short Interest	Average of short interest over months t-1 to t-12, where short interest in month t (item: shortintadj) is measured in % of shares outstanding (item: shrout) at the end of month t-1 and adjusted for median short interest in month t in the same FF48 industry.	Compustat Supplemental Short Interest File, CRSP, FF48 Industries
Size	A dummy variable that takes the value 1 if board size, i.e. the number of directors sitting on the board, is larger than the median value in the same year, and 0 otherwise.	Institutional Shareholder Services
Tenure	Tenure (in years) of the CEO in month t, calculated as the time between month t and the first month as CEO in the office (item: becameceo).	Execucomp
VIX	Monthly CBOE Volatility Index, averaged over months t-1 to t-12.	Chicago Board Options Exchange

B.2 Short interest as a predictor of forced turnover

In Section 3.4.3 of the paper, we use linear probability models to show that short interest significantly predicts forced turnovers even when controlling for a range of other firm performance indicators including idiosyncratic stock returns. We use linear probability models to analyze CEO turnover throughout the paper because, in most of our analyses, our main variables of interest are interaction variables, and interpreting significance levels and magnitudes of interaction effects in non-linear models is not straightforward (Ai and

Norton, 2003). However, hazard models and probit models are arguably more suitable for modeling CEO turnover. To show that the results in Section 3.4.3 are not artifacts of using the arguably less suitable linear probability model and since this analysis does not contain interaction effects, we repeat it using probit regressions and the Cox (1972) proportional hazard model.

[Insert Table B.1 about here]

Table B.1, Panel A shows the results from probit regressions of forced turnover on different sets of control variables. The coefficient on short interest is positive and statistically highly significant in all specifications. When setting all variables to their means in our most comprehensive model in column (3), a one standard deviation increase in short interest is associated with an increase in the probability of forced turnover by 0.19 percentage points. This constitutes a 15% increase in the probability of forced turnover compared to the probability of 1.3% when all variables are at their means.

Panel B in Table B.1 shows coefficients from Cox hazard regressions of forced turnover on short interest. In column (1), short interest is positive and highly statistically significant. When adding a set of control variables in column (2) and industry fixed effects in column (3), the coefficient remains highly statistically significant.[1] The magnitude of the effect is very similar to the effect we find in the probit model: A CEO in a firm with one standard deviation higher short interest than the industry mean faces a 14% ($exp(0.038 * 3.52) = 1.143$) higher probability of being fired in the next month.

[1]Since the model already takes the time the CEO has been in office into account, we do not control for CEO tenure as we do in the probit models.

Table B.1: Probit and Cox hazard regressions of forced CEO turnovers on short interest

This table shows the results of Probit and Cox models of forced CEO turnover. In column (1) of Panel A, we regress a dummy variable for forced turnover on our measure of short interest. Column (2) includes a set of control variables, and column (3) additionally includes year and industry fixed effects (FE). In Panel B, we repeat the regression from Panel A using Cox hazard regressions, except that we do not control for tenure in columns (2) and (3). z-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix B.1.

Table B.1: Probit and Cox hazard regressions of forced CEO turnovers on short interest cont'd

Panel A: Probit regressions			
Dependent Variable: Forced	(1)	(2)	(3)
Short Interest	1.9005***	1.4822***	1.4793***
	(5.24)	(3.90)	(3.66)
Idiosyncratic Return	-0.7174***	-0.7194***	-0.7051***
	(-8.93)	(-7.47)	(-7.36)
ROA		-0.6283***	-0.9213***
		(-3.37)	(-5.03)
BTM		0.2188***	0.2406***
		(4.19)	(4.53)
Industry Return		-0.2328***	-0.3786***
		(-2.58)	(-3.43)
Assets (log)		-0.0084	0.0228
		(-0.63)	(1.46)
Analysts Following		0.0061**	0.0024
		(1.96)	(0.69)
Analyst Dispersion		0.0794**	0.0780**
		(2.16)	(2.10)
VIX		0.0048*	0.0003
		(1.71)	(0.03)
Retirement Age		-0.4186***	-0.4110***
		(-6.28)	(-6.08)
High Ownership		-0.4423***	-0.4630***
		(-5.08)	(-5.25)
Tenure		-0.0091***	-0.0089***
		(-2.96)	(-2.86)
Constant	-2.1462***	-2.1634***	-2.9123***
	(-84.84)	(-20.94)	(-12.17)
Aux.p	0.0533	0.0881	0.1168
Observations	31,866	31,866	31,383
Year FE	N	N	Y
Industry FE	N	N	Y

Table B.1: Probit and Cox hazard regressions of forced CEO turnovers on short interest cont'd

Panel B: Cox hazard regressions			
Dependent Variable: Forced	(1)	(2)	(3)
Short Interest	5.7200***	3.7282***	3.5245***
	(6.81)	(4.21)	(3.74)
Idiosyncratic Return	-1.8846***	-2.0947***	-1.9874***
	(-14.54)	(-12.48)	(-11.53)
ROA		-1.7761***	-2.1474***
		(-4.19)	(-5.79)
BTM		0.5049***	0.6347***
		(4.55)	(5.78)
Industry Return		-0.7753***	-1.2017***
		(-4.06)	(-4.96)
Assets (log)		0.0483	0.1096***
		(1.62)	(3.08)
Analysts Following		0.0116	0.0111
		(1.62)	(1.38)
Analyst Dispersion		0.0904	0.1543*
		(1.09)	(1.92)
VIX		0.0241***	-0.0215
		(4.04)	(-0.83)
Retirement Age		-1.3667***	-1.2503***
		(-7.69)	(-6.79)
High Ownership		-1.7702***	-1.7853***
		(-7.34)	(-7.30)
Chi^2	294.691	603.086	2947.815
Observations	30636.000	30636.000	30636.000
Year FE	N	N	Y
Industry FE	N	N	Y

B.3 Shareholder activism during Regulation SHO

In Section 3.5, we report results on the effect of Regulation SHO on the probability of forced CEO turnover. We conduct two separate analyses, one for a sample of small firms and one for a sample of large firms because large control firms were subject to different conditions than small control firms. We find a significant effect of Regulation SHO on the probability of forced turnover in the large firm experiment but not in the small firm experiment.

