Taming Overconfident CEOs Through Stricter Financial Regulation*

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Abstract

A large body of literature finds that managerial overconfidence increases risk-taking by financial institutions. This paper shows that financial regulation can be effective at mitigating this type of risk. Exploiting regulatory changes introduced after the financial crisis as a natural experiment, I find that overconfidence-induced risk-taking decreases in financial institutions subject to stricter regulation. Following the easing of these regulations, overconfidence-induced risk-taking increases again. These findings confirm the effectiveness of financial regulation at correcting overconfident behavior, but also suggest that the impact fades away quickly once removed.

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JEL Codes: G28 · G32 · G38 · G40

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1 Introduction

Individual managers matter for a wide range of corporate decisions by imposing their own style on the firms they manage (see e.g., Bertrand and Schoar, 2003). The behavioral economics literature has identified managerial overconfidence as one particular personal trait that affects corporate decision-making (for an overview see e.g., Malmendier and Tate, 2015).[1] Risk is one of the dimensions of corporate outcomes that are influenced by overconfidence. From a general theoretical perspective, overconfidence affects risk-taking decisions in two ways: First, overconfident individuals underestimate risks associated with future cash flows and overestimate the probability of success (e.g., Hackbarth, 2008). Second, overconfident individuals overestimate the precision of noisy signals (e.g., Gervais et al., 2011). In line with the theory, the empirical behavioral finance literature shows that financial institutions with overconfident chief executive officers (CEOs) followed riskier strategies before and performed worse during financial crises (e.g., Ho et al., 2016; Ma, 2015; Niu, 2010).

Spurred by the consequences of the global financial crisis and the associated risk-taking, a substantial tightening of regulatory standards in financial markets has taken place worldwide. A wide range of regulatory frameworks addressing the opacity and complexity of the financial sector tried to increase transparency, improve regulatory oversight, strengthen internal risk management, and decrease risk-taking incentives (e.g., the Dodd-Frank Wall Street Reform and Consumer Protection Act (DFA) of 2010 in the U.S. or the Markets in Financial Instruments Directive (MiFID) 2 of 2014 and the Capital Requirements Directives (CRD) III/IV of 2010/2013 in Europe). Such stricter regulatory environments might be effective in restraining overconfident CEOs by decreasing the discretionary power of individual CEOs.

In this paper, I study whether and how stricter financial regulation affects risk-taking of financial institutions with overconfident CEOs. Using detailed financial data on listed firms in the U.S. financial sector, I document a decrease in overconfidence-induced risk – which is the additional risk at financial institutions with overconfident CEOs – during the period of stricter regulation after the global financial crisis in a first step. In a second step, I show that this decrease in overconfidence-induced risk is only observable for financial institutions subject to enhanced regulation and, hence, attributable to stricter regulation.

[1] Since strategic decisions are primarily influenced by the chief executive officer (CEO), this literature focuses on the level of overconfidence of the CEO as the top decision maker.

To document the changes in the relationship between CEO overconfidence and risk over time in the first step, I compare financial institutions with overconfident CEOs to financial institutions without overconfident CEOs. Following Malmendier and Tate (2005a), CEO overconfidence is thereby measured by their option exercising behavior. I find that risk-taking at financial institutions with overconfident CEOs is higher before the financial crisis. In the period of stricter regulation after the financial crisis, risk-taking at financial institutions with overconfident CEOs converges to the levels of financial institutions with non-overconfident CEOs. However, once large parts of the regulation are repealed – such as in the case of the Economic Growth, Regulatory Relief, and Consumer Protection ACT (EGRRCPA) of 2018 – overconfidence-induced risk-taking increases again. This holds for aggregate risk measures as well as for approval decisions on individual loans. These results provide initial evidence that the nexus between managerial overconfidence and risk-taking is influenced by the regulatory environment.

In the second step, I relate the observed changes in overconfidence-induced risk over time to regulation by distinguishing two groups of financial institutions differing in the degree of exposure to regulation. The first group includes larger depository institutions and designated non-depository institutions that were subject to enhanced regulation after the financial crisis. Part of the enhanced regulation, such as the establishment of risk committees and chief risk officers who constantly evaluate the strategies developed by the management, could have imposed a beneficial constraint on the behavior of overconfident CEOs. The second group comprises non-depository institutions (shadow banks) and smaller depository institutions, for which regulation remains lax after the financial crisis. I find that, while being similar across the two groups before the period of stricter regulation, overconfidence-induced risk only significantly decreases for the stricter-regulated financial institutions.[2] This result indicates that stricter financial regulation is effective in mitigating additional risk-taking by overconfident CEOs.

The results are robust to several modifications of the analysis. I address the potential concern of endogenous selection of overconfident CEOs in three ways: i) by closely examining the timing around the appointment of new CEOs, ii) by focusing on the subset of non-turnover CEOs, and iii) by instrumenting overconfidence using the age of the CEO. To rule out alternative explanations concerning the option-based overconfidence measure, I examine the degree of optimism in a linguistic analysis of the Management Discussion and Analysis (MD&A) sections of the annual reports as well as hypothetical diversifi-

[2]Importantly, these financial institutions did not, on average, perform worse during the financial crisis. Hence, it is unlikely that other general crisis effects drive the observed decline in risk-taking.

cation strategies of the CEOs. The results show that the option-based overconfidence measure is consistent with overconfident behavior across the entire observation period. The main results are further robust to the inclusion of additional control variables and to changes in the estimation methodology and the sample composition.

This paper relates to two strands of the literature. First, it relates to the broad literature on managerial overconfidence and corporate actions.[3] Malmendier and Tate (2005a) are the first to construct a measure for overconfidence based on the option-exercising behavior of CEOs. They show that overconfident CEOs overinvest when internal funds are abundant. Furthermore, several studies have shown that CEO overconfidence affects the choice of debt maturity (e.g., Graham et al., 2013; R. Huang et al., 2016; Landier and Thesmar, 2009), risk management (Adam et al., 2015), dividend policy (Deshmukh et al., 2013), merger decisions (Malmendier and Tate, 2008), and forecasting (Hribar and Yang, 2016). However, there are also positive aspects to CEO overconfidence. Hirshleifer et al. (2012) and Galasso and Simcoe (2011), for example, show that overconfident managers engage more in innovation and obtain more patents and thereby increase the value of the firm, while also increasing the volatility of the stock returns of the firm.

There is also evidence that CEOs and their personal traits have a significant impact on firm outcomes in the financial sector. Ho et al. (2016) show that financial firms with overconfident CEOs followed riskier strategies before the financial crisis and suffered more from the consequences during the financial crisis. In the same light, Ma (2015) shows that overconfident CEOs increased real estate investments before and performed worse during the financial crisis. Niu (2010) shows that banks with overconfident CEOs had a higher variation in daily stock returns and, thus, are perceived as riskier. Lee et al. (2020) find that CEO overconfidence increased systemic risk in the run-up to the global financial crisis.

I contribute to this literature by examining the relationship between CEO overconfidence and risk-taking in the financial sector in a dynamic setting. While this relationship has been treated as rather static in the existing literature, I document that the relationship between CEO overconfidence and risk-taking in the financial sector varies over

[3]While evidence from the psychology literature suggests that individuals, in general, are prone to overconfidence (e.g., Taylor and Brown, 1988), there are several reasons why this is especially the case for executives. These include, among others, sorting, abstractly defined and high-skilled tasks, position of ultimate control, and commitment to these tasks due to incentive payments (Malmendier and Tate, 2005b; Malmendier, Tate, and Yan, 2011). Furthermore, Goel and Thakor (2008) argue that, since promotion is usually based on performance, an overconfident manager is more likely to be promoted. In line with the theory, Graham et al. (2013) empirically show that CEOs are significantly more optimistic than the lay population.

time. The results indicate that overconfidence-induced risk is reduced in times that are characterized by stricter regulation. This helps to better understand whether risk in the financial sector caused by individual behavior reacts to changes in the economic environment and whether further scope for regulation remains to restrain overconfident behavior. Moreover, this paper is the first to examine individual loan approval decisions of financial institutions in the context of managerial overconfidence.

Second, this paper relates to the literature on the effects of regulation on risk-taking. Focusing on post-crisis financial regulation in the U.S. in general, Calluzo and Dong (2015) examine how risk-taking in the U.S. financial sector evolved after the financial crisis. They find that the financial sector has become more robust to idiosyncratic risk, but in general more vulnerable to systemic shocks. In the same light, Akhigbe et al. (2016) show that risk-taking in general decreased in the financial sector after the passage of the DFA in 2010 and that the decrease was strongest for 'too big to fail' institutions.[4] While also finding strong evidence that risk in the financial sector decreased after the passage of the DFA, Balasubramanyan et al. (2019) find no significant causal effect of increased corporate governance, in the form of risk committees and chief risk officers, as mandated by the DFA on risk.[5]

In contrast, Banerjee et al. (2015) show that the Sarbanes-Oxley Act (SOX) in 2002, which introduced substantial improvements concerning managerial excesses, transparency, and corporate governance, substantially improved the behavior of overconfident CEOs. Cheffins (2015), however, argues that the corporate governance movement related to the SOX did not affect CEOs in the financial sector in the period before the financial crisis. According to the author, a potential explanation for the less effective corporate governance in the financial sector could be that boards were weaker and too lenient in setting incentive compensation due to a higher opaqueness of operations, implicit guarantees, and trust in strict-enough financial regulation. This is consistent with the finding of Ho et al. (2016), who show that the divergence in risk-taking between firms with overconfident and non-overconfident CEOs was still prevalent in the financial sector in the period after the passage of the SOX.

[4]Related to these findings, Bhagat et al. (2015) examine the effect of size on risk-taking in the U.S. banking sector and find that risk-taking is positively correlated with size before and during the crisis. However, in the post-crisis period, this relationship vanishes.

[5]While the corporate finance literature finds mixed effects of increased corporate governance and internal oversight on the risk of firms in general (e.g., Ellul and Yerramilli, 2013; Hines and Peters, 2015), Hsu et al. (2017) show that increased corporate governance and internal oversight can indeed mitigate the adverse effects of CEO overconfidence.

This paper contributes to the literature by empirically estimating the effect of stricter financial regulation on the behavior of overconfident CEOs in the financial sector. Hence, this paper addresses a particular channel through which post-crisis financial regulation affected risk-taking in the financial sector, which is a decrease in the scope for overconfident CEOs to take additional risks. The results suggest that the stricter regulatory environment eliminated managerial overconfidence as one channel of increased risk-taking, which is consistent with the argumentation of Cheffins (2015). This underlines that designing regulation that not only strengthens the capital adequacy of financial institutions (i.e., capital requirements) but also addresses the behavior of individual decision-makers by strengthening corporate governance and promoting transparency is beneficial for the stability of the financial sector.

This paper proceeds as follows: Section 2 presents the main regulatory changes, the data, and discusses the overconfidence measure. Section 3 presents the estimation strategy, documents the changes in overconfidence-induced risk over time, and delivers robustness tests. Section 4 examines the role of the regulatory environment. Section 5 concludes.

2 Regulatory Background, Data, and Variables

2.1 Regulatory Background

To study the effects of regulation on risk-taking of financial institutions with overconfident CEOs, I analyze the U.S. financial sector during the period from 1999 to 2019. This period comprises three sub-periods that differ in the degree of regulation. First, the period from 1999 to 2007 during which financial regulation was rather lax, which, among other reasons, led to the buildup of the sub-prime mortgage crisis and ultimately the global financial crisis. Despite corporate governance movements related to the SOX in 2002, sparked by management scandals in the early 2000s, Cheffins (2015) argues that this movement did not affect CEOs of firms in the financial sector, sustaining their substantial discretionary power. Therefore, it is likely that during this period there was enough discretion for individual CEOs in the financial sector to significantly affect corporate strategies.

Second, the period from 2008 to 2017 during which regulatory oversight and strictness strongly increased in the financial sector. Starting from the peak of the sub-prime lending crisis in late 2008 with the bankruptcy of Lehman Brothers, the U.S. government heavily intervened in the financial sector (e.g., the Emergency Economic Stabilization Act of 2008 including the Troubled Asset Relief Program (TARP) and the Capital Purchase Program (CPP) or the bank stress tests under the Supervisory Capital Assessment Program (SCAP) of 2009). Associated rules and regulations, such as the Interim Final Rule on TARP Standards for Compensation and Corporate Governance, potentially limited the influence of individual CEOs. The DFA, enacted in 2010, then explicitly aimed to increase transparency, improve regulatory oversight, strengthen internal risk management, decrease risk-taking incentives, and impose stricter regulation for the larger depository institutions and designated non-depository institutions. These measures potentially limited risk-taking incentives and the scope for individual CEOs to affect corporate strategies.

In the third period from 2018 on, the EGRRCPA partly repealed the regulation imposed by the DFA, especially for medium-sized financial institutions, and thus led to a less strict regulatory environment potentially restoring the discretionary power of individual CEOs.

2.2 Data

For the empirical analysis, I use detailed financial data on listed financial institutions headquartered in the U.S. Balance sheet data for the years 1999 to 2019 is taken from the *Compustat North America Fundamentals* database.[6] The data is consolidated at the holding company level. Following Ho et al. (2016), I restrict the sample to banks and financial services firms with standard industrial classification (SIC) codes 6000-6300 excluding firms in sector 6282, which includes firms in the non-traditional banking industry. Hence, the sample includes both depository and non-depository institutions. Stock option data to construct the measure of overconfidence is taken from the *Execucomp Annual Compensation* database. The data set is supplemented with data on daily stock returns from the *CRSP* database.

I start with 308 financial institutions intersecting all three databases. I exclude *Freddie Mac* and *Fannie Mae* from the sample since both are government-sponsored enterprises, which were nationalized in 2007 and thus are subject to different regulatory standards. Further, I exclude observations where the fiscal year-end does not coincide with the calendar year-end since this could confound the results due to timing differences. Additionally, I follow the standard procedure in the literature and exclude observations with negative equity, assets, or liabilities and observations where the equity-to-assets ratio exceeds one.

[6]Note that the estimation period effectively spans the period from 2000 to 2019 since part of the variables are measured as first differences or lagged by one year.

Finally, I only keep financial institutions with more than two observations. The final unbalanced sample with non-missing observations in all relevant variables contains 238 firms and 2448 firm-year observations.[7] I winsorize the accounting variables at the 1^{st} and 99^{th} percentiles.

2.3 Variables

2.3.1 Risk Measures

In the baseline analysis, I use the daily stock return volatility (σ_t) as a measure of aggregate risk, the exposure to market volatility ($beta_t$), calculated by a single index model using daily stock returns, as a measure of systemic risk, and the mean squared error of the same model as a measure of idiosyncratic risk (mse_t), which are widely used as risk measures in the literature.[8]

Since the stock price represents a call option on the underlying assets, the stock return volatility (σ_t) serves as an indicator of the volatility of the firm's assets. Furthermore, in addition to the risk associated with the firm's equity, stock return volatility also captures the market's reaction to firm-related news (e.g., future profitability) and thus aspects concerning the firm which are important to the firm's shareholders (see e.g., Aabo et al., 2020; Bulan, 2005; Leahy and Whited, 1996). There is further evidence that stock return volatility is forward-looking since the firms' expectations about future returns from assets and from future growth options drive variation in stock returns. Since common stock represents claims on the firms' profits in the future, reactions to news about future profitability and future prospects are priced in by the market and represented by variation in the stock returns (Berk et al., 1999). Due to the skewed distribution, stock return volatility is calculated as the natural logarithm of the standard deviation of daily stock returns during fiscal year t.

Exposure to market volatility ($beta_t$), which signifies the co-movement with the market and therefore serves as a systemic risk indicator, is calculated as the β of a single index model, using the return on the S&P500 as a benchmark.[9] The natural logarithm of the mean squared error of the same single index model (mse_t) is used as a measure of idiosyncratic risk.

[7]Despite only covering a limited number of firms, the sample roughly covers 60% of the asset value of all listed firms in the respective SIC classifications.

[8]I only calculate these measures if there are more than 10 observations available in the respective fiscal year. If a firm has more than one security assigned, I use the primary security.

[9]Formally: $r_{i,t} = \alpha_{i,t} + \beta_{i,t}\bar{r}_{S\&P500,t} + \epsilon_{i,t}$ estimated for each year t and stock i separately.

2.3.2 Control Variables

The baseline firm-level control variables are standard in the literature and constructed as follows: size ($size_t$) is calculated as the natural logarithm of total assets, the annual return on assets (roa_t) is calculated as net income over total assets, book leverage ($leverage_t^b$) is calculated as book value of assets over book value of equity, deposits ($deposits_t$) are total deposits over total assets, and liquidity ($liquidity_t$) are cash and short-term investments over assets. Moreover, I control for the fiscal year-end stock price in all estimations.[10]

Risk aversion of the CEO, which is not directly observable, could have an effect on both risk-taking and, via the option-exercising behavior, on the option-based measure of overconfidence. Following the expected utility theory, at least part of the risk aversion should be explained by the wealth of the CEO, which could be used as a proxy for risk aversion. However, there is no information on CEO wealth available in the *Execucomp* database. Therefore, I follow previous analyses and use inside wealth ($wealth_t$) of the CEO to proxy for net worth (e.g., Harford and Li, 2007), which is calculated as the natural logarithm of the product of shares owned excluding options times the fiscal year-end stock price.

2.3.3 Overconfidence Measure

While different approaches to measure managerial overconfidence have been proposed in the literature, the revealed-beliefs approach using the option exercising behavior of managers, first introduced by Malmendier and Tate (2005a), has become standard in the literature. The idea behind the option-based approach is the following. The value of the CEO's human capital is tied to the firm. Moreover, CEOs have limited possibilities to address this under-diversification since they are usually contractually detained from taking short positions with respect to the firm. To diversify, rational and risk-averse CEOs should seek to exercise stock options, which they receive as part of their compensation, as soon as they are vested. Thereby, the degree of 'moneyness' of the option has to be sufficiently high.[11]

A CEO is overconfident when postponing the exercise of *exercisable* deep-in-the-money options. Since there is only aggregate data available for the option portfolios of the

[10] For a detailed presentation of the variables refer to Table A.1 in the appendix.

[11] 'Moneyness' describes the intrinsic value of an option. That is, how far the current market price of the option package exceeds the strike price at which the CEO has the option to buy the underlying stock (Malmendier and Tate, 2015). The rational degree of 'moneyness' is usually derived from the calibration of theoretical models (e.g., Hall and Murphy, 2002) and ensures that a rational CEO holding, for example, options with a market price below the strike price is not classified as overconfident.

respective CEOs prior to 2006, I follow earlier studies in constructing the overconfidence measure based on the average degree of moneyness of the CEO's option portfolio in a given year (e.g., Campbell et al., 2011; Ho et al., 2016). Average moneyness for *exercisable* options in a given year is calculated as the realizable value per option divided by the estimated average exercise price, which is the price at which the CEO has the option to buy the underlying stock. A CEO is classified as overconfident when postponing the exercise of options which were at least 100% in the money, i.e., the stock price is at least twice as high as the strike price. Using 100% as cutoff ensures that only highly overconfident CEOs are classified as overconfident (see e.g., Campbell et al., 2011).

To not capture inattentive behavior, the postponing has to be observed at least twice during tenure. The CEO is then classified as overconfident *after* the first time delaying the exercise.[12] Therefore, this measure allows for within-CEO variation and avoids forward-looking assumptions. However, it assumes that overconfidence is a persistent trait once adapted, which is consistent with evidence that overconfidence is a self-attribution bias (Billett and Qian, 2008) and that overconfidence increases in age (Bruine de Bruin et al., 2012).

The late-exercising behavior might, however, be rational if the CEOs ex-post systematically profit from holding the options longer due to, for example, superior information. To rule this out, I test whether CEOs with option portfolios above 100% moneyness benefited *ex-post* from holding these options by constructing an alternative hypothetical investment strategy. More precisely, I compare the returns from selling the options in year $t + 1$ at the highest possible price, to capture the highest degree of inside information, to the returns from selling these options at the highest price in year t, investing the proceeds into the S&P500, and selling again after the same period of time in $t + 1$. In other words, I test whether the late-exercising CEOs earned excess returns compared to the diversification strategy. The results in Table 1 show that, on average, the CEOs did not significantly earn more by holding their options as compared to the diversification strategy, even when assuming the highest degree of inside information.

Malmendier and Tate (2005a) and Malmendier and Tate (2008) discuss further alternative explanations, which might play a role in the late-exercising behavior of options, but

[12]If a CEO switches between firms in the observed period, all tenures are taken into account. Observations with zero options or a value of exercisable unexercised options of zero are treated as non-overconfident whereas observations where the realizable value per option equals the fiscal year-end stock price, which implies a strike price of zero, are treated as overconfident. If information about the CEO in tenure is missing for certain years, I impute the level of overconfidence from the previous period. I omit these observations in a robustness test in section 3.3.3.

Table 1: Returns to late-exercising

This table shows the distribution of excess returns of holding deep-in-the-money options over the diversification strategy. Excess return is calculated as follows: For each option portfolio above 100% moneyness in year t, the returns from keeping and selling the options at the highest price in year $t+1$, relative to the highest price in year t, are compared to the returns from selling the options at the highest price in year t and investing the amount in the S&P500 over the same period.

	mean	sd	p10	p25	p50	p75	p90
excess return	0.022	0.307	-0.327	-0.112	0.012	0.163	0.355
Observations	405						
p-value	0.151						

conclude that overconfidence is the most consistent explanation. Moreover, a high correlation between the option-based measure and a press-based measure of overconfidence, which classifies CEOs according to their portrayal in the press, underlines the discussion (see e.g., Hirshleifer et al., 2012; Malmendier and Tate, 2008). In a recent study, Kaplan et al. (2022) deliver evidence that the option-based measure indeed reflects overconfident behavior using detailed personality assessments of CEOs.

Nonetheless, post-crisis regulation might have influenced the option-exercising behavior of the CEOs directly via, for example, changes in executive compensation. To ensure that the option-based overconfidence measure consistently captures overconfident behavior over time, I analyze the tone of the *Management Discussion and Analysis* (MD&A) section of the annual reports (10-K). In the MD&A section, the firm's management analyzes the firm's performance with qualitative and quantitative measures. It is argued that in this section, the management, and thus the CEO, most likely reveal information via the tone (see e.g., Loughran and McDonald, 2011). A more overconfident CEO should use more positive words, relative to negative words, all else equal. For this purpose, I parse this section from the respective 10-K reports from the *SEC EDGAR* database. To end up in the sample, I require these sections to contain at least 250 words since in many cases this section is only incorporated by reference. For approximately two-thirds of the firms, I am able to obtain the respective MD&A sections. I then analyze the degree of optimism in the tone of these sections by contrasting the number of positive words ($f_{positive}$) to the number of negative words ($f_{negative}$) as defined by the Loughran and McDonald (2011) dictionary.[13] More precisely, I use the proportion of positive words to negative words ($tone_r = \frac{\sum f_{positive}}{\sum f_{negative}}$) as a first raw measure. As a second measure ($tone_w$), I weigh each word by the commonality across documents before computing the proportion. The

[13] Loughran and McDonald (2011) show that their dictionary is more appropriate when analyzing financial texts than standard dictionaries used for more general textual analysis.

Table 2: Option-based overconfidence and the tone of the MD&A section

This table presents the regression results for the analysis of the relationship between the option-based overconfidence measure and the tone of the MD&A sections of the annual reports for the years 1999 to 2019. The natural logarithm of the tonal measure for firm i in year t, which is either the share of positive over negative words, as defined by the Loughran and McDonald (2011) dictionary, (column (1)) or the weighted share of positive over negative words (column (2)), is regressed on $OC_{i,t}$, a binary variable which is one if a firm has an overconfident CEO at time t, as defined by the option-based measure, interacted with an indicator variable distinguishing four different periods, and a vector of controls including size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, the fiscal year-end stock price, and the number of words contained in the MD&A section as well as firm and year fixed effects. Variable definitions are in Table A.1. Hubert-White heteroskedasticity consistent standard errors in parentheses. Stars indicate significance: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

	Share of positive words	
	(1) Raw	(2) Weighted
OC_t	0.0944*	0.124**
	(0.057)	(0.061)
$period_{2008,2013} \times OC_t$	0.0122	0.0186
	(0.057)	(0.061)
$period_{2014,2017} \times OC_t$	-0.0139	-0.0159
	(0.060)	(0.065)
$period_{2018,2019} \times OC_t$	0.0455	0.0430
	(0.076)	(0.082)
Observations	1611	1611
adjusted R^2	0.62	0.62
Firm FE	Yes	Yes
Year FE	Yes	Yes

weight is calculated as $ln((e-1)+\frac{N}{df})$, where N is the total number of documents in the sample and df is the number of documents containing the respective word. Hence, less common words receive a higher weight whereas words that appear in every document receive a weight of 1.

To test whether the option-based measure consistently captures overoptimistic behavior over time, I regress the natural logarithm of the continuous tonal measures on the option-based overconfidence dummy interacted with a dummy variable distinguishing four different periods, based on the discussion in Section 2.2, using OLS. I control for the length of each MD&A section and include the baseline control variables, introduced above, to account for the financial situation and prospects of the firms, as well as firm and year fixed effects. The results are shown in Table 2. Column (1) shows the results for the raw measure and column (2) for the weighted measure. Both specifications show that the option-based overconfidence measure is significantly and positively correlated with the degree of optimism in the tone of the MD&A section. In terms of size, having an overconfident CEO, as classified by the option-based measure, is associated with a 10-12% higher proportion of positive words in the MD&A section, conditional on the firm's performance. Moreover, the results show that this relationship is similar across the

Table 3: Summary statistics

This table presents summary statistics for the main variables used in this study for the years 2000 to 2019. The sample is unbalanced. Balance sheet data is taken from *Compustat North America Fundamentals*, option data from *Execucomp Annual Compensation*, and stock market data from *CRSP*. Panel (1) shows the summary statistics for the full sample, column (2) for the overconfident sample, column (3) for the non-overconfident sample, and column (4) the difference. Variable definitions are in Table A.1. Stars indicate significance of a paired t-test: $^{*}p < 0.1$,$^{**}\ p < 0.05$,$^{***}\ p < 0.01$.