In Section 3.6.2 we identify shareholder activism as an important channel through which short interest influences CEO turnover decisions. If short sellers influence turnover decisions through shareholder activists, then Regulation SHO should also increase shareholder activism for the channel to be at work in this setting. In Section 3.6.2, we therefore also briefly analyze the effect of Regulation SHO on the probability of shareholder activism. In Figure 3.3 in the paper, we observe that the level of activism increases for treated firms in the large but not in the small firm sample. We test the differences that can be observed in Figure 3.3 using linear probability models of monthly activism in Table B.2 for both the small and the large firm sample. We regress a dummy variable equal to one if a firm was targeted by an activist campaign in this month and zero otherwise on difference-in-difference dummy variables for both the during and the post period as well as industry and month fixed effects. The two time dummies are subsumed by the month fixed effects. We find that the probability of being targeted by shareholder activists significantly increases for pilot firms in the treatment period compared to control firms in our large firm sample ($p = 6.6\%$). We do not find a comparable effect in our small firm sample, where the coefficient is negative and insignificant. Hence, Regulation SHO may have not impacted CEO dismissals in the small firm sample because it did not influence an important channel for the effect.

[Insert Table B.2 about here]

Table B.2: Regulation SHO: DiD models of shareholder activism

This table shows the results of linear probability models of activism in the Regulation SHO period. Columns (1) and (2) report the results for our small firm and large firm sample, respectively. We regress a dummy variable for activism on difference-in-difference variables for the treatment group and period. Both columns include industry fixed effects (FE). t-statistics are provided in parentheses. Robust standard errors are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Variables are defined in detail in Appendix B.1.

Dependent Variable: Activism	Small firms (1)	Large firms (2)
Pilot	-0.0001	-0.0001
	(-0.18)	(-0.10)
During × Pilot	-0.0015	0.0029*
	(-1.04)	(1.84)
Post × During	0.0024	0.0006
	(1.58)	(0.44)
R^2	0.002	0.002
Observations	173,815	91,274
Month FE	Y	Y
Industry FE	Y	Y

Appendix C

Appendix for Chapter 4

C.1 Variable description

This table defines all variables used in our empirical analysis. All data are collected from amazon mechanical turk (AMT).

Variable name	Description
Caring	A subject's perception of how caring the role model is measured on a 7-point semantic differential (0=not caring to 6=caring).
Choice 1	A dummy variable that takes on the value of 1 if a subject chooses the tournament payment scheme in round 3, and zero otherwise.
College education	A dummy variable equal to 1 if a subject indicated having a university degree or higher, and zero otherwise.
Competitiveness	A subject's perception of the role model's competitiveness based on 6 items taken from the competitive motivation part of the Motivational Trait Questionnaire by Heggestad and Kanfer (2000). Cronbach's alpha of the composite competitiveness variable is 0.8368.
Female role model	A dummy variable equal to one if a subject is allocated to the female role model condition, and zero otherwise.
Female subject	A dummy variable equal to one if a subject is female, and zero if it is male.

Variable name	Description
Female subject	A dummy variable equal to one for female subjects, and zero for male subjects.
Likeability	A construct measuring a subject's perception of the role model's likeability based on three semantic differentials.
Missrel	Percentage of missing answers weighted by the other participants' answering behavior. Questions that are rarely answered (e.g., voluntary text questions) are mostly irrelevant for this value, questions that most participants have answered weight worse. The linear weighting factor for a question/item is the number of answers given to this question/item divided by how often the question/item has been asked. Variable is provided by the Socsci platform.
Perceived performance	A subject's estimate of her performance rank in the piece-rate round, ranging from 1 (best) to 4 (worst).
Performance Choice 1	Number of correctly solved addition problems in the third round under the compensation scheme that the subject chose.
Piece rate performance	Number of correctly solved addition problems in the first round under the piece rate compensation scheme.
Role model	A subject's average response on a 7-point Likert scale to 4 items from Ragins (1999): "I think X's behavior is worth striving for," "X is someone I could identify with," "X could be a role model for me," and "X represents someone I would like to be," where "X" is replaced with the role models name and where 0 = "Very Untrue" and 6 = "Very True". Scale reliability coefficient (Cronbach's alpha): 0.8871.
Stereotype threat	A subject's degree of agreement to the statement "Men are more skilled at solving math-related problems.", ranging from 0 = "Very Untrue" to 6 = "Very True".
Subject age	Age of subject elicited in 11 bins.

Variable name	Description
Success	A subject's perception of how successful th role model is, measured on a 7-point semantic differential (unsuccessful - successful).
Tournament performance	Number of correctly solved addition problems in the second round under the tournament compensation scheme.
Tournament-piece rate	The difference in the number of correctly solved addition problems between the tournament and the piece rate round.

C.2 List of potential role models

This table shows the initial list of potential role models that were then used to isolate those that received the highest agreement on the question "the person in the video could be a role model for me". Some videos may not be online anymore, but are available from the authors upon request.

Table C.1: Potential role models

Female role models	1. Sheryl Sandberg https://www.youtube.com/watch?v=VqF2ZoGdbYM 2. Marissa Mayer https://www.youtube.com/watch?v=Dyvd9fyXpDM 3. Serena Williams https://www.youtube.com/watch?v=LSyyd4CgIBY https://www.youtube.com/watch?v=51WLGMseTL0 4. Jennifer Fan https://www.youtube.com/watch?v=a1zGAFYAvH8 5. Nour Al Nuaimi https://www.youtube.com/watch?v=e3MkSsPMGpw 6. Woman in Sales & Trading https://www.youtube.com/watch?v=q62WjCtP0yk
Male role models	1. Marc Cuban https://www.youtube.com/watch?v=QTbbCBqRi98 2. Kevin Systrom https://www.youtube.com/watch?v=EoksbaFBTwU &list=PLG7JvYPJw5oOcPzFaddOUt_zflOKj1T-p 3. Roger Federer https://www.youtube.com/watch?v=mzP8-4D0o9w 4. Ryan Israel https://www.youtube.com/watch?v=JoiCKo2WdTc 5. Rodolfo Martell https://www.youtube.com/watch?v=YxPiHbK_w7c 6. Wall street trading floor https://www.youtube.com/watch?v=EX33ZpRPoUU

C.3 Additional tables

Table C.2: Tournament entry controlling for Choice 2

This table shows odds ratios from logit regressions. The tournament-entry decision of Choice 1 is the dependent variable (1 for tournament and 0 for piece rate). In column (1) ((2)), the sample is restricted to subjects in the male (female) role model condition. In column (3), all observations including the neutral treatment are pooled and we interact the female role model dummy variable with an indicator for female subjects. z-statistics based on robust standard errors are reported in parentheses. All variables are defined in detail in Appendix C.1. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table C.2: Tournament entry controlling for Choice 2 cont'd