	(1) Full sample					(2) OC	(3) Non-OC	(4) Difference
	mean	sd	p25	p50	p75	mean	mean	Δ
OC_t	0.292	0.455	0.000	0.000	1.000	1.000	0.000	
$ln(\sigma_t)$	-3.938	0.475	-4.260	-4.058	-3.681	-3.909	-3.950	0.041^{*}
$beta_t$	1.189	0.421	0.891	1.135	1.425	1.206	1.182	0.024
$ln(mse_t)$	-8.355	0.974	-8.995	-8.583	-7.852	-8.268	-8.390	0.122^{***}
$size_t$	9.639	1.688	8.550	9.374	10.592	9.418	9.730	-0.313^{***}
roa_t	1.532	3.785	0.735	1.028	1.401	2.063	1.313	0.751^{***}
$leverage_t^b$	1.838	2.697	0.564	1.115	2.218	1.884	1.819	0.065
$deposits_t$	0.617	0.265	0.583	0.717	0.792	0.567	0.638	-0.072^{***}
$liquidity_t$	0.082	0.109	0.024	0.041	0.088	0.096	0.076	0.020^{***}
$wealth_t$	9.270	1.658	8.273	9.222	10.364	9.924	9.000	0.924^{***}
$stockprice_t$	36.226	30.548	16.525	28.930	45.535	46.881	31.821	15.060^{***}
Observations	2448					716	1732	2448

different time periods since the coefficients on the interaction terms with the respective periods are close to zero and insignificant.

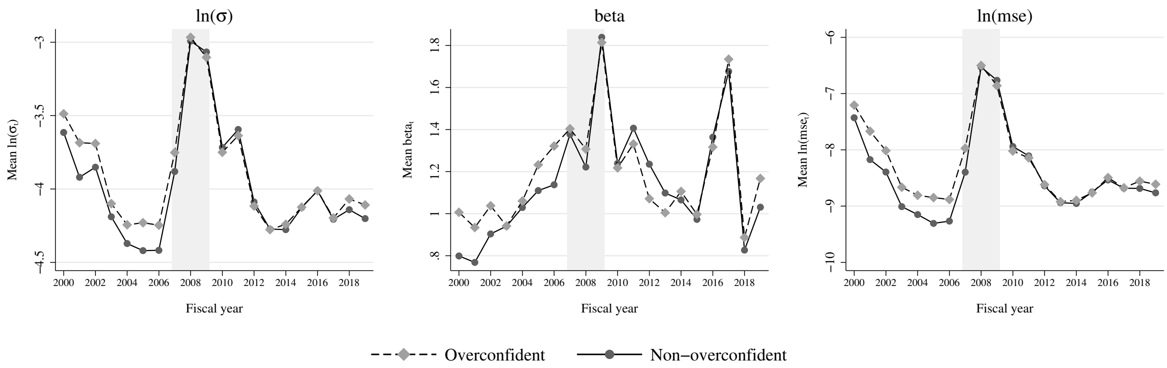
Thus, building on the results of the textual analysis of the MD&A sections of the annual reports as well as on the existing literature, I conclude that overconfidence is the most consistent explanation for the late exercising behavior and that the option-based overconfidence measure credibly captures overconfident behavior over time.

Table 3 shows summary statistics of the full unbalanced sample (panel (1)), the means of the overconfident (column (2)) and non-overconfident (column (3)) sub-samples, and the difference between the two samples (column (4)) to provide some indication of the nature of the sample. Around 30% of the CEO-year observations are classified as overconfident.[14] Further, the average daily stock return volatility is .02 ($e^{-3.938}$), the average beta 1.19, and the average mean squared error .00024 ($e^{-8.355}$). The difference between the two sub-samples is significantly different from zero for most of the control variables and confirms the need to control for these variables in the subsequent analysis.

[14] Of the 413 distinct CEOs in the sample, 33 CEOs switch from non-overconfident to overconfident during tenure, 76 CEOs are always overconfident, and 304 CEOs are never overconfident.

Figure 1: Development of risk over time

This figure shows the development of risk measured as the natural logarithm of the standard deviation of daily stock returns (left), the market beta (center), and the natural logarithm of the mean-squared-error of a single index model (right). Diamonds represent the average of the respective risk measure for firms with overconfident CEOs and dots the average risk for firms with non-overconfident CEOs. Variable definitions are in Table A.1. The shaded area indicates the financial crisis.



3 Managerial Overconfidence and Risk-Taking

3.1 Descriptive Evidence

Figure 1, which plots the sample mean of the three risk measures over time, shows that stock return volatility and the idiosyncratic risk component were highest during the financial crisis but at relatively low levels before and after. In contrast to that, the co-movement with the stock market already shows a buildup in systemic risk before the onset of the financial crisis. Turning to the difference between financial institutions with overconfident CEOs and without, the figure shows across all measures that, on average, risk at financial firms with overconfident CEOs is higher before 2008, with no different trend observable. During the period of increased regulatory oversight after 2008, both types converge across all risk measures. After deregulation in 2018, risk is, on average, again higher at financial firms with overconfident CEOs, despite not to the same degree as in the pre-crisis period.

Table 4, which shows the difference between financial institutions with overconfident CEOs and financial institutions with non-overconfident CEOs for the three different time periods observed in Figure 1, confirms these results. Risk of financial institutions with overconfident CEOs was, on average, significantly higher in the period before 2008 (column (1)). During the period from 2008 to 2017, both types of financial institutions con-

Table 4: Differences across CEO type

This table presents the differences in the means of the main variables used in this study between financial institutions with overconfident CEOs and non-overconfident CEOs for different time periods. The sample is unbalanced. Variable definitions are in Table A.1. Stars indicate significance of a paired t-test: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	Difference between overconfident and non-overconfident financial institutions		
	(1) $period_{2000,2007}$	(2) $period_{2008,2017}$	(3) $period_{2018,2019}$
$ln(\sigma_t)$	0.135***	0.002	0.087***
$beta_t$	0.110***	-0.004	0.078**
$ln(mse_t)$	0.355***	0.021	0.146**
$size_t$	-0.472***	-0.342***	-0.051
roa_t	-0.104	1.184***	1.337***
$leverage^b_t$	-0.116	-0.034	-0.407
$deposits_t$	-0.012	-0.107***	-0.051
$liquidity_t$	0.033***	0.016**	0.007
$wealth_t$	0.639***	0.935***	1.214***
$stockprice_t$	3.976**	20.378***	25.039***
Observations	762	1410	276

verged in their level of risk (column (2)) with no significant difference remaining. Starting from 2018, risk is again significantly higher at financial institutions with overconfident CEOs (column (3)) albeit at a smaller difference.

Thus, the descriptive analysis reveals heterogeneous changes in risk across time. This evidence is consistent with additional risk and uncertainty about future returns that are priced in by the market during times of higher discretionary power of overconfident CEOs, as discussed in Section 2. Table 4, however, also shows heterogeneous changes in other firm characteristics over time. Therefore, it is important to control for these firm characteristics in the regression analysis in the following section.

3.2 Regression Analysis

The descriptive analysis in the previous section reveals that the difference in risk between firms with overconfident CEOs and without varies over time. To precisely estimate the relationship between overconfidence and risk-taking over time, I regress the respective measure of risk on the binary overconfidence variable interacted with year dummies and firm-level controls in a fixed effects framework using OLS.[15] The econometric model is designed as follows:

$$\begin{aligned} risk_{i,t} =& \alpha + \sum_{j \neq 2006} \mu_j \mathbb{1}[t=j]_{i,t} \\ &+ \beta_0 OC_{i,t-1} + \sum_{j \neq 2006} \beta_j OC_{i,t-1} \times \mathbb{1}[t=j]_{i,t} \\ &+ \boldsymbol{\gamma' X_{i,t}} + \nu_i + u_{i,t}, \end{aligned} \tag{1}$$

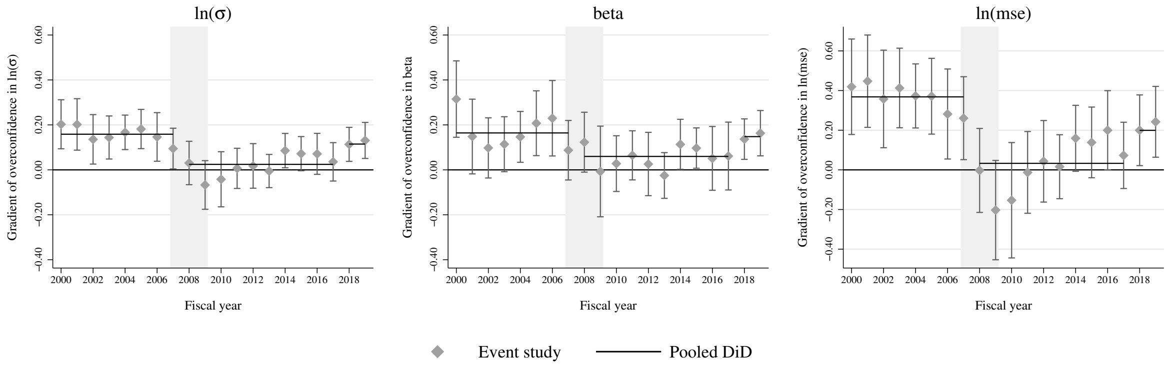
where $risk_{i,t}$ is the risk variable for firm i at time t, $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t=j]_{i,t}$ is an indicator variable which equals one for the respective year j, μ_j are year fixed effects, $\boldsymbol{X_{i,t}}$ is a vector of firm characteristics, ν_i are firm fixed effects, and $u_{i,t}$ is the random error term. In the baseline analysis, $\boldsymbol{X_{i,t}}$ includes the control variables size, return on assets, leverage, deposit ratio, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. By using firm fixed effects, I account for time-invariant unobserved differences between firms. The identification of the coefficients of interest β_0 and β_j thus relies on within-firm variation, i.e., a replacement of the CEO, and on within-CEO variation, i.e., CEOs who become overconfident during tenure. Since the financial sector is likely to be prone to common trends, I include year fixed effects. I choose the last year before the financial crisis, 2006, as the base year since it is not affected by the ramifications of the financial crisis. In all specifications, I use Hubert-White heteroskedasticity consistent standard errors clustered at the firm level.

The coefficient β_0 denotes the average difference in risk-taking between financial institutions with overconfident CEOs and financial institutions with non-overconfident CEOs in the left-out year conditional on the covariates. If overconfidence increases risk-taking, this coefficient is positive. Due to the fixed effects, identification relies on within-firm variation in overconfidence. The β_j coefficients denote the change of the difference in risk-taking in year j from the difference in risk-taking in the left-out year (β_0). The gradient of overconfidence, which is the difference in risk-taking between firms with overconfident CEOs and firms with non-overconfident CEOs in a given year j, is the main coefficient of interest and is calculated as the linear combination of β_0 and the respective β_j.

[15] Following Ho et al. (2016), I also estimate a weighted least squares version of the above-specified equation using weights related to size in a robustness test in section 3.3.5.

Figure 2: CEO Overconfidence and risk-taking – Dynamic results

This figure shows the gradient of overconfidence in risk-taking (diamonds), which is the linear combination of β_0 and β_j for each year j in the OLS estimation of Equation (1), along with the gradient of overconfidence of the pooled OLS estimation of Equation (2) (black line) for the three aggregate measures of risk-taking in the U.S. financial sector in the years 2000 to 2019 (natural logarithm of the standard deviation of daily stock returns (left), market beta (center), and the natural logarithm of the mean-squared-error of a single index model (right)). The vector of controls $\boldsymbol{X_{i,t}}$ includes the control variables size, return on assets, leverage, deposit ratio, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Variable definitions are in Table A.1. Hubert-White heteroskedasticity consistent standard errors are clustered at the firm level. 95% confidence intervals are shown. The shaded area indicates the crisis years.



In addition to the dynamic event study model in Equation (1), I also estimate a pooled version by pooling the years in the three periods observed in Figure 1 and discussed in Section 2. For this, the measures of risk are regressed on the binary overconfidence variable interacted with an indicator variable for each of the three periods and firm-level controls in a fixed effects framework using OLS. The econometric model is designed as follows:

$$\begin{aligned} risk_{i,t} =& \alpha + \sum_{j \neq 2006} \mu_j \mathbb{1}[t = j]_{i,t} \\ &+ \beta_0 OC_{i,t-1} + \sum_{p \neq \{2000,2007\}} \beta_p OC_{i,t-1} \times \mathbb{1}[t \in p]_{i,t} \\ &+ \boldsymbol{\gamma' X_{i,t}} + \nu_i + u_{i,t}, \end{aligned} \tag{2}$$

where $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The three periods are the periods from 2000 to 2007, from 2008 to 2017, and from 2018 to 2019 as observed in Figure 1 and discussed in Section 2.

Figure 2 plots the gradient of overconfidence of the dynamic event study model, which is the above-mentioned linear combination of β_0 and β_j, for each year j of the OLS regression of Equation (1) along with the gradient of overconfidence of the OLS regression of the pooled model in Equation (2) for the three measures of risk. The results show that risk is significantly higher at financial institutions with overconfident CEOs in the period from 2000 to 2007, with no significant pre-trend observable. This result is consistent with the existing evidence from the literature (see e.g., Ho et al., 2016) and consistent with a laxer regulatory environment giving the overconfident CEOs more discretionary power. Consistent with the argumentation of Cheffins (2015), the passage of the SOX in 2002, which was effective in mitigating the negative consequences of CEO overconfidence in the general economy (Banerjee et al., 2015), did not affect overconfident CEOs in the financial sector. The gradient of overconfidence, however, is not significantly different from zero during the period of stricter regulation between 2008 and 2017. Albeit not formalized in legislation, the risk-decreasing effect is stronger during the period from 2008 to 2013 and weaker during the period from 2014 to 2017, reflected in a slight increase in overconfidence-induced risk-taking in the latter period. With deregulation in 2018 risk-taking again diverges with significantly higher risk at financial institutions with overconfident CEOs, which is consistent with an increase in the discretionary power of individual CEOs.

The results of the OLS regression of the pooled model in Equation (2) are summarized in Table 5. Columns (1) to (3) show the results excluding control variables and columns (4) to (9) including controls. In columns (7) to (9), I additionally split the regulation period into two separate periods lasting from 2010 to 2013 and from 2014 to 2017, based on the observation in Figure 2. In the period from 2000 to 2007, risk is significantly higher at financial institutions with overconfident CEOs across all risk measures as indicated by the positive and highly significant coefficient for the overconfidence dummy (β_0) in all specifications. Again, this is consistent with previous results in the literature for the financial sector (e.g., Ho et al., 2016). In terms of size, firms with overconfident CEOs had a 17.2% ($(e^{(0.159)} - 1) \times 100$) higher standard deviation of daily stock returns (column (4)) and a 44.5% higher loading of idiosyncratic risk (column (6)). Since the sample's average exposure to market risk is 1.19, the coefficient of the overconfidence dummy in column (5) indicates an additional market exposure of 13.8% for firms with overconfident CEOs.

The coefficient $\beta_{2008,2017}$ across all specifications indicates a risk-decreasing effect at financial institutions with overconfident CEOs in the period between 2008 and 2017 relative to financial institutions with non-overconfident CEOs. As mentioned before, starting from the financial crisis the government heavily intervened in the financial sector potentially limiting the individual scope of the management. Comparing the coefficients

Table 5: CEO Overconfidence and risk-taking – Pooled results

This table presents the regression results of the OLS estimation of the fixed effects model in Equation (2) for risk-taking in the U.S. financial sector in the years 2000 to 2019. The dependent variables are the three aggregate measures of risk-taking, i.e., the natural logarithm of the standard deviation of daily stock returns, the market beta, and the natural logarithm of the mean-squared-error of a single index model. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Variable definitions are in Table A.1. Hubert-White heteroskedasticity consistent standard errors clustered at the firm level in parentheses. Stars indicate significance: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

	excl. controls			incl. controls					
	(1) $ln(\sigma_t)$	(2) $beta_t$	(3) $ln(mse_t)$	(4) $ln(\sigma_t)$	(5) $beta_t$	(6) $ln(mse_t)$	(7) $ln(\sigma_t)$	(8) $beta_t$	(9) $ln(mse_t)$
OC_{t-1}	0.144***	0.142***	0.337***	0.159***	0.164***	0.368***	0.153***	0.161***	0.354***
	(0.032)	(0.045)	(0.069)	(0.031)	(0.045)	(0.067)	(0.031)	(0.045)	(0.067)
$period_{2008,2017} \times OC_{t-1}$	-0.145***	-0.0973*	-0.369***	-0.134***	-0.105**	-0.335***			
	(0.043)	(0.055)	(0.098)	(0.040)	(0.052)	(0.089)			
$period_{2008,2013} \times OC_{t-1}$							-0.160***	-0.120**	-0.402***
							(0.043)	(0.055)	(0.097)
$period_{2014,2017} \times OC_{t-1}$							-0.0862*	-0.0759	-0.213**
							(0.044)	(0.061)	(0.098)
$period_{2018,2019} \times OC_{t-1}$	-0.0843**	-0.00396	-0.283***	-0.0438	-0.0164	-0.169*	-0.0287	-0.00739	-0.130
	(0.043)	(0.062)	(0.098)	(0.043)	(0.057)	(0.098)	(0.044)	(0.059)	(0.103)
Observations	2448	2448	2448	2448	2448	2448	2448	2448	2448
Clusters	238	238	238	238	238	238	238	238	238
Mean	-3.94	1.19	-8.35	-3.94	1.19	-8.35	-3.94	1.19	-8.35
adjusted R^2	0.83	0.58	0.79	0.85	0.60	0.82	0.85	0.60	0.82
Controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

of the overconfidence dummy (β_0) and of the interaction term ($\beta_{\{2008,2017\}}$), the effects before and after 2008 offset each other such that the risk of firms with overconfident CEOs and firms with non-overconfident CEOs fully converges.[16] Splitting the period from 2010 to 2017 into two sub-periods, the results show that the observed effect is stronger in the first sub-period (columns (7) to (9)). The coefficient $\beta_{\{2018,2019\}}$ again shows a significant difference between risk-taking at financial institutions with and without overconfident CEOs after 2018 when focusing on the specifications including control variables (columns (4) to (9)). Taken together, the results support the hypothesis that a change in the economic environment in the post-crisis period limits the scope for overconfident CEOs to take additional risks.

[16] Using a standard Wald test, the hypotheses $\beta_0 = -\beta_{\{2008,2017\}}$ cannot be rejected on conventional significance levels.

3.3 Robustness Tests

In the following section, I test the robustness of the results of the previous analysis. The first set of robustness tests is concerned with a potentially endogenous selection of CEOs. In a second robustness test, I instrument CEO overconfidence with the age of the CEO. This is followed by further robustness tests concerning the inclusion of additional CEO and firm characteristics, the estimation methodology, and the sample. Throughout the section, I will focus on the pooled specification in Equation (2).

3.3.1 CEO Selection

Particular firm characteristics might influence the likelihood to appoint an overconfident CEO. As such, the selection of overconfident CEOs into financial institutions might be endogenous and the estimates from the baseline analysis might be the result of underlying firm characteristics. Including the vector of covariates in the baseline analysis controls for matching on observables. If persistent latent firm characteristics drive the matching between overconfident CEOs and firms, including fixed effects in the baseline analysis mitigates these concerns. If, however, these latent characteristics are time-varying, one approach to mitigate these concerns is to focus on a subsample where effects from matching are less severe. Depending on the persistence of the latent variable, matching effects should be stronger for newly hired CEOs i.e., for CEOs with a lower tenure (see e.g., Aktas et al., 2019; Hirshleifer et al., 2012). If overconfident CEOs are replaced due to a change in the firm's strategy, this should particularly materialize in the first years of tenure. Therefore, I rerun the regression in Equation (2) for subsamples of CEOs with more than one, three, and five years of tenure.[17]

The results in Table 6 show that the baseline estimates remain robust to excluding the first years of tenure of a CEO. This further alleviates concerns that the results are driven by an endogenous selection of overconfident CEOs.

3.3.2 Instrumental Variable Analysis

To further address the concern of endogenous selection of CEOs, as well as other potential endogeneity concerns, I set up an instrumental variable estimation using the age of the CEO as an instrument for overconfidence (see e.g., Ho et al., 2016). The choice of the

[17] Starting dates of CEOs who came into office before 1992 are partly not recorded in the database. For these observations tenure cannot be computed and, therefore, 63 observations are omitted from the analysis.

Table 6: Robustness tests – Tenure

This table presents the regression results of the OLS estimation of the fixed effects model in Equation (2) for risk-taking in the U.S. financial sector in the years 2000 to 2019 when excluding the first, the first three, and the first five years of tenure of each CEO. The dependent variables are the three aggregate measures of risk-taking, i.e., the natural logarithm of the standard deviation of daily stock returns, the market beta, and the natural logarithm of the mean-squared-error of a single index model. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Variable definitions are in Table A.1. Hubert-White heteroskedasticity consistent standard errors clustered at the firm level in parentheses. Stars indicate significance: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	1 Year			3 Years			5 Years		
	(1) $ln(\sigma_t)$	(2) $beta_t$	(3) $ln(mse_t)$	(4) $ln(\sigma_t)$	(5) $beta_t$	(6) $ln(mse_t)$	(7) $ln(\sigma_t)$	(8) $beta_t$	(9) $ln(mse_t)$
OC_{t-1}	0.186***	0.205***	0.418***	0.199***	0.224***	0.449***	0.186***	0.220***	0.408***
	(0.033)	(0.050)	(0.071)	(0.037)	(0.056)	(0.077)	(0.043)	(0.064)	(0.089)
$period_{2008,2017} \times OC_{t-1}$	-0.148***	-0.136**	-0.356***	-0.144***	-0.126**	-0.339***	-0.133***	-0.135*	-0.286***
	(0.041)	(0.053)	(0.092)	(0.044)	(0.061)	(0.097)	(0.048)	(0.069)	(0.103)
$period_{2018,2019} \times OC_{t-1}$	-0.0648	-0.0471	-0.207**	-0.0757	-0.0556	-0.234**	-0.0588	-0.0777	-0.177
	(0.045)	(0.060)	(0.104)	(0.048)	(0.065)	(0.109)	(0.052)	(0.072)	(0.120)
Observations	2255	2255	2255	1873	1873	1873	1531	1531	1531
Clusters	228	228	228	224	224	224	213	213	213
Mean	-3.93	1.20	-8.35	-3.95	1.19	-8.39	-3.96	1.19	-8.39
adjusted R^2	0.86	0.62	0.82	0.86	0.62	0.83	0.87	0.64	0.84
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

instrument follows the empirical observation that, in cognitively demanding tasks, older people tend to be more overconfident (see e.g., Bruine de Bruin et al., 2012).

Since the endogenous variable is binary, I set up a three-step procedure as proposed by Wooldridge (2002). In a non-linear first step, I estimate a probit regression of overconfidence on age and firm-level control variables of the form:

$$Pr(OC_{i,t} = 1 | age_{i,t}, \boldsymbol{X_{i,t}}) = \Phi(\delta_0 + \delta_1 age_{i,t} + \boldsymbol{\gamma' X_{i,t}} + \mu_t), \tag{3}$$

where $age_{i,t}$ is the age of the CEO in tenure.[18] Then, I use the fitted values of overconfidence $\widehat{OC}_{i,t}$ from Equation (3) as instruments in a linear 2SLS estimation of Equation (2).[19] This three-step procedure avoids the so-called 'forbidden regression', which uses predicted values from a non-linear first stage directly in a linear second stage regression (Angrist and Pischke, 2009), and has previously been applied in related contexts

[18]The variable age is taken from the *Execucomp Annual Compensation* database. Missing variables were hand-collected.

[19]Moreover, I use the interaction of the fitted values of overconfidence $\widehat{OC}_{i,t}$ with the different periods as instruments for the interaction terms in Equation (2)

Table 7: Robustness tests – Instrumental variable regression

This table presents the regression results of the three-step instrumental variable regression for risk-taking in the U.S. financial sector in the years 2000 to 2019 as discussed in Section 3.3.2. The first step (column (1)) regresses the overconfidence dummy on the instrument $age_{i,t}$, which denotes the age of the CEO in tenure, and the control variables in the probit model in Equation (3). The fitted values of the first step are then used as instruments in a 2SLS estimation of the fixed effects model in Equation (2) (second stage results in columns (2) to (4)). The dependent variables are the three aggregate measures of risk-taking, i.e., the natural logarithm of the standard deviation of daily stock returns, the market beta, and the natural logarithm of the mean squared error of a single index model. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Variable definitions are in Table A.1. *KP F-stat* denotes the Kleibergen-Paap Wald test statistic for multiple instruments and *SW F-stat* denotes the Sanderson-Windmeijer F-statistic for individual instruments. Hubert-White heteroskedasticity consistent standard errors clustered at the CEO level (column (1)) and at the firm level (columns (2)-(4)) in parentheses. Stars indicate significance: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

	Probit	Second stage of 2SLS		
	(1)	(2)	(3)	(4)
	OC_t	$ln(\sigma_t)$	$beta_t$	$ln(mse_t)$
OC_{t-1}		0.397***	0.334**	0.951***
		(0.126)	(0.159)	(0.294)
$period_{2008,2017} \times OC_{t-1}$		-0.389***	-0.340**	-0.957***
		(0.141)	(0.167)	(0.336)
$period_{2018,2019} \times OC_{t-1}$		-0.00781	0.0261	-0.189
		(0.170)	(0.226)	(0.401)
age_t	0.0195*			
	(0.011)			
Observations	2448	2448	2448	2448
Clusters	402	238	238	238
pseudo R^2	0.13			
adjusted R^2		0.80	0.45	0.72
KP F-stat		8.86	8.86	8.86
SW F-stat	29.83			

(e.g., Adams et al., 2009; S.-C. Huang et al., 2018). The advantages of the approach are twofold. First, the procedure considers the non-linear nature of the endogenous variable. Second, the non-linear first step is not required to be correctly specified. It only requires the instrument to be correlated with the probability of the CEO being overconfident. As a result of this procedure, the standard errors of the 2SLS estimation remain valid (see Wooldridge, 2002, procedure 18.2).