	Male role models (1)	Female role models (2)	Interactions (3)
Female subject	–0.097**	0.009	–0.112**
	(–2.22)	(0.20)	(–2.20)
Female subject × Female role model			0.174*
			(1.96)
Female role model			–0.057
			(–0.88)
Tournament performance	0.007	0.005	0.003
	(1.58)	(1.08)	(0.71)
Tournament-piece rate	0.020	0.019	0.037
	(1.01)	(0.21)	(0.44)
College education	–0.037	0.061	0.023
	(–0.87)	(1.31)	(0.55)
Subject age	0.008	–0.007	–0.006
	(0.82)	(–0.54)	(-0.61)
Choice 2	0.315***	0.333***	0.530***
	(9.70)	(9.30)	(6.79)
Importance of math			–0.016
			(–1.26)
Perceived performance			–0.036
			(–1.55)
Time choice 1			0.004*
			(1.71)
Session FE	Yes	Yes	Yes
Missrel<= 1	Yes	Yes	Yes
Pseudo/Adj. R^2	0.361	0.224	0.340
Observations	247	238	274

C.4 Overview of experimental procedure

1	2	3	4	5	6	7	7	8
Demo-graphic question-naire	Treat-ment	Manipu-lation check 1	**Addition task 1:** Piece Rate	**Addition task 2:** Tour-nament	**Addition task 3:** Choice 1	**Submit task 1:** Choice 2	**Relative self-assess-ment**	Manipu-lation check 2

C.5 Instructions and questions

C.5.1 Intro

Screen 1 (Introduction and summary of the experiment)

Welcome!

Thank you very much for supporting our research. This HIT consists of three parts. You will receive a fixed payment of $5 for completing all parts of this HIT. In addition, you can earn a bonus depending on your performance in the second part. All of your information will be treated anonymously and used solely for our research.

At the end of the HIT we will show you a random code. You must copy the code into the original window of Amazon Mechanical Turk in order to receive your payment for this HIT. Therefore, it is very important that you **leave the original window open for the whole time**.

Next

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C.5.2 Demographic questionnaire

Screen 2 (Demographic questionnaire)

What is your gender?

- ◯ male
- ◯ female

How old are you?

[Please choose]

What is your highest educational achievement?
Please select the highest level of qualification you have obtained.

- ◯ Left school with no qualifications
- ◯ Still in school
- ◯ Secondary school-leaving certificate / Junior High Diploma
- ◯ High school diploma / Intermediate / General Certificate of Secondary Education, secondary school-leaving certificate or equivalent
- ◯ Completed apprenticeship
- ◯ Vocational baccalaureate diploma / vocational secondary certification
- ◯ A-levels / International Baccalaureate / higher education entrance qualification
- ◯ Vocational university / university of applied sciences / university degree
- ◯ Other degree:

Next

C.5.3 Treatment

[In the experiment, subjects view one of 5 videos. There are two different videos for the female role model treatment, two different videos for the male role model treatment, and one video for the no role model treatment. In this Appendix, we show a screenshot from the video and the corresponding control and manipulation check questions for the video about Nour Al Nuaimi and for the video for the neutral condition. The questions for the other male and female role model videos are the same as for the video on Nour Al Nuaimi except for the respective names.]

Screen 3 (Introduction to Treatment)

Part 1

Before clicking on "Next", please TURN ON THE SOUND of your computer.

On the next screen, we will show you a video. The video will be followed by questions on how you perceive the person you saw in the video.

The video is about 5 minutes long. After the video is finished, you will be automatically forwarded to the next page.

Please make sure that the SOUND of your computer is now ON as you will not be able to repeat the video.

Next

Screen 4 (Treatment video)

[Screenshot from the video of Nour Al Nuaimi (female role model treatment)]

[Screenshot from the video on Uluru (no role model treatment)]

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Screen 5 (Control question)

[Control question for the role model videos]

What is the occupation of the main character in the video?

Next

[Control question for the neutral video]

Name one thing that appeared in the video.

Next

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C.5.4 Manipulation check 1

[This part of the experiment consists of a survey on the perceived personal characteristics of the role models shown in the video. The answers serve as part of our manipulation check.

Here, we show which questions subjects received who saw Nour Al Nuaimi. In other role model treatment, the respective name of the role model was displayed. In addition, we show the items subjects in the no role model treatment received.]

Screen 6 (Instructions for the manipulation check questionnaire)

Please note when answering the following questionnaire:

- There are no right or wrong answers in this part of the HIT. Simply describe your perceptions honestly and accurately.
- Deciding on an answer may be difficult for some of the statements. If you have a hard time deciding, choose the answer that is MOST true.
- Some of the items will seem repetitive. Do not look back at your previous answers, simply answer each question honestly.