Table 7 summarizes the results of the three-step instrumental variable estimation. Column (1) displays the results for the non-linear probit regression. The coefficient of age shows that age is a significant predictor for the overconfidence dummy and thus confirms earlier findings in the literature. The results of the second stage of the 2SLS in columns (2) to (4) do not change qualitatively compared to the fixed effects regression in Section 3.2. While overconfidence increases risk-taking in the period prior to 2008, the coefficients of the overconfidence dummy and the interaction term indicate a convergence in the risk-taking behavior in the period between 2008 and 2017 and again a significant difference in the period after 2018. The coefficients are larger than in the OLS estimation pointing towards an underestimation of the effect in the fixed effects regression.

3.3.3 CEO Characteristics

The following robustness tests are concerned with the potential omission of different CEO characteristics. For brevity reasons, I only report the results for the stock return volatility for the rest of the robustness section. Table A.2 in the appendix shows the results for the estimation of Equation (2), with the baseline results in column (1).

For a few firms, the information for the CEO in tenure was missing for some years within the observed period. In the baseline analysis, I impute the overconfidence measure and income information from the previous period if there was no information on the CEO in tenure, which I omit in column (2). In column (3), I omit observations with zero exercisable options from the construction of the overconfidence measure. With zero exercisable options CEOs cannot reveal beliefs through their exercising behavior and, thus, the concern arises that these are mistakenly classified as non-overconfident.

In column (4), I include gender and tenure of the CEO as further control variables since both characteristics could be related to overconfidence and risk-taking. Since data on tenure is not available for all CEOs in the sample, this slightly decreases the sample size.

In column (5), I include the price and volatility sensitivity of the CEOs' stock option portfolio (e.g., Fahlenbrach and Stulz, 2011). I follow Core and Guay (2002) and Coles et al. (2006) in constructing the option portfolio *Delta* (sensitivity of the option portfolio to changes in the stock price) and the option portfolio *Vega* (sensitivity of the option portfolio to changes in the volatility of the stock price). Including both measures decreases the sample size due to data availability. To further rule out that compensation is confounding the results, I follow Correa and Lel (2016) and construct a measure for excessive compensation, which I include in column (6). For that, I regress total compensation on return on assets, annualized excess returns over the risk-free rate, market-to-book value, the annualized standard deviation of the daily stock returns, book leverage, and time and industry fixed effects. I then subtract the predicted values of income from the actual values of total income to derive a measure of excessive compensation. In column (7), I additionally control for the number of exercisable options, which influences the measure of overconfidence. In the specification in column (8), I predict the wealth of the

CEO using age and income instead of using inside wealth, which disregards any outside wealth.[20]

For all the specifications mentioned above, the results in Table A.2 remain qualitatively and quantitatively similar.

3.3.4 Firm Characteristics

The next robustness tests are concerned with the potential omission of additional firm characteristics. Table A.4 in the appendix shows the results for the estimation of Equation (2), with the baseline results in column (1).

In column (2), I include *Tobin's Q* as a measure of firm valuation as an additional control variable. Firm valuation might influence both the decision to hire an overconfident manager as well as risk-taking. Tobin's Q is calculated as the sum of total assets and the difference between the market value and the book value of equity, i.e., the product of common shares outstanding and fiscal year-end stock price less book value of common equity, over total assets. Since the late exercising behavior of CEOs might be influenced by past performance or inside information, I include two lags of the annual stock returns as a proxy for past performance as well as two leads to proxy for inside information in column (3).[21] If past performance or inside information were positively correlated with the overconfidence measure, leaving out the proxies would overestimate the coefficients.

The size of the executive board could play a role in containing the scope of senior executives and in appointing overconfident CEOs. In column (4), I therefore control for the size of the executive board.[22] Another concern is the possibility of an increase in market concentration after the financial crisis due to failures, mergers, and takeovers. This increase in competition can affect the risk-taking decisions in both directions in the search for profits as well as the competition for managers. In column (5), I therefore control for the number of competitors in the SIC sub-industry in which the respective institution is active in.

[20]This choice is justified with the observation that in the U.S., for the income distribution observed in the sample, net worth and income are highly correlated. Using the 2016 Survey of Consumer Finances (SCF), the raw correlation of income and net worth between the 1st and 99th percentile in logarithmic terms is highly significant with a correlation coefficient of .77. Moreover, regression results of net worth on income in Table A.3 in the appendix reveal an elasticity of close to one. Since including age in the predictions of wealth in Table A.3 significantly increases the R^2, I predict each CEO's wealth using age and total income based on the coefficients of the weighted regression in column (4) of Table A.3.

[21]Since two lags are included, the coefficient of the interaction between the binary overconfidence variable and the deregulation period cannot be estimated.

[22]Size of the executive board is proxied by the number of executives in *Execucomp*.

Again, the results for all changes to the specification as outlined above and shown in Table A.4 remain qualitatively and quantitatively similar.

3.3.5 Estimation Methodology and Sample Composition

The last set of robustness tests is concerned with different aspects of the estimation methodology and the sample composition and is shown in Table A.5 in the appendix, with the baseline results in column (1).

In column (2), I use weighted least squares (WLS) instead of OLS, following Ho et al. (2016), using weights related to the size of the financial institution. The reason is that the size distribution in the financial sector is highly skewed. In column (3), I re-estimate Equation (2) using industry fixed effects instead of firm fixed effects. Since overconfidence is modeled as a semi-fixed effect, there is relatively little variation in the variable itself. The identification in the firm fixed effect model relies on within-CEO variation, i.e., CEOs who become overconfident during tenure, and within-firm variation, i.e., a replacement of a CEO. This might lead to a sample selection bias. Using industry fixed effects allows for across-firm identification. The results remain robust to these changes.

The robustness test in column (4) is concerned with sample attrition. The baseline sample is unbalanced and includes firms which enter and more importantly exit the sample during the sample period. These firms might drop out of the sample after the crisis since they followed riskier strategies and thus failed. Therefore, I re-estimate the baseline regression for the 35 financial institutions which remain in the sample for the entire period. The coefficients are slightly larger with the qualitative result remaining unchanged.

The robustness tests in columns (5) to (7) are concerned with a change in the composition of the CEO sample and only focus on those CEOs who were in tenure in either of the years between 2007 and 2010. In column (6) I re-estimate the model in Equation (2) only using CEOs who were replaced during the financial crisis, including their replacement, while in column (7) I re-estimate the model only using CEOs who were not replaced during the crisis to examine the source of variation more closely. Column (5) takes both groups together. Financial institutions with overconfident CEOs who were replaced during the financial crisis increased risk-taking more before the financial crisis than financial institutions with overconfident CEOs who were not replaced. Despite this difference before the financial crisis, risk at financial institutions with both replaced and non-replaced overconfident CEOs decreases to the same levels as the risk at financial institutions with non-overconfident CEOs during the period between 2008 and 2017. Hence, the disciplining effect after 2008 is similar for newly hired CEOs as well as for CEOs who remained in office. By focusing only on non-turnover CEOs in column (7), I ensure that the effects are not only driven by the replacement of CEOs further alleviating concerns about the strategic selection of CEOs. Since I am excluding variation that is driven by the replacement of CEOs, the statistical power decreases. The results do not change qualitatively.

In the robustness tests in column (8), I exclude the last year of tenure of each CEO. Since overconfidence is measured in the previous period, one might worry that the results are influenced by the previous CEO if there is a turnover. Moreover, since the dataset is imprecise about the exact point in time when a CEO is in place in some cases, I exclude the first year of each CEO tenure similar to the case before in column (9). The results show that these modifications do not have an effect on the qualitative results.

Taken together, the robustness tests in this section deliver evidence that the results from the baseline estimation of Equation (2) are robust.

3.4 Lending Behavior

The results from the analysis so far show that financial institutions with overconfident CEOs, which were riskier before the financial crisis, decreased risk-taking more and almost fully converged to the levels of financial institutions with non-overconfident CEOs in the period after 2008. However, the stock market-based risk measures used so far potentially capture a wider range of factors. Therefore, in the following, I examine lending behavior as an alternative measure of risk-taking based on the findings of Ho et al. (2016) who show that financial institutions with overconfident CEOs eased lending standards prior to the financial crisis. It is, however, unclear to what extent changes in aggregate balance sheet positions reflect active risk-taking decisions since loan demand could be different for these financial firms. Therefore, I examine decisions on individual loan applications in the following section. This allows me to disentangle general demand effects from active risk-taking decisions with respect to lending (see e.g., Duchin and Sosyura, 2014).

To examine active risk-taking decisions, I use loan-level data from the Home Mortgage Disclosure Act (HMDA) Loan Application Registry, which delivers information on the creditworthiness of borrowers. This data roughly covers 90% of the mortgages in the U.S. Each observation is a mortgage application and includes different borrower characteristics that are collected in the application process (e.g., gender, race, location, and income) as well as certain loan characteristics (e.g., loan amount, type, or rate spread) and the final decision on the loan.

Since the analysis so far is at the financial holding company level and these parent companies usually do not directly issue mortgages, I link the respective holding companies to their direct subsidiaries. To do so, I use detailed bank relationship information from the Federal Reserve System.[23] When linking the subsidiaries to the parent companies, I only keep direct relationships and controlled subsidiaries. If several parent companies overlap within a certain time period, I drop these observations. Since the HMDA data is only recorded at an annual frequency, I only keep parent-subsidiary pairs that were active for at least half a year in a respective calendar year.

To examine the loan approval behavior by the financial firms, I only keep approved or denied applications and omit applications with other statuses such as withdrawn applications or incomplete filings. Moreover, I restrict the analysis to new loans and exclude purchases of existing loans and applications for refinancing. In the latter case, different terms regarding the borrower might apply. Finally, I exclude loans that are sold upon origination since their effect on the aggregate bank risk is limited (see e.g., Duchin and Sosyura, 2014).

To assess the riskiness of a loan, I compute the loan-to-income ratio of the borrower using the information provided by the loan application. A higher loan-to-income ratio increases the risk of not being able to service the debt and thus proxies for creditworthiness of the borrower. I winsorize the loan-to-income ratio at the 0.01% and 99.99% levels to exclude implausibly large outliers. Since this is the variable of interest, I only keep observations with data on the loan-to-income ratio. The final sample amounts to 7,062,126 observations for 321 direct subsidiaries at 163 holding companies for the years 2005-2019 with all necessary information provided.[24] To differentiate between credit demand and

[23]This dataset lists relationships between entities with detailed information on the dates of the relationship as well as the type of relationship. To link the *RSSD* identifier in both the HMDA data and the bank relationship data with the *permco* identifier of the Compustat database, I use the linking table provided by the Federal Reserve Bank of New York (Federal Reserve Bank of New York. 2021. `https://www.newyorkfed.org/research/banking_research/datasets.html`). Note that this limits the data to banks and financial institutions for which the Federal Reserve has a regulatory, supervisory, or research interest and, thus, mainly comprises depository institutions as well as designated non-depository institutions with bank holding company status. 173 of the financial institutions in the main dataset can be assigned a *RSSD* identifier. To ensure that the results are not driven by a different sample composition, the analysis from Section 3.2 was re-estimated using the matched sample only. The untabulated results show similar results.

[24]The sample starts in 2004 since the HMDA reporting standards changed in 2004.

active lending decisions, I follow Duchin and Sosyura (2014) and estimate the following model:

$$\begin{aligned} y_{i,b,m,t} =& \alpha + \beta_0 OC_{b,t-1} + \sum_{p \neq \{2000,2007\}} \beta_p OC_{b,t-1} \times \mathbb{1}[t \in p]_{i,t} \\ & + \eta_0 lti_{i,b,m,t} + \sum_{p \neq \{2000,2007\}} \eta_j lti_{i,b,m,t} \times \mathbb{1}[t \in p]_{i,t} \\ & + \lambda_0 OC_{b,t-1} \times lti_{i,b,m,t} + \sum_{p \neq \{2000,2007\}} \lambda_j OC_{b,t-1} \times \mathbb{1}[t \in p]_{i,t} \times lti_{i,b,m,t} \\ & + \boldsymbol{\gamma' X_{b,t}} + \boldsymbol{\delta' X_{i,t}} + \nu_i + \nu_b + \nu_m + \mu_t + \nu_m \times \mu_t + \epsilon_{i,b,m,t}, \end{aligned} \tag{4}$$

where $y_{i,b,c,t}$ is a binary that equals one if a loan application i at bank b for a property in metropolitan statistical area (MSA) m during year t was approved, $OC_{b,t-1}$ is a binary variable which is one if a financial institution has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p, $lti_{i,b,m,t}$ is the loan-to-income ratio of the borrower of loan i at bank b for a property in MSA m in year t. The vector of bank controls ($\boldsymbol{X_{b,t}}$) includes the standard controls as in the baseline estimation (size, return on assets, leverage, deposit ratio, liquidity, inside wealth, and the fiscal year-end stock price). The vector of loan controls ($\boldsymbol{X_{i,t}}$) includes the loan amount. Furthermore, ν_i denotes categorical borrower characteristics (i.e., gender, race, ethnicity, and co-applicant status) as well as categorical loan characteristics such as, in the full specification, loan type (insured loans), property type, and occupancy, ν_b denotes bank holding company fixed effects, ν_m MSA fixed effects and μ_t year fixed effects. I include the interaction of MSA and year fixed effects to account for MSA characteristics that are varying with time. The standard errors are clustered at the bank holding company level to allow for within-bank correlation of residuals. I estimate Equation (4) using OLS.

Coefficients β_0 and β_p denote how the likelihood to approve loans varies with overconfidence and could also reflect general demand effects. Coefficients η_0 and η_p denote the effect of the loan-to-income ratio on the likelihood to approve a loan. A positive coefficient indicates that a riskier loan is being accepted. The coefficients of interest, λ_0 and λ_p, denote the marginal effect of overconfident CEOs on the likelihood to approve a loan varying with borrower risk. A positive coefficient indicates that financial institutions with overconfident CEOs tend to approve riskier loans with a higher loan-to-income ratio.

The results are shown in Table 8. Column (1) shows the results when only controlling for bank characteristics, borrower characteristics, and firm, MSA, and year fixed effects.

Table 8: Overconfidence and approval of mortgage applications

This table presents the regression results of the OLS estimation of the HMDA loan-level estimation in Equation (4) for the U.S. financial sector for the years 2004 to 2019. The dependent variable is a binary variable which is one if a loan application i at bank b for a property in metropolitan statistical area (MSA) m during year t was approved. $OC_{b,t-1}$ is a binary variable which is one if a financial institution b has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. $lti_{i,b,m,t}$ is the loan-to-income ratio of the borrower of loan i at bank b for a property in MSA m in year t. Variable definitions are in Table A.1. Standard errors clustered at the bank holding company level in parentheses. Stars indicate significance: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

	Baseline (1) approve1	MSA (2) approve1	Loan I (3) approve1	Loan II (4) approve1	Flag (5) approve1
OC_{t-1}	0.0713	0.0674*	0.0525	0.0519	0.0508
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
$period_{2008,2017} \times OC_{t-1}$	-0.00844	-0.00967	-0.00365	0.000386	0.00173
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
$period_{2018,2019} \times OC_{t-1}$	-0.0727	-0.0644	-0.0441	-0.0379	-0.0367
	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)
lti_i	-0.0175***	-0.0179***	-0.0257***	-0.0281***	-0.0285***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$period_{2008,2017} \times lti_i$	0.0146***	0.0141***	0.0187***	0.0195***	0.0199***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$period_{2018,2019} \times lti_i$	0.00868**	0.00937**	0.0147***	0.0150***	0.0154***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$OC_{t-1} \times lti_i$	0.0114**	0.0121**	0.0126**	0.0130**	0.0134**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$period_{2008,2017} \times OC_{t-1} \times lti_i$	-0.0198***	-0.0206***	-0.0215***	-0.0219***	-0.0223***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$period_{2018,2019} \times OC_{t-1} \times lti_i$	-0.00417	-0.00473	-0.00513	-0.00541	-0.00578
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
Observations	7062131	7062126	7062126	7062126	7032561
Clusters	163	163	163	163	161
Mean	0.55	0.55	0.55	0.55	0.55
adjusted R^2	0.15	0.15	0.17	0.18	0.18
Firm controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes
Loan FE	No	No	Yes	Yes	Yes
Loan controls	No	No	No	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
MSA x Year FE	No	Yes	Yes	Yes	Yes

Column (2) includes MSA times year fixed effects. Column (3) adds categorical loan characteristics and column (4) adds additional loan characteristics. Column (5) excludes all observations where a parent-subsidiary relationship was non-existent for the entire calendar year.

The results across all specifications suggest that banks with an overconfident CEO have a higher likelihood of approving a loan (β_0) after controlling for loan and borrower characteristics. This is consistent with the finding in the literature that banks with overconfident CEOs had a higher loan growth before the crisis (Ho et al., 2016). As one would expect, the coefficient η_0 on the loan-to-income ratio is significant and negative. That means that the likelihood of loan approval declines with the loan-to-income ratio. The coefficient λ_0 on the interaction of overconfidence and the loan-to-income ratio is significant and positive indicating that banks with an overconfident CEO are more likely to accept a loan application with a higher loan-to-income ratio, all else equal, as compared to banks without an overconfident CEO. In terms of size, moving from 10% below the median loan-to-income ratio to 10% above results in an increase of in the loan-origination rate of $0.0130*(1.70-0.73) = 0.0126$ or 1.26 percentage points, or a 2.29% increase relative to the mean, using the point estimate from the preferred specification in column (4).

Despite an overall increase in the marginal effect of the loan-to-income ratio on the loan approval rate after the financial crisis, the difference in the likelihood to approve a loan with a higher loan-to-income ratio for banks with overconfident CEOs decreases. Again, the coefficients suggest a convergence across banks with overconfident CEOs and non-overconfident CEOs. This disciplining effect disappears again after 2018.

Overall, the loan-level results are consistent with the results from the baseline analysis and show that banks with overconfident CEOs extended riskier loans before the crisis. During the period between 2008 and 2017, they converged towards the behavior of banks with non-overconfident CEOs by tightening lending standards.

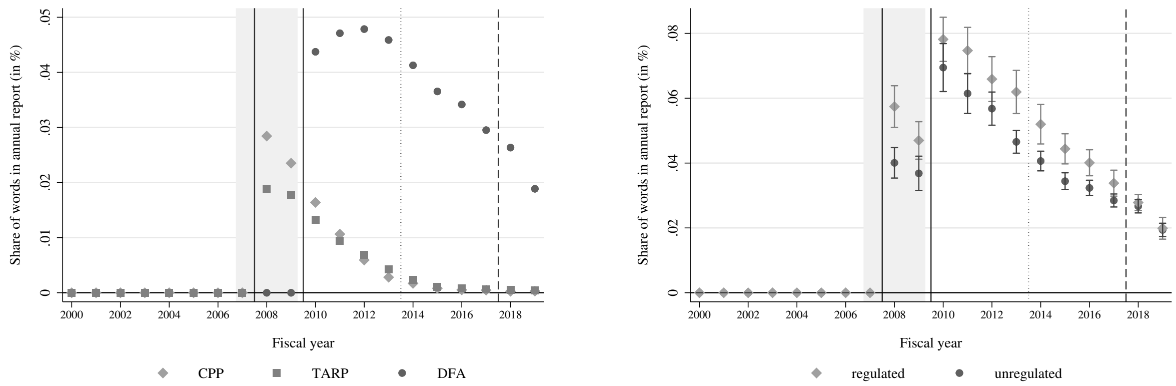
4 The Role of Stricter Financial Regulation

The results so far indicate that financial institutions with overconfident CEOs were riskier prior to the financial crisis and decreased risk towards the level of firms with non-overconfident CEOs during the period from 2008 to 2017 – a period characterized by stricter regulation. This result is consistent with a tightening of regulatory standards limiting the discretionary power of overconfident CEOs. In the following, I deliver further evidence for this hypothesis and factor out general crisis effects by distinguishing financial institutions differing in their exposure to regulation during this period.

As already introduced in Section 2, the period between 2008 and 2017 was characterized by stricter financial regulation in the U.S. financial sector. The main regulatory frameworks introduced during that period were the DFA in 2010 and the rules and regulations associated with the CPP and TARP in 2008. To get a feeling about the importance of these regulatory provisions, I examine the number of references to either of them in the annual reports of the financial institutions in the sample. Figure 3a shows the av-

Figure 3: Importance of regulatory provisions in annual reports

This figure plots the share of words referring to either of the three regulatory frameworks DFA, TARP, and CPP. Panel a) plots the average share for each of the regulatory frameworks separately for the full sample. Panel b) plots the average share for the three frameworks together split by regulated and non-regulated financial institutions as discussed in Section 4. The error bars show a one standard deviation from the mean. The shaded area indicates the crisis years. The solid vertical lines denote the timing of the respective regulatory frameworks and the dashed vertical line the timing of deregulation.



(a) Full sample

(b) By group

erage share of words referring to either of the three regulatory frameworks within the annual reports of the financial institutions in the sample. There was a strong focus on these frameworks during the period from 2008 to 2013 with a swift decline starting in 2014. Consistent with the official end of TARP/CPP in 2014 and the deregulation by the EGRRCPA in 2018, which repealed parts of the DFA, the share of words referring to either the TARP/CPP or the DFA declines further.

A large share of the enhanced regulation by the DFA only applied to larger financial institutions above certain size thresholds. To distinguish the effects of stricter regulation from general crisis effects, I divide the sample into two groups of financial institutions differing in the degree of exposure to the regulation in the period between 2008 and 2017.

The first group includes smaller depository institutions ($< \$10bn$ in total assets) and non-depository institutions.[25] Depository institutions, in general, are overseen by depository regulators such as the Federal Reserve (FED), the Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation (FDIC), or the National

[25] Note that this classification is based on the Standard Industrial Classification (SIC). A depository institution is any financial firm with SIC codes 6000-609x. Compustat assigns the SIC in an iterative process depending on the revenue generated by the primary business segments which might differ from the classification that is relevant for the regulatory assignment and, thus, only serves as a proxy. Using the SIC assigned by CRSP, which makes use of the SEC Directory, does not significantly affect the results (for a discussion on the differences in classification see, e.g., Guenther and Rosman, 1994).

Credit Union Administration (NCUA) depending on the status of the holding company (for an overview see, e.g., Labonte, 2020), and are, thus, subject to deposit insurance requirements, safety and soundness regulations, such as capital requirements, and consumer compliance regulations (Demyanyk and Loutskina, 2016). However, the smaller depository institutions were not subject to enhanced regulation after the financial crisis. Non-depository institutions, or shadow banks, are not subject to the same regulation that applies to depository institutions. As Demyanyk and Loutskina (2016) and Buchak et al. (2018) document, these financial institutions enjoyed laxer regulation before the financial crisis than depository institutions since they were neither overseen by the aforementioned institutional regulators nor strictly by the functional regulators such as the Securities and Exchange Commission (SEC) (for an overview see, e.g., Labonte, 2020). For example, non-depository institutions did not have to meet the same capital requirements as depository institutions. Despite acknowledging the risks stemming from this laxer regulation and the implementation of the Financial Stability Oversight Council (FSOC), the post-crisis regulation remained lax for non-depository institutions which were not designated to be systemically important by the FSOC (Acharya and Richardson, 2012).

The second group includes larger financial institutions ($> 10bn$ in total assets), which comprise both depository institutions and non-depository financial institutions if they hold a bank holding company status, and non-depository institutions which are designated by the FSOC to be subject to enhanced regulation. After the financial crisis, these financial institutions were subject to *enhanced* regulation. According to the DFA, for example, banks and other designated financial institutions with more than $50 billion in total assets were required to appoint a chief risk officer and banks with more than $10 billion in total assets were required to appoint a risk committee. This enhanced corporate governance as part of the enhanced regulation, among other measures, might have contained the scope of overconfident CEOs.

Table 9 shows summary statistics for both groups for the year 2007. As expected, the financial institutions subject to stricter regulation are, on average, larger, have a higher share of deposits, a higher stock price, and, associated with that, a higher level of inside wealth of the CEO.

Figure 3b, depicting the average share of words referring to either of the three regulatory frameworks after 2008 for both groups separately, shows a higher importance within the group of stricter regulated financial institutions. Despite the sample split not perfectly reflecting the take-up of TARP and, thus, the exact treatment status in the years 2008 and 2009, Figure 3b shows that even during this time, on average, there seems to be

Table 9: Regulated und unregulated financial institutions – Summary statistics

This table presents summary statistics for the main variables used in this study in the year 2007 for the two groups as described in Section 4 separately. Variable definitions are in Table A.1. Stars indicate significance of a paired t-test: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

	(1) Unregulated			(2) Regulated			(3) Difference
	count	mean	sd	count	mean	sd	Δ
OC_t	97	0.340	0.476	60	0.267	0.446	-0.074
$size_t$	97	8.580	1.539	60	10.416	1.497	1.836***
roa_t	97	1.694	3.270	60	1.231	2.204	-0.464
$leverage_t^b$	97	3.191	7.416	60	2.596	2.001	-0.596
$deposits_t$	97	0.540	0.310	60	0.626	0.168	0.086**
$liquidity_t$	97	0.086	0.142	60	0.064	0.088	-0.021
$wealth_t$	97	8.515	2.025	60	9.683	1.401	1.168***
$stockprice_t$	97	26.556	27.789	60	35.032	26.784	8.476*

a higher importance of the provisions for the stricter regulated group. A misclassification during this time, however, would only lead to an underestimation of the effects of stricter regulation. With deregulation in 2018, the difference between the two groups disappears.