Next

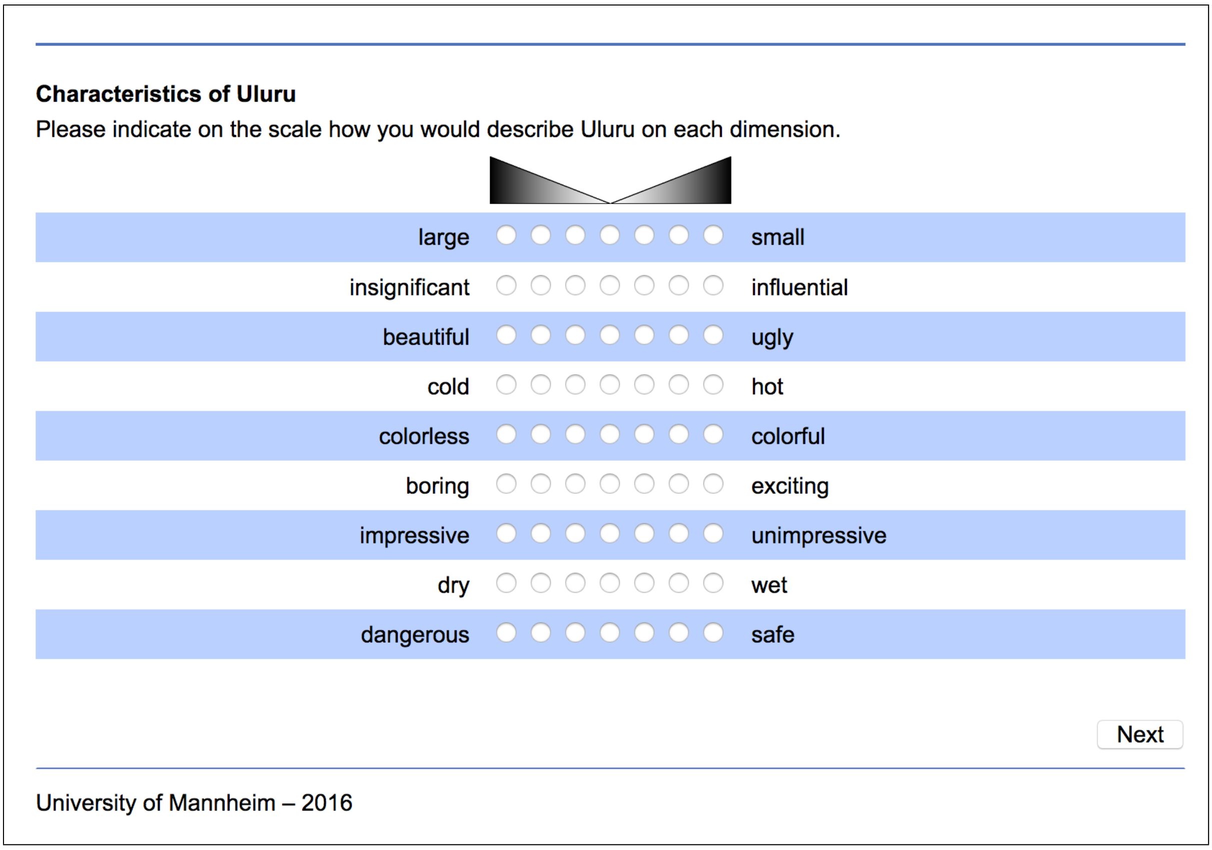
Screen 7 (Questions on characteristics)

Characteristics of Nour Al Nuaimi

Please indicate on the scale how you would describe Nour Al Nuaimi on each dimension.

successful	○ ○ ○ ○ ○ ○ ○	unsuccessful
unlikeable	○ ○ ○ ○ ○ ○ ○	likeable
powerful	○ ○ ○ ○ ○ ○ ○	powerless
agreeable	○ ○ ○ ○ ○ ○ ○	disagreeable
mathematically talented	○ ○ ○ ○ ○ ○ ○	mathematically untalented
risk averse	○ ○ ○ ○ ○ ○ ○	risk loving
insignificant	○ ○ ○ ○ ○ ○ ○	influential
selfish	○ ○ ○ ○ ○ ○ ○	not selfish
competent	○ ○ ○ ○ ○ ○ ○	incompetent
ineffective	○ ○ ○ ○ ○ ○ ○	effective
not manipulative	○ ○ ○ ○ ○ ○ ○	manipulative
unsupportive	○ ○ ○ ○ ○ ○ ○	supportive
pleasant	○ ○ ○ ○ ○ ○ ○	unpleasant
not caring	○ ○ ○ ○ ○ ○ ○	caring

Next



Characteristics of Uluru

Please indicate on the scale how you would describe Uluru on each dimension.

large	small
insignificant	influential
beautiful	ugly
cold	hot
colorless	colorful
boring	exciting
impressive	unimpressive
dry	wet
dangerous	safe

Next

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Screen 8 (Items on competitiveness and similarity)

[This screen was only shown to subjects who were either in the male or female role model condition, not to subjects in the neutral treatment condition.]

Behavior of Nour Al Nuaimi

Please indicate the degree to which each of the following statements is true of Nour Al Nuaimi.

Some of the statements may refer to situations that you have not directly observed for Nour Al Nuaimi. Respond to these statements in terms of how true you think it would be.

	Very UNTRUE						Very TRUE
Nour Al Nuaimi performs best when she competes with others.	○	○	○	○	○	○	○
Nour Al Nuaimi tries to avoid competitive situations.	○	○	○	○	○	○	○
Nour Al Nuaimi likes to turn things into a competition.	○	○	○	○	○	○	○
Even in non-competitive situations, Nour Al Nuaimi finds ways to compete with others.	○	○	○	○	○	○	○
Nour Al Nuaimi is a competitive person.	○	○	○	○	○	○	○
Nour Al Nuaimi would rather cooperate than compete.	○	○	○	○	○	○	○

	NOT similar at all						Very similar
How similar do you perceive Nour Al Nuaimi to be to you?	○	○	○	○	○	○	○

Next

C.5.5 Addition task 1

Screen 9 (Introduction to Addition tasks)

Part 2

Part 2 consists of **four rounds** where we will assess your mathematical skills. None of the rounds will take more than 3 minutes. One of these rounds will be randomly selected as a basis for an **additional performance-dependent bonus**, which you can earn on top of the fixed payment of $5 that you get for completing all parts of this HIT.

Next

Screen 10 (Introduction to the Piece Rate task)

Round 1 - Piece Rate

In the following, you will be asked to calculate the sum of five randomly chosen two-digit numbers. You will be given 3 minutes to calculate as many of these sums as possible.

You are welcome to use a calculator or make notes on scratch paper.

Next

Screen 11 (Instructions Piece Rate task)

Example:

67	46	76	88	95
372	Submit			

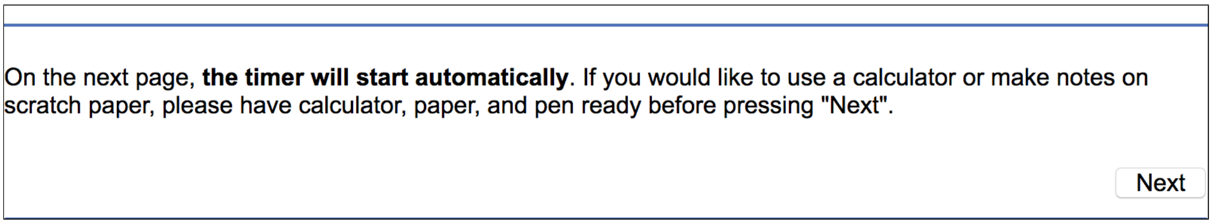
In this round you need to add up the five numbers given and then insert your answer using your keyboard. You submit an answer by clicking the submit button with your mouse. When you enter an answer you are immediately told whether your answer is correct or not. In the above example, the given answer is correct: 67 + 46 + 76 + 88 + 95 = 372. As soon as you submit an answer, the next 5 numbers will appear. **Remember, you have 3 minutes to calculate as many of these sums as possible.**

If Round 1 is the one which is randomly selected to determine your bonus payment, you get **50 cents for each correct answer.**

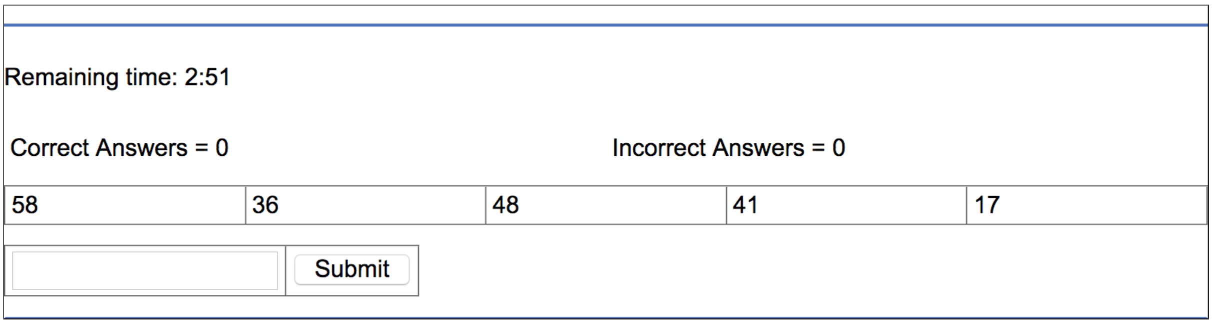
Please let us know if you understand these instructions. If anything, what did you not understand?

Next

Screen 12 (Note on timer and calculator)



Screen 13 (Addition task)



Screen 14 (Number of correct answers)

C.5.6 Addition task 2

Screen 15 (Explanation on tournament groups)

Round 2 - Tournament

As in Round 1, you will be given 3 minutes to calculate the correct sum of a series of five 2-digit numbers.

However, for this round your payment depends on your performance relative to that of a group of other workers in this HIT. Including yourself, each group consists of four people: two male and two female participants. We will assign the three other members of your group randomly over all AMT workers who complete this HIT.

Next

Screen 16 (Explanation on tournament payment)

If Round 2 is the one which is randomly selected for your bonus payment, then your earnings depend on the number of correct answers you give compared to the three other people in your group. The group member with the highest number of correct answers will receive a bonus of **$4 for each correct answer**, while the other participants receive **no bonus** payment.

You will not be informed of how you performed in the tournament until all rounds have been completed. If there are ties the winner will be randomly determined.

Please let us know if you understand these instructions. If anything, what did you not understand?

Next

Screen 17-18 (Addition task and number of correct answers as in Task 1)

[Subjects worked on the addition task using an identical screen as in Addition Task 1. Afterwards, they were shown the number of correct answers as in Addition Task 1.]

C.5.7 Addition task 3

Screen 19 (Explanation on payment scheme choice)

Round 3 - Choice

As in the previous two rounds, you will be given 3 minutes to calculate the correct sum of a series of five 2-digit numbers. This time, you can **choose** yourself which of the two previous **payment schemes** you prefer to apply to your performance on the third round.

Your earnings for this round are determined as follows:

- If you choose the **piece rate** you receive **50 cents per correct answer** .
- If you choose the **tournament** your performance will be evaluated relative to the performance of the other three participants of your group in the previous tournament. If you give more correct answers than your group members did in Round 2, then you receive eight times the payment from the piece rate, which is **$4 per correct answer**. You will receive no payment for this round if you choose the tournament and do not give more correct answers than the others in your group did in the previous tournament. You will not be informed of how you did in the tournament until all rounds have been completed. If there are ties, the winner will be randomly determined.

Please let us know if you understand these instructions. If anything, what did you not understand?

Next

Screen 20 (Choice between payment schemes)

Please select the payment scheme you would like to apply to your performance in the third round.

- ○ Piece rate
- ○ Tournament

Next

Screen 21-22 (Addition task and number of correct answers as in Task 1)

[Subjects worked on the addition task using an identical screen as in Addition Task 1. Afterwards, they were shown the number of correct answers as in Addition Task 1.]

C.5.8 Submit task 1

Screen 23 (Explanation on submitting task 1 results)

Round 4 - Submit Your Round 1 Answers

You do not have to perform anymore calculations in this round. Instead, your bonus payment in this round depends again on the number of correct answers you provided in Round 1. You now have to **choose** which **payment scheme** you want applied to your previous performance in Round 1. You can either choose the piece rate payment scheme or the tournament payment scheme.

Next

Screen 24 (Choice between payment schemes)

Your score in Round 1 – Piece Rate was:

Choice

Please select the payment scheme you would like to apply to your performance in Round 1.

- ○ Piece rate
- ○ Tournament

Next

C.5.9 Relative self-assessment

Screen 25 (Explanation relative self-assessment)

On the next page you will be asked to estimate your performance relative to your other group members. If you think you performed better than all other group members, your estimated rank would be 1. If you think you performed worst, your estimated rank would be 4. For each correct estimation you will receive a **bonus of $1** .

In case of ties in the actual ranks, we will count all possible ranks as correct. For example, if you tied for the second place, then answering rank 2 and rank 3 is correct.

Next

Screen 26 (Relative self-assessment)

Rank in Round 1 – Piece Rate

Please select a number between 1 [best] and 4 [worst] to indicate how well you think you performed in the piece rate round.

[Please choose]

Rank in Round 2 – Tournament

Please select a number between 1 [best] and 4 [worst] to indicate how well you think you performed in the tournament round.

[Please choose]

Next

C.5.10 Manipulation check 2

Screen 27 (Introduction for the final questionnaire)

Part 3

We only have a couple of questions left.

As in Part 1, there are no right or wrong answers in this part of the HIT.

Next

Screen 28 (Manipulation check 2 questionnaire and subjects' math background)

[Questions on whether the role model is perceived as a role model are taken from Ragins (1999).]

Personal attitudes

Please indicate the degree to which the following statements are true.

	Very UNTRUE … Very TRUE
I knew Nour Al Nuaimi before seeing this video.	
I think Nour Al Nuaimi's behavior is worth striving for.	
Nour Al Nuaimi is someone I could identify with.	
Nour Al Nuaimi could be a role model for me.	
Nour Al Nuaimi represents someone I would like to be.	
If I perform poorly, others will attribute my poor performance to my gender.	
Men are more skilled at solving math-related problems.	
It is important for me to be good at math.	

1. What is your background in math?

Please indicate all the options that apply to you.

- I have no special knowledge / interest in math.
- I am taking / took advanced math classes in highschool.
- I major / have majored in a mathematical field in college (e.g., engineering, math, physics, economics).
- I have had or have a job that involves math skills.

Next

C.5.11 Outro

Screen 29 (Instructions for payment code)

Thank you for completing this HIT!

You will receive a reward of **$5** plus your **bonus**, which depends on your performance in Part 2. We will calculate your bonus after the HIT has been completed and add it to your reward through AMT's "award a bonus" function.

Below you can find the code you need in order to complete the HIT on Amazon Mechanical Turk. Please copy and paste this code into the original window in Amazon Mechanical Turk. Do not press "Next" without having copied the code. **You will not receive payment for this HIT without the code!** After copying the code, you can close this browser window.

Code: B75LhwgJHN

Next

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Screen 30 (Thank you)

Thank you for completing this HIT!

Your answers were transmitted, you may close the browser window or tab now.

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C.6 Transcripts

C.6.1 Serena Williams

Anchorwoman: Serena Williams is in pursuit of her 17th Grand Slam singles title at the US Open. Andy Roddick sat down with Williams to talk legacy, fashion, and being Andy's second tennis star during his stay in the Big Apple.

Serena Williams: I'm always behind Roger.

Andy Roddick: So you're a little bitter that I interviewed Roger before I interviewed you?

Serena: No, I'm just always behind Roger. In Grand Slams, everything. Everyone is behind Roger, though.

Serena: I'm always saying when I am playing my best, it is difficult for anyone to beat me.

[sound cut]

Serena: Just staying positive, and staying happy and calm on the court.

Andy: I have known you since we were kids.

Serena: Yes, when I beat you.

Andy: Well, you did not even let me get to my first question. You just had to pipe in with that "you beat me." I mean--

Serena: [laughs]

Andy: So the next thing I was going to say before you completely ruined it was that you beat me when we were ten years old. Where does that rank in your list of career accomplishments?

Serena: Well for me it is number one or number two. The reason it ranks so high is because through you I have indirectly basically beaten everyone on the men's door.

Andy: So it is like the Kevin Bacon rule of tennis: You're only one win away from Pete, Roger--

Serena: Exactly, I have beaten Roger, because I have beaten you; I have beaten Raphael Nadal, I have beaten Pete Sampras. You name them I have beaten them because I beat you.

Speaker: From the public courts of Compton, California, to US Open Champion--

Andy: You have a lot of history here, good and bad: your first slam victory, some on-court incidents. We both had some meltdowns here before [laughs].

Serena: [laughs]

Andy: What is your relationship like with this tournament when you come back? Is it good, bad?

Serena: Being American is always, you know-- It is so special to play on [sic] Arthur Ashe Stadium. It is so special to come out here and play in the Grand Slam. Even though I've had some different experiences here, my first and best memory is winning here in 1999. So it doesn't get better than that.

Andy: I'd be remiss if we were at the US Open and we didn't talk about unfortunate wardrobe choices. How do you--

Serena: Tell me, what are you talking about? I've liked my wardrobe choices at the open.

Andy: What I want to know is how do you think I would look like in a catsuit?

Serena: I think you would look really hot in a catsuit. I think you would look really hot. We would of course have to adjust it and make it a little longer. Maybe we just gave it a full length leg.

Andy: Would my butt be bigger than yours in a catsuit?

Serena: That catsuit was fabulous. Yes, because you have a really big butt [laughs].

Andy: [laughs]

Serena: You have a huge butt. It's underrated.

Andy: That's heights of hypocrisy. That's heights of hypocrisy that I haven't seen before.

Serena: It is underrated.

Andy: Two girls from Compton in a predominantly white sport, coming through, being the best. I mean, if you get one story like that–but you have a sister who has accomplished the same thing. Are you ever able to grasp the enormity of that and what it all means?

Serena: Not yet. I feel like myself and my sister we still are playing and we want to do well. I feel like if I were to sit back and I were to think, "Oh my god that is kind of cool!", then I would become satisfied. I would be, like, "Why am I still playing tennis?" So, I try not to think about it too much, but I do see somewhat the fruits of our labor. There is [sic] so many American ladies playing right now. So many African American ladies doing well. It is really exciting to see everyone doing so well and knowing that the torch will be passed.

[music and infograph are blended in: "Most Grand Slam Women's Singles Titles (Open Era): Steffi Graf 22, Chris Evert 18, M. Navratilova 18, Serena Williams 16"]

Andy: What's left to accomplish?

Serena: Records. Right?

Andy: Don't ask "Right?" to me. I never broke a record.

Serena: You did, you had a serving record.

Andy: That's broken. That's gone now. I don't even know I had one.

Serena: You had it for a while.

Andy: For a little bit. It's called renting it. You own it.

Serena: [laughs] Records are always made to be broken. I don't know if I can break some records, but there's [sic] some records that I would like to break and that I have broken. So, I play now for history, and I also play now for fun.

C.6.2 Nour Al Nuaimi

Nour Al Nuaimi: My name is Nour Al Nuaimi. I recently graduated from the Harvard Business School with an MBA. Let me start off from the beginning. I went to high school in Sharjah and I went to [foreign language] private school. I graduated and went to the American University of Sharjah. Initially my major was architecture. My parents wanted me to be an engineer. I loved drawing and it was just a natural fit. However, a good mentor/friend of mine suggested that I consider majors in business administration. Amongst these majors I selected finance, because it was the most technical of majors. In addition to the fact that it opens up so many different career paths such as corporate finance, investments, banking.

During my time in the US, my English wasn't that great. I had kind of a thick accent. So I would watch TV series such as Grey's Anatomy or Friends. I would listen to how someone is pronouncing a certain word. I would pause, repeat it, and then continue watching all my show [sic]. It took some time, about a year or so, to have good English. After the US, I graduated and wanted to be a trader. That came from my time interning with Deutsche Bank. I walked into the trading floor and I saw, and I heard, and I felt the excitement coming from the trading desks. Eight computer screens in front of them. They were speaking on two phones, sometimes, yelling, buying, selling stuff. I knew that I wanted to do that. Trading basically is buying and selling securities, like stocks, to make a profit. The strategy is simple, but it takes experience to learn how to do that correctly over and over again.

I decided to do it [**unintelligible 00:02:11**] full-time at Standard Chartered Bank. So I was with Standard Chartered Bank for about three years. I was very successful in my role. I'm glad to have had a mentor that believed in tough love. He gave me thirty seconds, literally, to prepare for a meeting. My first meeting ever. And told me go. That was a terrifying feeling. It was in my first month on the job, but with time and going through a lot of other experiences like that, I've developed a thicker skin.

After my time at Standard Chartered Bank, I decided to get an MBA in order to benefit my career in the long run. I decided to go to the Harvard Business School. A lot of people actually asked me, "Why do you have to go abroad to get your MBA?" To me, the value of an MBA was 30%, only 30% academic, and 70% everything else. And by everything else, I mean extracurricular activities, CEOs coming to school and giving talks. Even socializing with your friends. My peers were very successful, from all over the world, and have had amazing experiences in their life. I learned a lot from them.

After my time at HBS, I decided to work in New York for a couple of months to supplement my learning and my MBA. I worked at Perella Weinberg Partners, which is a boutique investment bank in New York City. I did that for three months. I learned a lot from the asset management function. It was a different working environment, working in a city like New York. If you asked me five, ten, fifteen years ago that I'd be where I am today, I wouldn't believe you. What I feel drove me to here was, number one, my education, number two, my experience at Standard Chartered Bank, and, number three, my MBA at the Harvard Business School. It opened up so many doors and opportunities that I did not think possible. My goal with these three things that I have is to, number one, continue to challenge myself both professionally and personally in the years to come. To continue to be a sponge, to learn as much as possible, and to further develop my skillset. From a more long-term perspective, is to hopefully one day start my own investment company or fund that invests in companies in emerging markets across the globe that emphasize and focus on social development.

C.6.3 Roger Federer

Andy Roddick: --talk about Michael Jordan, you talk about Tiger Woods, they all talk about, they are competitors. These guys are built. They'll rip your head off. They are just these insane guys. But I don't feel like that adjective is applied to you, when people are discussing you. It has to be in there, right? It is not all talent?

Roger Federer: No, it cannot be all talent. I mean, I have worked hard. I think it has got to be that fire and ice. I think, I am more in the part where I love winning, and the other guys are maybe more in the "I hate losing" bit. And because I really enjoy winning, I enjoy playing. Maybe I don't show it, but I have that grit.

Andy: With all you've accomplished and the long list of accolades you have: What would you rate as your proudest moment or accomplishment of your career? Must be nice to have options by the way--

Roger: It is good to have options, yes, absolutely. It probably is winning Wimbeldon the first time in 2003 and then becoming world number one at the beginning of 2004. It is just like the ultimate achievement in my opinion. That is when the career could have ended right there already.

Andy: You took my spot of number one, so I don't really appreciate that.

[sound cut]

Andy: We've never talked about the Wimbeldon 2009 final. Going to the locker room and I am at my locker, being very emotional, breaking down. It was a heartbreaking loss. The thing that I remember is your team coming in, you giving them silent fist pounds, and giving them hugs, but it was in a very reserved manner. Because it was like you were taking into consideration that this was hard for me. Do you remember that moment at all?

Roger: That moment is probably tougher for you than it was happier for me. I think it is so important to respect your fellow athletes and competitors. I know how hard you've tried and how difficult it must be, because unfortunately you can't have it all and that match--

Andy: Well you can. You selfish bastard.

Roger: Sort of-- No, but seriously, you deserved it so much. I think that was for me a totally normal thing to do and nothing extraordinary, really.

Andy: It was impressive to me. I certainly appreciated it.

If you had to choose one person who's had the biggest impact over the course of your career, who would that be?

Roger: Peter Carter. For me, he was a very important figure. He was my coach when I was about 10 years old until 14 and then from 16 again until about 19. He was like a bigger brother for me, almost like a father figure.

Andy: How did his death change you?

Roger: It shook me. It woke me up and made realize how fortunate I am to be a tennis player and how much he would want me not to waste anything. I think this is when maybe my career went into overdrive. I was like, “Okay, I want to make Peter proud even though he is not with us anymore today.”

Andy: Looking back, is there anything you regret?

Roger: I wish I could have maybe realized my potential two years earlier, start to work really hard earlier, understand what I was trying to achieve, what was possible. But at the same time, I think, all of that was good for me later on. That I got all the stuff out early: the anger, the sadness, the pressure. I had to deal with so much, I felt, between 16 and 22 that later on made me the player I am today.

Andy: So the storyline is coming into the US open: There’s a weird number next to your name in the draws: Number 7, which just looks foreign. How do you react to that?

Roger: I am more focused on myself than on what the people are saying or what people think of my game. Because I was struggling with a bit of a back thing, my confidence maybe went away for a little bit. I feel really confident again and know that I have got a chance. Whereas maybe a month or two ago, I was really not sure.

Andy: Evidently in sports, no matter how great you are, even the greatest deal with time and age.

Commentator: Roger Federer is out of Wimbledon.

Commentator: [crosstalk] **[unintelligible 00:03:55]**

Andy: What is the hardest part for you, as far as realizing you’re mortal?

Roger: I am aware that it’s been a difficult year. I am sort of fighting back. When you are younger—17, 19, 21—you have a bad back half a day and then it’s all gone. Then it becomes two days. And then all of the sudden, next thing is like five days. That’s when it becomes unsettling and not a lot of fun when you’re playing too often with pain. But I think it’s going to be definitely more the mind and the body dictating how long I can play. But if I take care of it, I have passion for it, and the results are still there, I think I am going to still play for some time.

C.6.4 Marc Cuban

Interviewer: Realize, that you were going to be exceptional-- If you go back to Pennsylvania, Indiana or Dallas, at what point did you kind of have a feeling that things were going to happen?

Marc Cuban: When I was about twelve years old. I remember asking my dad-- I wanted new basketball shoes because I was a basketball junkie back then. He was like, “Well your shoes work. If you want a new pair of tennis shoes, you have to go out there and get a job.” I’m like, “Dad, I’m twelve years old.” It just so happens, he was playing poker with his buddies. One of his buddies was like, "Well, I got a job for you. I've got these garbage bags that we distribute. You could sell them door to door." I am like, "Okay." It was when I was selling them and realizing that I like to sell and that I could sell. I recognized that selling was about providing a service and creating value for people. I knew literally back then that I could always succeed. I mean, I remember I was sixteen, I think, when I started a stamp company and started going to stamp shows and trade shows. Just working a little bit harder than other people and trading up from one stamp to the next. I remember one time, I started with a quarter and bought a stamp and left with fifty dollars thinking, "Hey if I could do this I could do anything." It is not that everything worked. I failed a lot, but I never ever felt like I wouldn't be able to work hard enough to succeed.

Interviewer: Well, you have an extreme passion for the Mavs. Even the casual viewer can see how passionate you are. Do you think that that passion transcends into the way you approach business?

Marc: Yes, I think it was the other way around. I think it was the passion I've always had for business and being an entrepreneur that transfers into the Mavs. I've always been passionate. Some people thought it's more OCD than anything else, which I think is a great trait for an entrepreneur. I mentioned the stamp business. I would stay up till three, four in the morning, even though I had to get up and go to school, and read Linn's Stamp News and Scott's Stamp Journals, and have them all memorized. I used that to give myself an edge. Even when I was in college, I'd be in the library reading business books, looking for business biographies, and reading all I could about business. When I had Microsolutions, I started with no money. I'd pull all-nighters in front of borrowed computers, teaching myself software and how to program. It is just I've always just really enjoyed the competition of business. I think in the sports business I'll talk to our players. It'll be, like, "Well, you guys compete for 48 minutes. You practice a couple of hours. You work on your game independently a couple of hours." But the ultimate sport is business, because you have to compete with everybody. You have to do it 24 by 7 by 365 days a year forever. There's always somebody out there trying to kick your butt. There is always somebody who looks at your business and says, "I can do that better. I have a better idea." You have to compete with that person. All the while you have to make your customers happy, your employees happy. It is the competitive side of me and any entrepreneur that I think that has to drive you. I think that carries over into the Mavericks: I want to win and I want to compete.

Interviewer: Well, when you started Microsolutions it was a small company.

Interviewer: What advice would you give small business owners?

Marc: Love what you do. I think too many people think they have to find the one idea. There is nothing wrong with failing. I've told a lot of people it doesn't matter how many times you fail, if you get it right you're an overnight success. All you've got to do is get it right one time and you're that overnight success. I sold powdered milk and that was a disaster. My senior year project in Indiana was opening up a bar that got closed because of a wet-t-shirt-contest with a sixteen-year old. That was a disaster. That was good, because it kept me out of the bar business. I got fired from my first job in the software business because I wanted to close a deal instead of going out and closing a sale. I mean instead of coming in and sweeping the floor. It didn't matter how many times I failed, I just kept on going and going and going. Entrepreneurs need to realize that sometimes it is not the idea, it's not who you know, it's not how much money you have access to. It is really finding something that you really love to do. I had no idea I loved computers and technology. None. I mean I took one class in Indiana in computers, and I cheated to get through it. I was [**unintelligible 00:04:51**]. Then I bought a little PC a 99/4a from Texas Instruments for 99 dollars. I started teaching myself to program. Four hours later, five hours later, I would look up and I'd been working this entire time, and I loved it. So that was the difference: I failed a lot of times. I really didn't know where I'd find my success. Then all of a sudden I started playing with PCs and technology, and it just clicked. [cut]

Interviewer: In what order of importance would you put when you look at technical understanding, instinct, creativity, or believing that you can do something. What is most important?

Marc: I think the most important is knowing your strengths and weaknesses and knowing what you enjoy doing. If you look at it as a job, you've already lost. It is not going to be your passion. You are going to count the hours. If you look at it as something you love to do and then you know what your strengths are, then you can leverage those strengths in your business and in helping others. Once you recognize your weaknesses, then you can work with people that complement you. I mean, in every one of my businesses, I've had a partner who is very anal. Martin Woodall, Todd Wagner—incredibly anal people. Perfectionists, because I am a slop. I am a big picture, think about what's around the corner, how is technology going to change things, how can I change this industry. Making sure that there is somebody there to dot the i's cross the t's and keep me on the baselines. Recognizing my weaknesses is just as important as recognizing my strengths and my core competencies and having a passion to do them.

C.7 Validation of role model choice

This section describes our procedure to identify potential female and male role models for our experiment. For our treatment to work, the individuals we present in our videos need to be perceived as role models for competitiveness. In a pretest, we searched and collected twelve videos of female and male individuals that we thought could serve as role models (see Appendix C.2 for the list of potential role models).

These videos were then evaluated by 1,405 AMT workers (different from the subject pool in our experiment) who answered a short survey including four questions to examine whether they perceived these individuals as role models for competitiveness. Subjects gave their answer to all items on 7-point Likert scales and the exact questions are displayed in Online appendix B. Cronbach's alpha of the composite role model variable is 0.8871, indicating its reliability. All of the potential role models are successfully working in competitive environments and are interviewed about their career path. In the videos, they stress their willingness to engage in competitive behavior in order to be successful, and how much they enjoy to compete. Role models' perceived competitiveness is measured using the six items on competitive motivation from the Motivational Trait Questionnaire from Heggestad and Kanfer (2000). Cronbach's alpha of the composite competitiveness variable is 0.8368, indicating that it is reliable.

According to the literature, role model behavior is more likely to be imitated if the role model is perceived as likeable, if her behavior is rewarded, and if she is similar to the observer (Bandura, 1986). To examine whether likeability, perceived success, and similarity predict whether a person is seen as a role model, we run ordered probit regressions where the dependent variable is subjects' answer to the question whether the person seen in the video could be a role model. Answers were given on a scale ranging from 0(=very untrue) to 6(=very true). As independent variables, we include subjects' ratings on whether they thought the person in the video was likeable, successful, competitive, and caring. We proxy for similarity between role model and subject by including a dummy reflecting subjects' gender. Results are presented in table 4.3 at the end of this section.

We find that perceived likeability and the extent to which a person is seen as caring, positively predicts whether she is seen as a role model. This result holds for both, female and male role models. However, being perceived as competitive generally has a negative impact on the eligibility of female role models (column (1)), but it has no such impact for male role models (column (2)). Furthermore, female subjects are much less likely than male subjects to accept a male person as potential role model (column (2)).

Out of the twelve potential role models in our pre-test, we select two male and female role models who are perceived as competitive and still displayed equal levels of likeability and role model potential.

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