To be able to disentangle the effects of stricter regulation from other confounding effects, the two groups should only differ in their exposure to regulation, other than differences in the control variables, and not be assigned to regulation based on certain characteristics or select themselves into or out of stricter regulation by manipulating their size around the threshold. According to Labonte and Perkins (2017), the size thresholds, especially the \$10 billion and \$50 billion threshold, are rather arbitrarily chosen. Therefore, it is unlikely that assignment based on specific characteristics is a concern in this case. To alleviate concerns about assignment to regulation, I exclude large financial institutions subject to the Supervisory Capital Assessment Program (SCAP) from the estimations as a robustness test, which were presumably targeted by the regulators. Moreover, I exclude financial institutions crossing the size threshold during the period of stricter regulation in a further robustness test to alleviate concerns about by self-selection.

The results from the baseline analysis could also be consistent with a higher exposure to the financial crisis and higher losses for those financial institutions subject to enhanced regulation. Thus, these financial institutions could have learned from the adverse experience and contained the scope of their CEO. To test this hypothesis, I estimate exposure to the financial crisis by estimating the following cross-sectional model using OLS:

$$exp_{i,\tau} = \alpha + \beta_1 \mathbb{1}[regulated = 1]_i + \boldsymbol{\gamma}' \boldsymbol{X_{i,2006}} + \varepsilon_i, \tag{5}$$

Table 10: Regulated financial institutions – Crisis exposure

This table presents the regression results of the OLS estimation of the cross-sectional model in Equation (5) for crisis exposure. The dependent variable $exp_{i,\tau}$ is one of the following measures of exposure to the financial crisis: i) the percent decline in the fiscal year-end stock price from the year 2006 to the year 2009, ii) the amount of write-offs accumulated during the crisis years 2007-2009 as a share of total assets in 2006, iii) the cumulative net income during the crisis years over assets in 2006, and iv) the share of mortgage loans in total lending in the year 2006. $\mathbb{1}[regulated = 1]_i$ is a binary variable that equals one for regulated financial institutions as described above. The vector of controls $\boldsymbol{X_{i,2006}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price as of 2006. Variable definitions are in Table A.1. Hubert-White heteroskedasticity consistent standard errors in parentheses. Stars indicate significance: $^{*}p < 0.1$,$^{**}\,p < 0.05$,$^{***}\,p < 0.01$.

	Stock price decline (1)	Write-offs (2)	Return on assets (3)	Real estate (4)
regulated	-0.145	-0.00395	0.0129***	-0.0926
	(0.093)	(0.006)	(0.005)	(0.071)
Observations	107	86	110	53
Mean	0.48	0.03	0.01	0.45
R^2	0.23	0.13	0.61	0.21

where $\mathbb{1}[regulated = 1]_i$ is an indicator variable that equals one for regulated financial institutions, $\boldsymbol{X_{i,2006}}$ is a vector of firm characteristics in the year 2006 including size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price, and ε_i is a random error term. The dependent variable $exp_{i,\tau}$ is one of the following measures of exposure to the financial crisis: i) the percent decline in the fiscal year-end stock price from the year 2006 to the year 2009, ii) the amount of write-offs accumulated during the crisis years 2007-2009 as a share of total assets in 2006, iii) the cumulative net income during the crisis years over assets in 2006, and iv) the share of mortgage loans in total lending in the year 2006.[26] Standard errors are adjusted for heteroskedasticity.

The results in Table 10 show no significant difference in the stock price decline after the crisis with the average decline in stock prices amounting to 48% (column (1)). Furthermore, the regulated financial institutions neither experienced a significantly larger share of write-offs (column (2)) nor a lower return on assets (column (3)) during the crisis. The share of mortgage loans in total lending shows no significantly different direct exposure to the mortgage market in the year prior to the financial crisis (column (4)). Taken together, the results suggest that the regulated financial institutions, on average, were not significantly more exposed to and adversely affected by the financial crisis than the other financial institutions.

[26]Since the financial crisis originated in the mortgage sector, a higher share of mortgage lending signifies a higher direct exposure. However, data availability for this variable is limited. Write-offs and returns on assets are only calculated for financial institutions observed in each of the crisis years.

To estimate the heterogeneous effect of the different regulatory environments, I re-estimate the event study model in Equation (1) interacted with a binary variable for the regulatory status of the financial institution as described above of the form:

$$\begin{aligned}
risk_{i,t} =& \alpha + \sum_{j\neq 2006} \mu_j \mathbb{1}[t=j]_{i,t} \\
&+ \delta_0 \mathbb{1}[regulated=1]_i + \sum_{j\neq 2006} \delta_j \mathbb{1}[t=j]_{i,t} \times \mathbb{1}[regulated=1]_i \\
&+ \beta_0 OC_{i,t-1} + \sum_{j\neq 2006} \beta_j OC_{i,t-1} \times \mathbb{1}[t=j]_{i,t} \\
&+ \eta_0 OC_{i,t-1} \times \mathbb{1}[regulated=1]_i + \sum_{j\neq 2006} \eta_j OC_{i,t-1} \times \mathbb{1}[t=j]_{i,t} \times \mathbb{1}[regulated=1]_i \\
&+ \boldsymbol{\gamma' X_{i,t}} + \nu_i + u_{i,t},
\end{aligned} \tag{6}$$

where $\mathbb{1}[regulated=1]_i$ is an indicator variable that equals one for financial institutions in the stricter regulated group. In a similar way, I re-estimate the fixed effects model in Equation (2) interacted with the indicator variable for the regulatory status. Unregulated financial institutions serve as the base category. The coefficient of interest, η_j denotes the change in the difference between the groups relative to the difference in the base year 2006. If stricter regulation is indeed one of the mechanisms behind the decline observed in Figure 2, one would expect η_j to be significantly negative in the period between 2008 and 2017.

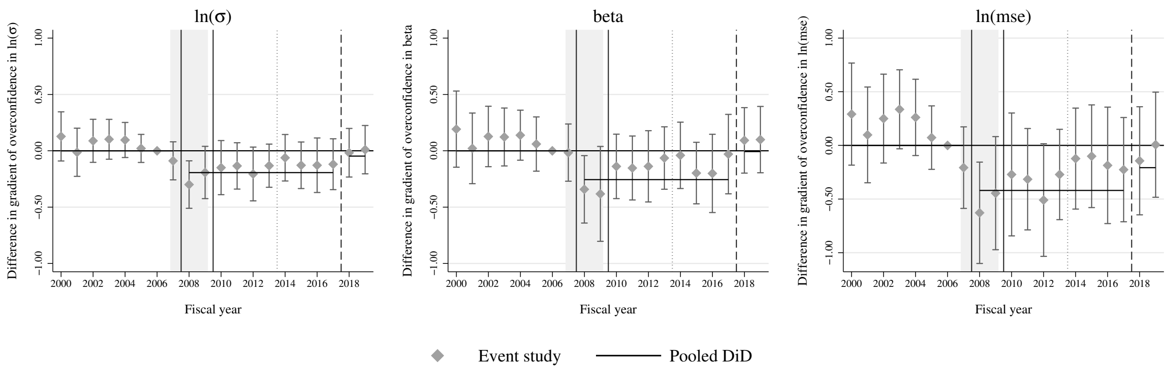
The coefficients η_j and η_p shown in Figure 4, with the corresponding values of η_p in columns (1) to (3) in Table 11, confirm the conjunction as outlined above. The decrease in overconfidence-induced risk during the period of stricter regulation is attributable only to financial institutions subject to enhanced regulation, as shown by significantly negative coefficients η_j and η_p and the insignificant and close to zero coefficients β_j and β_p for the period between 2008 and 2017.[27] The result that unregulated financial institutions remain largely unaffected supports the hypothesis that the regulatory intervention is the mechanism behind the decline in risk-taking during the period of stricter regulation. After deregulation in 2018, there is again no significant difference between the two groups.

Columns (4)-(6), excluding financial institutions crossing the size threshold during the period from 2008 to 2017, show that the results are not affected by financial institutions

[27]Note that the power of the dynamic regression is not sufficient to estimate significant coefficients η_j during the period from 2008 to 2017 due to the low number of observations per year. However, the pooled coefficient η_p for the period between 2008 and 2017 is significantly negative.

Figure 4: The role of stricter regulation – Dynamic results

This figure shows the coefficients η_j in the OLS estimation of Equation (6) (diamonds) along with the coefficients η_p of the pooled model (black line) for the three aggregate measures of risk-taking in the U.S. financial sector in the years 2000 to 2019 (natural logarithm of the standard deviation of daily stock returns (left), market beta (center), and the natural logarithm of the mean-squared-error of a single index model (right)). The vector of controls $\boldsymbol{X_{i,t}}$ includes the control variables size, return on assets, leverage, deposit ratio, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Variable definitions are in Table A.1. Hubert-White heteroskedasticity consistent standard errors are clustered at the firm level. 90% confidence intervals are shown. The shaded area indicates the crisis years. The solid vertical lines denote the timing of the respective regulatory frameworks and the dashed vertical line the timing of deregulation.



that select into our out of stricter regulation. Excluding the largest financial institutions that are still subject to stricter regulation after 2008 in columns (7)-(9) does not change the results qualitatively but amplifies the effect during the period of deregulation after 2018. Excluding the financial institutions subject to the SCAP in columns (10)-(12) does not change the results qualitatively either.

The results in this section show that the observed decrease in overconfidence-induced risk during the period between 2008 and 2017 is attributable to financial institutions subject to enhanced regulation. Hence, the results suggest that stricter regulation was successful in decreasing the discretionary power of overconfident CEOs. However, the results also suggest that the impact fades away quickly once removed.

5 Conclusion

Managerial overconfidence plays an important role in the risk-taking of financial institutions, with higher risk at financial institutions with overconfident CEOs. In this paper, I show that stricter financial regulation can discipline overconfident CEOs in the financial sector. While financial institutions with overconfident CEOs significantly contributed to risk-taking prior to the global financial crisis, partly reflected by an easing of the lend-

Table 11: The role of stricter regulation – Pooled results

This table presents the regression results of the OLS estimation of the fixed effects model in Equation (2) interacted with a binary variable for the regulatory status of a financial institution for risk-taking in the U.S. financial sector in the years 2000 to 2019. The dependent variables are the three aggregate measures of risk-taking, i.e., the natural logarithm of the standard deviation of daily stock returns, the market beta, and the natural logarithm of the mean-squared-error of a single index model. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. $\mathbb{1}[regulated = 1]_i$ is a binary variable that equals one for regulated financial institutions as described above. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Variable definitions are in Table A.1. Hubert-White heteroskedasticity consistent standard errors clustered at the firm level in parentheses. Stars indicate significance: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

	Baseline			w/o switchers			w/o > $250bn			w/o SCAP		
	(1) $ln(\sigma_t)$	(2) $beta_t$	(3) $ln(mse_t)$	(4) $ln(\sigma_t)$	(5) $beta_t$	(6) $ln(mse_t)$	(7) $ln(\sigma_t)$	(8) $beta_t$	(9) $ln(mse_t)$	(10) $ln(\sigma_t)$	(11) $beta_t$	(12) $ln(mse_t)$
OC_{t-1}	0.126***	0.149**	0.268***	0.126***	0.120	0.287***	0.125***	0.147**	0.265***	0.123***	0.144**	0.258***
	(0.041)	(0.068)	(0.091)	(0.044)	(0.074)	(0.095)	(0.041)	(0.068)	(0.091)	(0.041)	(0.067)	(0.091)
$period_{2008,2017} \times OC_{t-1}$	-0.0326	0.0262	-0.112	-0.0503	0.0495	-0.167	-0.0348	0.0237	-0.114	-0.0323	0.0260	-0.107
	(0.058)	(0.082)	(0.128)	(0.062)	(0.094)	(0.135)	(0.058)	(0.082)	(0.127)	(0.057)	(0.082)	(0.125)
$period_{2018,2019} \times OC_{t-1}$	-0.00453	0.00779	-0.0362	-0.0283	0.0486	-0.121	-0.00574	0.00562	-0.0359	-0.000368	0.0113	-0.0236
	(0.062)	(0.086)	(0.142)	(0.069)	(0.100)	(0.155)	(0.061)	(0.086)	(0.140)	(0.061)	(0.085)	(0.139)
$OC_{t-1} \times regulated$	0.0358	-0.00901	0.136	0.0273	0.00812	0.0988	0.00102	-0.0381	0.0484	0.0259	0.0116	0.0768
	(0.058)	(0.089)	(0.127)	(0.060)	(0.095)	(0.129)	(0.059)	(0.093)	(0.126)	(0.064)	(0.096)	(0.134)
$period_{2008,2017} \times OC_{t-1} \times regulated$	-0.194***	-0.256**	-0.419**	-0.164**	-0.272**	-0.333**	-0.162**	-0.226**	-0.355**	-0.152**	-0.207*	-0.349**
	(0.073)	(0.101)	(0.163)	(0.075)	(0.112)	(0.164)	(0.073)	(0.102)	(0.163)	(0.075)	(0.105)	(0.167)
$period_{2018,2019} \times OC_{t-1} \times regulated$	-0.0468	-0.00715	-0.207	-0.0254	-0.0784	-0.0806	0.00790	0.0586	-0.109	0.0123	0.0599	-0.107
	(0.086)	(0.119)	(0.199)	(0.091)	(0.128)	(0.209)	(0.083)	(0.121)	(0.190)	(0.087)	(0.126)	(0.199)
Observations	2448	2448	2448	2131	2131	2131	2273	2273	2273	2142	2142	2142
Clusters	238	238	238	212	212	212	228	228	228	221	221	221
Mean	-3.94	1.19	-8.35	-3.94	1.18	-8.35	-3.93	1.18	-8.32	-3.92	1.17	-8.30
adjusted R^2	0.85	0.61	0.82	0.85	0.61	0.82	0.86	0.62	0.82	0.85	0.62	0.81
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

ing standard, the analysis reveals that risk at financial institutions with overconfident CEOs and risk at financial institutions with non-overconfident CEOs converges during periods of stricter regulation. This holds for aggregate risk measures as well as individual loan approval rates. The results are driven by financial institutions subject to enhanced regulation, which suggests that the stricter regulatory environment was successful in reducing the risk-taking of overconfident CEOs. This is further supported by the finding that when parts of the post-crisis regulation were repealed, overconfidence-induced risk-taking re-emerged. Taken together, the analysis shows that while managerial overconfidence increases risk-taking in times of regulatory forbearance, overconfident CEOs have less discretionary power in times of stricter regulation.

Notwithstanding that this paper documents changes in the relationship between overconfidence and risk-taking influenced by stricter financial regulation after the financial crisis, it remains silent about the actual mechanism by which regulation brings about a decrease in risk-taking. Two channels could potentially be important. First, regulation could improve corporate governance. The DFA, for example, mandates chief risk officers and risk committees for large financial firms depending on the size of the financial institution. Cheffins (2015) argues that these reforms have attenuated the discretionary power of CEOs in the financial sector. Second, the reduction in risk-taking could also be due to changes in managers' compensation. Since overconfident CEOs overestimate the probability of positive outcomes, they overvalue bonus payments and could therefore be more influenced by a decrease in incentive compensation (e.g., Gietl and Kassner, 2020; Goel and Thakor, 2008).[28] Eliciting specific channels of the additional decrease in risk-taking at large banks after the financial crisis is, therefore, an important avenue for future research.

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[28] For example, financial institutions in the Capital Purchase Program (CPP) after the financial crisis had to comply with certain standards regarding the remuneration of senior executives. These included provisions on incentive compensation as well as no tax deductibility of CEO compensation above $500,000 for each executive.

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Appendices

A Additional Tables

Table A.1: List of variables

Variable	Definition	Source
Overconfidence:		
OC_t	Dummy variable that equals one if a CEO, during his tenure, held options which were at least 100% in the money at least twice. Classified as overconfident after first exhibiting the behavior. Average moneyness for *exercisable* options is thereby calculated as the realizable value per option divided by the estimated average exercise price. The realizable value per option is calculated as the value of exercisable unexercised options (*opt_unex_exer_est_val*) divided by the number of exercisable unexercised options (*opt_unex_exer_num*). The average exercise price of the options is calculated as the difference between the fiscal year-end stock price (*prcc_f*) and the realizable value per option. The percentage of average moneyness is then calculated as realizable value per option divided by the estimated average exercise price.	Execucomp Compustat
Risk measures:		
$ln(\sigma_t)$	Natural logarithm of standard deviation of daily stock returns in year t if at least ten observations are available.	CRSP
$beta_t$	Beta of the estimation of a single index model in the form $r_{i,t} = \alpha_{i,t} + \beta_{i,t}\bar{r}_{S\&P500,t} + \epsilon_{i,t}$ estimated for each stock separately in fiscal year t.	CRSP
$ln(mse_t)$	Natural logarithm of the mean-squared-error of the estimation of a single index model in the form $r_{i,t} = \alpha_{i,t} + \beta_{i,t}\bar{r}_{S\&P500,t} + \epsilon_{i,t}$ estimated for each stock separately in fiscal year t.	CRSP
Control variables:		
$size_t$	Size. Calculated as natural logarithm of total assets ($ln(at_t)$).	Compustat
roa_t	Return on assets. Calculated as net income over total assets in year t ($\frac{ni_t}{at_t}$).	Compustat
$leverage^b_t$	Book leverage. Calculated as book value of debt plus book value of equity over book value of equity in year t ($\frac{lt_t+seq_t}{seq_t}$).	Compustat
$deposits_t$	Deposits. Calculated as total deposits over assets in year t ($\frac{dptc_t+dptb_t}{at_t}$).	Compustat
$liquidity_t$	Liquidity. Calculated as cash and short-term investment over assets in year t ($\frac{che_t}{at_t}$).	Compustat
$wealth_t$	Inside wealth calculated as the number of shares owned excluding stock options times the fiscal year-end stock price ($shrown\_excl\_opts_t \times prcc\_f_t$).	Execucomp
Additional control variables (robustness):		
$tobin_t$	Firm valuation. Calculated as sum of total assets and common shares outstanding times fiscal year-end stock price less common equity over total assets in year t ($\frac{at_t+prcc\_f_t \times csho_t - ceq_t}{at_t}$).	Compustat
$delta_t$	Price sensitivity of the CEOs stock option portfolio following Core and Guay (2002) and Coles et al. (2006).	Execucomp
$vega_t$	Volatility sensitivity of the CEOs stock option portfolio following Core and Guay (2002) and Coles et al. (2006).	Execucomp
$excess_t$	Excess compensation calculated as the difference between total compensation and the predicted values from a regression of total compensation on return on assets, annualized excess returns over the risk-free rate, market to book value, the annualized standard deviation of the daily stock returns, book leverage and time and industry fixed effects following Correa and Lel (2016).	Execucomp Compustat
$wealth_t$	Predicted wealth using age and total income ($tdc1_t$).	Execucomp

Table A.2: Robustness tests – CEO characteristics

This table presents the robustness test concerning CEO characteristics of the OLS estimation of the fixed effects model in Equation (2) for risk-taking in the U.S. financial sector in the years 2000 to 2019. The dependent variable is the natural logarithm of the standard deviation of daily stock returns. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Column (1) displays the baseline results. Column (2) excludes imputed CEO observations, column (3) excludes all observations with zero exercisable options from the construction of the overconfidence measure, column (4) additionally includes gender and tenure of the CEO, column (5) includes the price sensitivity (*Delta*) and the volatility sensitivity (*Vega*) of the CEOs option portfolio, column (6) includes a measure of excess compensation of the CEO, column (7) includes the number of exercisable options, and column (8) uses an alternative proxy of wealth. Variable definitions are in Table A.1. Hubert-White heteroskedasticity consistent standard errors clustered at the firm level in parentheses. Stars indicate significance: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	(1) $ln(\sigma_t)$	(2) $ln(\sigma_t)$	(3) $ln(\sigma_t)$	(4) $ln(\sigma_t)$	(5) $ln(\sigma_t)$	(6) $ln(\sigma_t)$	(7) $ln(\sigma_t)$	(8) $ln(\sigma_t)$
OC_{t-1}	0.159***	0.159***	0.168***	0.165***	0.175***	0.159***	0.158***	0.138***
	(0.031)	(0.031)	(0.033)	(0.033)	(0.033)	(0.031)	(0.031)	(0.032)
$period_{2008,2017} \times OC_{t-1}$	-0.134***	-0.134***	-0.138***	-0.136***	-0.129***	-0.134***	-0.134***	-0.128***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.041)	(0.040)	(0.040)	(0.041)
$period_{2018,2019} \times OC_{t-1}$	-0.0438	-0.0438	-0.0762*	-0.0441	-0.0458	-0.0440	-0.0434	-0.0366
	(0.043)	(0.043)	(0.045)	(0.043)	(0.051)	(0.042)	(0.043)	(0.044)
Observations	2448	2447	2057	2385	1871	2448	2447	2448
Clusters	238	238	222	230	216	238	238	238
Mean	-3.94	-3.94	-3.92	-3.93	-3.90	-3.94	-3.94	-3.94
adjusted R^2	0.85	0.85	0.86	0.85	0.86	0.85	0.85	0.85
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.3: Wealth and income in the U.S.

This table presents the OLS estimation results for regressing wealth on income based on data from the Survey of Consumer Finances (SCF) 2016 excluding the 1st and the 99th percentile of the wealth distribution. Columns (1) and (2) are unweighted, columns (3) and (4) are weighted by the sampling weights. Hubert-White heteroskedasticity consistent standard errors used. P-values in brackets. Stars indicate significance: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	(1) $ln(networth_t)$	(2) $ln(networth_t)$	(3) $ln(networth_t)$	(4) $ln(networth_t)$
$ln(income_t)$	1.069***	1.030***	0.942***	0.955***
	(0.031)	(0.029)	(0.080)	(0.071)
age_t		0.0294***		0.0288***
		(0.003)		(0.007)
Constant	1.884***	0.409	2.216***	0.506
	(0.237)	(0.267)	(0.549)	(0.448)
Observations	934	934	934	934
weighted	No	No	Yes	Yes
R^2	0.57	0.62	0.31	0.41

Table A.4: Robustness tests – Firm characteristics

This table presents the robustness tests concerning firm characteristics of the OLS estimation of the fixed effects model in Equation (2) for risk-taking in the U.S. financial sector in the years 2000 to 2019. The dependent variable is the natural logarithm of the standard deviation of daily stock returns. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Column (1) displays the baseline results. Column (2) includes *Tobin's Q*, column (3) two lags and leads of the stock return, column (4) the size of the executive board, and column (5) a measure for market concentration. Variable definitions are in Table A.1. Hubert-White heteroskedasticity consistent standard errors clustered at the firm level in parentheses. Stars indicate significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	(1) $ln(\sigma_t)$	(2) $ln(\sigma_t)$	(3) $ln(\sigma_t)$	(4) $ln(\sigma_t)$	(5) $ln(\sigma_t)$
OC_{t-1}	0.159***	0.158***	0.143***	0.159***	0.159***
	(0.031)	(0.031)	(0.042)	(0.031)	(0.031)
$period_{2008,2017} \times OC_{t-1}$	-0.134***	-0.133***	-0.130***	-0.134***	-0.134***
	(0.040)	(0.040)	(0.046)	(0.040)	(0.039)
$period_{2018,2019} \times OC_{t-1}$	-0.0438	-0.0483		-0.0448	-0.0426
	(0.043)	(0.043)		(0.043)	(0.042)
Observations	2448	2448	1685	2448	2448
Clusters	238	238	214	238	238
Mean	-3.94	-3.94	-3.95	-3.94	-3.94
adjusted R^2	0.85	0.85	0.87	0.85	0.85
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table A.5: Robustness tests – Estimation and sample

This table presents the robustness tests concerning the estimation methodology and the sample composition of the estimation of the fixed effects model in Equation (2) for risk-taking in the U.S. financial sector in the years 2000 to 2019. The dependent variable is the natural logarithm of the standard deviation of daily stock returns. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Column (1) displays the baseline results. Column (2) uses weighted least squares (WLS), column (3) uses industry fixed effects, column (4) only keeps financial institutions which are in the sample over the entire sample period, column (5) only keeps CEOs who were in office either in 2007 or 2010, column (6) only keeps CEOs who were replaced between 2007 and 2010, column (7) only keeps CEOs who were in office both in 2007 and in 2010, column (8) omits the last year of each CEO's tenure, and column (9) the first year. Variable definitions are in Table A.1. Hubert-White heteroskedasticity consistent standard errors clustered at the firm level in parentheses. Stars indicate significance: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

	(1) $ln(\sigma_t)$	(2) $ln(\sigma_t)$	(3) $ln(\sigma_t)$	(4) $ln(\sigma_t)$	(5) $ln(\sigma_t)$	(6) $ln(\sigma_t)$	(7) $ln(\sigma_t)$	(8) $ln(\sigma_t)$	(9) $ln(\sigma_t)$
OC_{t-1}	0.159***	0.188***	0.149***	0.167***	0.189***	0.334***	0.104*	0.154***	0.180***
	(0.031)	(0.052)	(0.030)	(0.046)	(0.053)	(0.103)	(0.060)	(0.031)	(0.032)
$period_{2008,2017} \times OC_{t-1}$	-0.134***	-0.203***	-0.125***	-0.189***	-0.168***	-0.318*	-0.0917*	-0.114***	-0.141***
	(0.040)	(0.062)	(0.036)	(0.062)	(0.046)	(0.157)	(0.047)	(0.040)	(0.040)
$period_{2018,2019} \times OC_{t-1}$	-0.0438	-0.111	-0.0109	-0.0337	-0.0501	0.132	-0.0305	-0.0259	-0.0527
	(0.043)	(0.069)	(0.043)	(0.056)	(0.056)	(0.225)	(0.057)	(0.043)	(0.043)
Observations	2448	2448	2448	669	1536	397	1139	2251	2255
Clusters	238	238	238	35	153	40	113	238	237
Mean	-3.94	-4.04	-3.94	-4.00	-3.88	-3.89	-3.87	-3.95	-3.94
adjusted R^2	0.85	0.94	0.77	0.88	0.87	0.89	0.88	0.85	0.86
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes