Taming Overconfident CEOs – Managerial Overconfidence, Risk-Taking, and Financial Regulation*

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Abstract

Managerial overconfidence influences the risk-taking behavior of financial institutions. Using detailed financial data of U.S. financial institutions, I study how changes to the regulatory environment affect the nexus between managerial overconfidence and risk-taking. I find that overconfidence-induced risk-taking decreases during periods of stronger regulatory oversight. Since this decrease is only observable for financial institutions subject to enhanced regulation, this is consistent with financial regulation mitigating the risk-increasing effect of managerial overconfidence.

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JEL Classification: G20 · G41 · H81

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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 personal trait that significantly affects risk-taking decisions.[1] There are two main explanations for this relationship: First, overconfident chief executive officers (CEOs) underestimate risks associated with future cash flows and overestimate the probability of success (e.g. Hackbarth, 2008). Second, overconfident CEOs overestimate the precision of noisy signals (e.g. Gervais et al., 2011). In line with the theory, the empirical literature shows that financial institutions with overconfident CEOs followed riskier strategies before and performed worse during the last financial crisis (e.g. Ho et al., 2016; Ma, 2015; Niu, 2010).

Spurred by the global financial crisis, a substantial tightening of regulatory standards in financial markets, such as the Dodd-Frank Wall Street Reform and Consumer Protection Act (DFA) of 2010 in the U.S., tried to decrease risk-taking incentives, improve regulatory oversight, and strengthen internal risk management. Such stricter regulatory environments might be effective in restraining overconfident CEOs.

This paper uses detailed financial data on listed firms in the U.S. financial sector to study whether and how stricter financial market regulation affects the risk-taking behavior of overconfident CEOs. Following Malmendier and Tate (2005a), I measure CEO overconfidence by their option exercising behavior. By comparing financial institutions with overconfident CEOs to financial institutions without overconfident CEOs across time, I find that risk-taking at financial institutions with overconfident CEOs, which was higher before the financial crisis, converges to the levels of firms with non-overconfident CEOs during the period of stricter regulation after the financial crisis. This holds for aggregate risk measures as well as for approval decisions on individual loans. In contrast, with deregulation in form of the Economic Growth, Regulatory Relief, and Consumer Protection ACT (EGRRCPA) of 2018, which repealed parts of the DFA, risk-taking at financial institutions with overconfident CEOs increases again, compared to financial institutions with non-overconfident CEOs. These results, in general, provide suggestive evidence that the nexus between managerial overconfidence and risk-taking is influenced by the regulatory environment.

However, this result could also be explained by more cautious risk-taking decisions

[1] Since strategic decisions are primarily influenced by the CEO, this literature focuses on the level of overconfidence of the CEO as the top decision maker (see e.g. Ho et al., 2016).

of financial institutions with overconfident CEOs due to a worse performance during the financial crisis (Ho et al., 2016). To rule out this explanation and to further analyze the role of regulation, I distinguish two types of financial institutions differing in the degree of regulatory oversight. The first group comprises non-depository institutions (shadow banks) and smaller depository institutions, for which regulation remains lax after the financial crisis. The second group includes larger depository institutions and designated non-depository institutions that were subject to enhanced regulation after the financial crisis. Some parts 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.[2]

The results show that the decline in overconfidence-induced risk during the period of stricter regulation is only observable for the subset of financial institutions subject to enhanced regulation. Before the financial crisis, overconfidence-induced risk is similar across the two types. Moreover, the financial institutions subject to enhanced regulation did, on average, not perform worse during the financial crisis. Hence, it is unlikely that learning effects due to the worse performance of financial institutions with overconfident CEOs during the crisis drive the decline in risk-taking. This suggests that stricter regulation is the reason for the decline in risk-taking by overconfident CEOs.

The results are robust to several modifications of the analysis. I address the potential concern of endogenous selection by closely examining the timing around the appointment of new CEOs, focusing on the subset of non-turnover CEOs, and instrumenting overconfidence using the age of the CEO. Moreover, I exploit 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 investment strategies of the CEOs. The results show that the option-based overconfidence measure captures overconfident behavior both before and after the financial crisis. The main results are further robust to the inclusion of additional control variables and to changes to the estimation methodology and the sample composition.

[2]It is known from other contexts, such as the Sarbanes-Oxley Act (SOX) in 2002, that substantial changes in regulation concerning corporate governance significantly improved decision making of overconfident CEOs. Banerjee et al. (2015) show that the SOX substantially improved the behavior of overconfident CEOs. Cheffins (2015), however, argues that the corporate governance movement related to the SOX did not affect CEOs of firms in the financial sector. This is consistent with the finding of Ho et al. (2016), who find 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.

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, thereby increasing the value of the firm, despite the stock returns of the firm being more volatile.

For 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 an overconfident CEO had a higher variation in daily stock returns and, thus, are perceived 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 effects of changes in the economic and regulatory environment on the risk-taking behavior of overconfident CEOs specifically in the financial sector. The results reveal that in times of stricter regulatory oversight overconfidence-induced risk is reduced whereas in times of forbearance overconfidence increases risk-taking. This helps to better understand how risk induced by individual behavior reacts to changes in the economic and regulatory environment, how public scrutiny and regulation can affect the relation between overconfidence and risk-taking, and whether further scope for regulation remains to restrain overconfident behavior. Moreover, this paper is the first to examine individual loan approval behavior in the context of managerial overconfidence.

Second, this paper relates to the literature on risk-taking after the financial crisis in

[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). Goel and Thakor (2008) argue that, since promotion is usually based on performance, an overconfident manager is more likely to be promoted. Graham et al. (2013) empirically show that CEOs are significantly more optimistic than the lay population.

general and on the effects of post-crisis regulation on risk-taking in particular. 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. 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. Besides the overall effects of the post-crisis period, Akhigbe et al. (2016) show that risk-taking in general decreased in the financial sector after the passage of the DFA and that the decrease was strongest for 'too big to fail' institutions.

This paper contributes to the literature by addressing a particular channel through which post-crisis regulatory changes might have had an effect on risk-taking, i.e. 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 excessive risk-taking. 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 data and discusses the overconfidence measure. Section 3 presents the estimation strategy as well as the results of the effects of overconfidence on aggregate risk measures. Section 4 examines the role of the regulatory environment. Section 5 extends the analysis to the individual lending behavior of financial institutions. Section 6 concludes.

2 Data and Variables

2.1 Data

For the main 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.[4] 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 indus-

[4]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.

try. 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 calender 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. 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.[5] I winsorize the accounting variables at the 1^{st} and 99^{th} percentile.

The observation period can be divided into four sub-periods that differ in individual CEOs' degree of influence. First, the period from 1999 to 2006, which I denote as the *pre-crisis* period. During this period, financial regulation was rather lax which, among others, lead to the buildup of the sub-prime mortgage crisis and the global financial crisis. Despite corporate governance movements in the general economy related to the Sarbanes-Oxley Act (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, giving them substantial discretionary power. Second, the *crisis* period from 2007 to 2009 originating in the sub-prime lending crisis with its peak in late 2008 with the bankruptcy of Lehman brothers. Already during this period, the U.S. government heavily intervened in the financial sector (e.g. Emergency Economic Stabilization Act of 2008 including the Troubled Asset Relief Program (TARP) or the bank stress tests under the Supervisory Capital Assessment Program (SCAP) of 2009) potentially limiting the influence of individual CEOs. Third, the period from 2010 to 2017, which I denote as the *regulation* period. In this period, the DFA aimed to decrease risk-taking incentives, improve regulatory oversight, strengthen internal risk management, and to impose stricter regulation for the larger depository institutions and designated non-depository institutions. These measures likely limited limited the scope and incentives for individual

[5] 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.

CEOs to take additional risks. The fourth period, which I denote as *deregulation* period starts with the EGRRCPA in 2018, which partly repealed the regulation imposed by the DFA.

2.2 Variables

2.2.1 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 widely used as aggregate stock market-based measures of risk in the literature.[6] Since the stock price represents a call option on the underlying assets, the stock price volatility serves as an indicator for the volatility of the firm's assets (see e.g. Aabo et al., 2020). Stock return volatility is calculated as the standard deviation of daily stock returns during fiscal year t. Since the distribution of the standard deviation of the daily stock returns is skewed, I use the natural logarithm of the standard deviation. Exposure to market volatility is calculated as the *beta* of a single index model, using the return on the S&P500 as a benchmark.[7] The natural logarithm of the mean squared error of the same single index model is used as measure of idiosyncratic risk.

2.2.2 Control Variables

The baseline firm-level control variables are standard 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.[8]

Risk aversion of the CEO, which is not directly observable, could have an effect on both risk-taking and the option exercising behavior and thereby on the option-based measure of overconfidence. Following the expected utility theory, at least part of the

[6] 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.

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

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

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 of the CEO to proxy for net worth (e.g. Harford and Li, 2007), which is calculated as the natural logarithm of shares owned excluding options times the fiscal year-end stock price.

2.2.3 Overconfidence Measure

While different approaches to measure managerial overconfidence have been proposed, 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.[9]

Since there is only aggregate data available for the option portfolios of the 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 (e.g. Campbell et al., 2011; Ho et al., 2016). A CEO is overconfident when postponing the exercise of deep-in-the-money options. Average moneyness for *exercisable* options in a given year is thereby calculated as the realizable value per option divided by the estimated average exercise price. 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, i.e. the price at which the CEO hast the option to buy the underlying stock.

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.[10] Therefore, this measure allows for within-CEO variation and avoids forward-

[9]'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.

[10]If a CEO switches between firms in the observed period, all tenures are taken into account. Ob-

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, I compare the returns from keeping and selling the options at the highest price in year $t+1$, relative to the highest price in year t, 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						

looking assumptions, however, it assumes that overconfidence is a persistent trait once adapted. Using 100% as cutoff ensures that only highly overconfident CEOs are classified as overconfident (see e.g. Campbell et al., 2011).

However, the late-exercising behavior might 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. To do so, I construct 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 the 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 and conclude that, even though these additional alternative explanations might play a role in the late-exercising behavior of options, 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. (2021) deliver evidence

servations 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 for 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.

that the option-based measure indeed reflects overconfidence using detailed assessments of CEO personalities.

However, post-crisis regulation might have influenced the option-exercising behavior of the CEOs directly via changes in executive compensation. To ensure that the option-based overconfidence measure captures overconfident behavior across time, I analyze the tone of the *Management Discussion and Analysis* (MD&A) section of the annual reports (10K). 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, is most likely to reveal information via the tone (see e.g. Loughran and McDonald, 2011). For this purpose, I parse this section from the respective 10K-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 obtain the respective MD&A sections. I then analyze the tone of these sections by contrasting the number of positive words to the number of negative words as defined by the Loughran and McDonald (2011) dictionary.[11] A more overconfident CEO should use more positive words, relative to negative words, all else equal. 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. That is by $ln(1.718 + \frac{N}{df})$, 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 which appear in every document receive a weight of 1.

To test whether the option-based measure captures overoptimistic behavior across periods, I regress the natural logarithm of the continuous tonal measures on the option-based overconfidence dummy interacted with a dummy variable distinguishing the different periods described in section 2.1 using OLS in the largest possible sample. 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 tone of the MD&A section. That is, having an overconfident CEO, as classified

[11] 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 the share of positive over negative words as defined by the Loughran and McDonald (2011) dictionary, 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, 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. *Pre-crisis* denotes the period from 2000 to 2006, *crisis* the period from 2007-2009, *regulation* the period from 2010 to 2017, and *deregulation* the period from 2018 to 2019 as described in Section 2.1. 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	
	Raw	Weighted
	(1)	(2)
OC_t	0.0918*	0.124**
	(0.052)	(0.056)
$crisis_t \times OC_t$	-0.00532	0.00183
	(0.056)	(0.060)
$regulation_t \times OC_t$	-0.0459	-0.0445
	(0.052)	(0.055)
$deregulation_t \times OC_t$	0.0146	0.0131
	(0.073)	(0.078)
$words_t$	-0.00933***	-0.00958***
	(0.003)	(0.003)
Observations	1781	1781
adjusted R^2	0.60	0.60
Controls	Yes	Yes
Firm FE	Yes	Yes
Year FE	Yes	Yes

by the option-based measure, is associated with a 10-12% higher proportion of positive words in the MD&A section, conditional on the firms performance. Moreover, the results show that this relationship still holds after the financial crisis since the coefficient on the interaction terms is 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 both before and after the financial crisis.

Table 3 shows summary statistics of the unbalanced sample to provide some indication of the nature of the sample. Around 30% of the CEO-year observations are classified as overconfident.[12] Further, the average daily stock return volatility is .02 ($e^{-3.938}$), the average beta 1.19, and the average mean squared error .00024 ($e^{-8.355}$).

[12]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.

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*. Variable definitions are in Table A.1.

	(1) mean	(2) sd	(3) p25	(4) p50	(5) p75
OC_t	0.292	0.455	0.000	0.000	1.000
$ln(\sigma_t)$	-3.938	0.475	-4.260	-4.058	-3.681
$beta_t$	1.189	0.421	0.891	1.135	1.425
$ln(mse_t)$	-8.355	0.974	-8.995	-8.583	-7.852
$size_t$	9.639	1.688	8.550	9.374	10.592
roa_t	1.532	3.785	0.735	1.028	1.401
$leverage_t$	1.838	2.697	0.564	1.115	2.218
$deposits_t$	0.617	0.265	0.583	0.717	0.792
$liquidity_t$	0.082	0.109	0.024	0.041	0.088
$wealth_t$	9.768	1.044	9.016	9.710	10.477
$stockprice_t$	36.226	30.548	16.525	28.930	45.535
Observations	2448				

3 Overconfidence and Risk-Taking

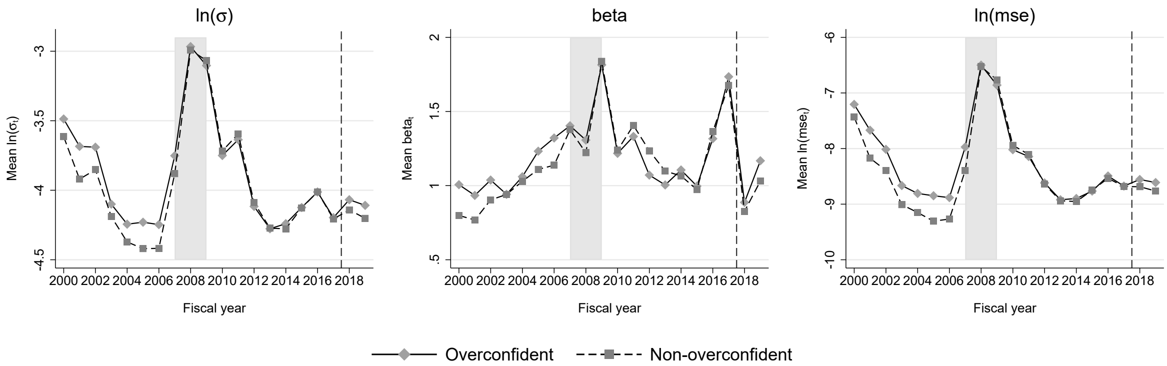
3.1 Descriptive Evidence

Figure 1, plotting the sample mean of the three risk measures by year, shows that, on average, risk-taking at financial firms with overconfident CEOs is higher before the crisis with no different trend observable and converges during and after the financial crisis. After deregulation, risk-taking is, on average, again higher at financial firms with overconfident CEOs, despite not reaching the same level as in the pre-crisis period.

Table 4 confirms the results from Figure 1. Firms with overconfident CEOs were, on average, significantly riskier before the crisis (column (1)). During and the crisis, both types of financial institutions converged in their level of risk-taking (column (2) and (3)). With deregulation in 2018, risk-taking is again significantly higher at financial institutions with overconfident CEOs (column (4)). Thus, the descriptive analysis reveals heterogeneous changes in risk-taking across time. Table 4, however, also shows that other firm characteristics of changed over time. Therefore, I control for these firm characteristics as well as other time-invariant unobservable factors in the dynamic regression analysis in the following section.

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 squares the average risk for firms with non-overconfident CEOs. Variable definitions are in Table A.1. The shaded area indicates the crisis years, the dashed line the moment of deregulation.



3.2 Dynamic Regression Analysis

The descriptive analysis in the previous section reveals that firms with overconfident CEOs differ in their risk-taking behavior across time. To precisely estimate the dynamic relationship between overconfidence and risk-taking, I regress the respective measure of risk on the binary overconfidence variable interacted with year dummies as well as firm-level controls in a fixed effects framework using OLS.[13] The precise econometric model is designed as follows:

$$\begin{aligned} risk_{i,t} = \alpha &+ \beta_0 OC_{i,t-1} \\ &+ \sum_{j=2000}^{2019} \beta_j OC_{i,t-1} \times \mathbb{1}[t=j]_{i,t} \\ &+ \boldsymbol{\gamma' X_{i,t}} + \nu_i + \mu_t + u_{i,t}, \end{aligned} \tag{1}$$

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, $\boldsymbol{X_{i,t}}$ is a vector of firm characteristics, ν_i are firm fixed effects, μ_t are year 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,

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

Table 4: Differences across periods and 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 each period separately. The sample is unbalanced. *Pre-crisis* denotes the period from 2000 to 2006, *crisis* the period from 2007-2009, *regulation* the period from 2010 to 2017, and *deregulation* the period from 2018 to 2019 as described in Section 2.1. 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 and non-overconfident financial institutions			
	(1) Pre-crisis	(2) Crisis	(3) Regulation	(4) Deregulation
$ln(\sigma_t)$	0.137***	-0.023	-0.018	0.087***
$beta_t$	0.127***	0.008	-0.015	0.078**
$ln(mse_t)$	0.344***	-0.004	-0.007	0.146**
$size_t$	-0.437***	-0.444**	-0.322***	-0.051
roa_t	-0.204	0.471	1.431***	1.337***
$leverage_t$	-0.155	0.436	-0.198	-0.407
$deposits_t$	-0.004	-0.095***	-0.105***	-0.051
$liquidity_t$	0.036***	0.009	0.019**	0.007
$wealth_t$	-0.009	0.057	0.202***	0.192
$stockprice_t$	3.340**	12.286***	22.354***	25.039***
Observations	644	394	1134	276

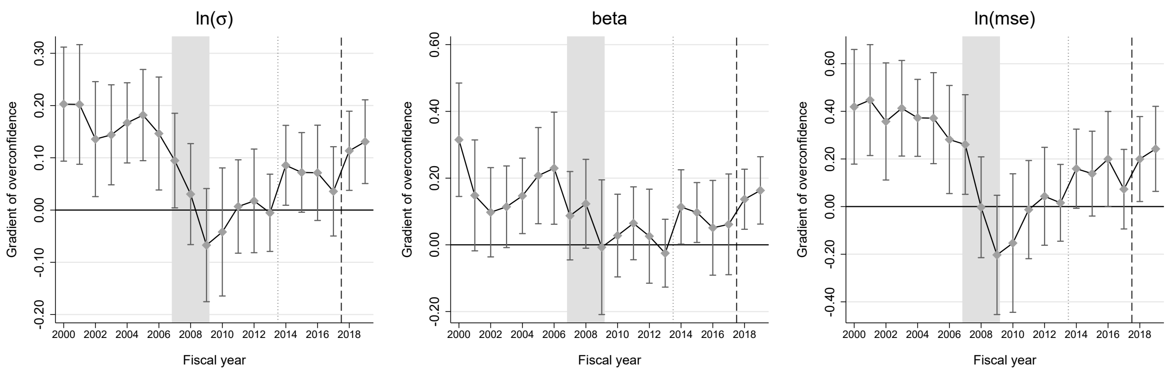
a proxy for CEO wealth, and the fiscal year-end stock price. By using firm fixed effects, I account for time-invariant unobserved differences between firms. The identification of the β coefficients thus relies on within-firm variation, i.e. a replacement of the CEO, and on within CEO variation, i.e. CEOs who become overconfident during tenure. Since the financial sector is likely to be prone to common trends, I include year fixed effects. 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 across the entire observation period. If overconfidence increases risk-taking, this coefficient is positive. Due to the fixed effects, identification relies on within firm variation in overconfidence by either CEO turnover or by a CEO becoming overconfident during tenure. The coefficients β_j, which denote the deviation in risk-taking from the average difference in risk-taking (β_0) at firms with overconfident CEOs relative to other firms in year j, are the main coefficients of interest. The total difference in risk-taking between firms with overconfident CEOs and firms with non-overconfident CEOs for year j is, thus, calculated as the sum of β_0 and the respective β_j.

Figure 2 plots the gradient of overconfidence, which is the above-mentioned linear combination of β_0 and β_j, for each year j of the OLS regression of Equation (1). The

Figure 2: Overconfidence and risk-taking – Dynamic results

This figure shows the gradient of overconfidence, which is the linear combination of β_0 and β_j for each year j in the OLS estimation of Equation (1), 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. The shaded area indicates the crisis years, the dotted line an informal change in the strictness of regulation, and the dashed line the moment of deregulation.



results show a significant difference in risk-taking between financial institutions with overconfident CEOs and without before the financial crisis with no differential trend observable. This difference disappears during the crisis period and the period of stricter regulation between 2010 and 2017. As noted before, already during the financial crisis, the U.S. government heavily intervened in the financial sector (e.g. Troubled Asset Relief Program, Supervisory Capital Assessment Program) potentially limiting the influence of individual CEOs, which can explain the results observed during the crisis period. Albeit not formalized in legislation, regulation was effectively stricter during the period from 2010 to 2013 and laxer during the period from 2014 to 2017, as indicated by the dotted vertical line in Figure 2. This is reflected in a slight increase in overconfidence-induced risk-taking in the latter period. With deregulation in 2018, indicated by the dashed vertical line in Figure 2, risk-taking again diverges with significantly higher risk-taking at financial institutions with overconfident CEOs.

To distinguish on the different regulatory periods, I pool the respective periods and regress the measures of risk on the binary overconfidence variable interacted with an indicator variable for each of the four periods as well as firm-level controls in a fixed

Table 5: 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 $t-1$, $\mathbb{1}[crisis = 1]_{i,t}$ is an indicator variable for the crisis period from 2007 to 2009, $\mathbb{1}[regulation = 1]_{i,t}$ for the period from 2010 to 2017, and $\mathbb{1}[deregulation = 1]_{i,t}$ for the period from 2018 to 2019. 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)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$ln(\sigma_t)$	$beta_t$	$ln(mse_t)$	$ln(\sigma_t)$	$beta_t$	$ln(mse_t)$	$ln(\sigma_t)$	$beta_t$	$ln(mse_t)$
OC_{t-1}	0.158***	0.162***	0.354***	0.167***	0.182***	0.373***	0.164***	0.179***	0.365***
	(0.035)	(0.050)	(0.076)	(0.034)	(0.051)	(0.073)	(0.034)	(0.051)	(0.073)
$crisis_t \times OC_{t-1}$	-0.145***	-0.111	-0.349***	-0.140***	-0.108*	-0.332***	-0.142***	-0.110*	-0.337***
	(0.050)	(0.069)	(0.114)	(0.047)	(0.065)	(0.106)	(0.047)	(0.065)	(0.106)
$reg_t \times OC_{t-1}$	-0.153***	-0.121**	-0.361***	-0.132***	-0.127**	-0.300***			
	(0.045)	(0.057)	(0.102)	(0.042)	(0.056)	(0.094)			
$reg_{hard,t} \times OC_{t-1}$							-0.167***	-0.155***	-0.381***
							(0.046)	(0.057)	(0.103)
$reg_{soft,t} \times OC_{t-1}$							-0.0956**	-0.0970	-0.215**
							(0.046)	(0.065)	(0.102)
$dereg_t \times OC_{t-1}$	-0.0957**	-0.0254	-0.290***	-0.0482	-0.0359	-0.157	-0.0381	-0.0277	-0.134
	(0.045)	(0.066)	(0.102)	(0.045)	(0.061)	(0.102)	(0.046)	(0.063)	(0.105)
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	0.81	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

effects framework using OLS. The econometric model is designed as follows:

$$\begin{aligned} risk_{i,t} = \alpha &+ \beta_0 OC_{i,t-1} \\ &+ \beta_1 OC_{i,t-1} \times \mathbb{1}[crisis = 1]_{i,t} \\ &+ \beta_2 OC_{i,t-1} \times \mathbb{1}[regulation = 1]_{i,t} \\ &+ \beta_3 OC_{i,t-1} \times \mathbb{1}[deregulation = 1]_{i,t} \\ &+ \boldsymbol{\gamma' X_{i,t}} + \nu_i + \mu_t + u_{i,t}, \end{aligned} \tag{2}$$

where $\mathbb{1}[crisis = 1]_{i,t}$ is an indicator variable for the crisis period from 2007 to 2009, $\mathbb{1}[regulation = 1]_{i,t}$ for the period from 2010 to 2017, and $\mathbb{1}[deregulation = 1]_{i,t}$ for the period from 2018 onwards.

The results of the OLS regression of Equation (2) are summarized in Table 5. Column (1) to (3) show the results excluding control variables, column (4) to (9) including controls. In column (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. On average, financial institutions with overconfident CEOs are riskier across all risk measures as indicated by the positive and highly significant coefficient for the overconfidence dummy (β_0) in all specifications. 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 18.2% ($(e^{(0.167)} - 1) \times 100$) higher standard deviation of daily stock returns (column (4)) and a 45.1% 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 15.5% for firms with overconfident CEOs.

The coefficients β_1 and β_2 across all specifications indicate a risk-decreasing effect at financial institutions with overconfident CEOs during the financial crisis and the period after the financial crisis. As mentioned before, already during the crisis the government heavily intervened into the financial sector potentially limiting the individual scope of the management. Comparing the coefficients of the overconfidence dummy (β_0) and the interaction terms (β_1 and β_2), the effects before and after the crisis offset each other such that the risk of firms with overconfident CEOs and firms with non-overconfident CEOs converges.[14] Splitting the period from 2010 to 2017 in two sub-periods differing in the effective strictness of regulation, the results show that the observed effect is stronger in the first sub-period (column (7) to (9)). The coefficient β_3 shows no significant difference between risk-taking at financial institutions with overconfident CEOs and without after deregulation when focusing on the specifications including control variables (column (4) to (9)). Taken together, the results support the hypothesis that a change in the regulatory environment in the post-crisis period limits the scope for overconfident CEOs to take additional risks. To provide further evidence for the role of regulation, I will show in section 4 that this result only holds for financial institutions subject to regulation, which precludes general crisis effects.

[14]Using a standard Wald test, the hypotheses $\beta_0 = -\beta_1$ and $\beta_0 = -\beta_2$ cannot be rejected on conventional significance levels.

3.3 Robustness Tests

To test the robustness of the results of the main analysis in section 3.2, I focus on the specification in Equation (2) in the following. 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.

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 hired due to a change in the 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.[15]

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 effect is 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 the other endogeneity concerns discussed in section 3.1, I set up an instrumental variable estimation using the age of the CEO as an instrument for overconfidence (Ho et al., 2016). The choice

[15]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 – CEO selection

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 $t-1$, $\mathbb{1}[crisis = 1]_{i,t}$ is an indicator variable for the crisis period from 2007 to 2009, $\mathbb{1}[regulation = 1]_{i,t}$ for the period from 2010 to 2017, and $\mathbb{1}[deregulation = 1]_{i,t}$ for the period from 2018 to 2019. 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}	0.192***	0.225***	0.412***	0.208***	0.256***	0.440***	0.189***	0.248***	0.385***
	(0.037)	(0.056)	(0.077)	(0.041)	(0.063)	(0.083)	(0.049)	(0.071)	(0.100)
$crisis_t \times OC_{t-1}$	-0.139***	-0.124*	-0.309***	-0.118**	-0.120	-0.236**	-0.0993	-0.116	-0.164
	(0.049)	(0.068)	(0.110)	(0.054)	(0.075)	(0.118)	(0.062)	(0.083)	(0.134)
$reg_t \times OC_{t-1}$	-0.145***	-0.165***	-0.313***	-0.151***	-0.177***	-0.311***	-0.133**	-0.179**	-0.244**
	(0.044)	(0.059)	(0.098)	(0.048)	(0.067)	(0.104)	(0.055)	(0.074)	(0.117)
$dereg_t \times OC_{t-1}$	-0.0667	-0.0709	-0.184*	-0.0834	-0.0967	-0.212*	-0.0599	-0.113	-0.142
	(0.048)	(0.066)	(0.108)	(0.052)	(0.071)	(0.116)	(0.058)	(0.079)	(0.132)
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

of the 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.[16] 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).[17] 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 re-

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

[17]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 (3.2)

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, 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 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 $t-1$, $\mathbb{1}[crisis = 1]_{i,t}$ is an indicator variable for the crisis period from 2007 to 2009, $\mathbb{1}[regulation = 1]_{i,t}$ for the period from 2010 to 2017, and $\mathbb{1}[deregulation = 1]_{i,t}$ for the period from 2018 to 2019. 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 firm level 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}		0.393***	0.354**	0.898***
		(0.132)	(0.171)	(0.299)
$crisis_t \times OC_{t-1}$		-0.589***	-0.770***	-1.357***
		(0.178)	(0.226)	(0.415)
$reg_t \times OC_{t-1}$		-0.253*	-0.151	-0.558
		(0.152)	(0.199)	(0.348)
$dereg_t \times OC_{t-1}$		0.0722	0.120	0.0716
		(0.190)	(0.262)	(0.434)
age_t	0.0195*			
	(0.011)			
Observations	2448	2448	2448	2448
Clusters	402	238	238	238
pseudo R^2	0.13			
adjusted R^2		0.78	0.37	0.70
KP F-stat		6.47	6.47	6.47
SW F-stat	30.32			

gression (Angrist and Pischke, 2009), and has previously been applied in related contexts (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. Moreover, 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 logistic regression. Note again that the specification does not necessarily have to be correct using this approach. The coefficient of age shows that age is a significant predictor for the overconfidence dummy and thus confirms earlier findings in the literature. The overall results in columns (2) to (4) do not change qualitatively compared to the fixed effects regression in Section 3.2, however, being estimated less precise. While overconfidence in general increases risk-taking, the coefficients of the overconfidence dummy and the interaction term indicate a convergence in the risk-taking behavior after the crisis and a divergence in the period of deregulation. The coefficients are slightly larger than in the OLS estimation, however, 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 certain years within the observed period. In the baseline analysis, I impute the overconfidence measure and income 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 by 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 (7). 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.[18]

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).[19] 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 size of the executive board.[20] Another concern is the possibility of an increase in market concentration after the crisis due to failures, mergers, and takeovers. This increase in competition can affect the risk-taking decisions in both directions in the search of profits as well as the competition for managers. In column (5), I therefore control for the number

[18]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.

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

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

of competitors in the SIC sub-industry in which the respective institution is active in.

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.

In the robustness test in column (4), I re-estimate the model in Equation (2) only using 107 CEOs which were not replaced during the crisis to examine the source of variation more closely. By focusing only on those CEOs, I ensure that the effects are not driven by the replacement of CEOs further alleviating concerns about strategical selection of CEOs. The results do not change qualitatively. However, since I am excluding variation that is driven by the replacement of CEOs, the statistical power decreases.

The robustness test in column (5) 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 somewhat larger with the qualitative result remaining unchanged.

In the robustness tests in column (6), I exclude the last year of tenure of each CEO tenure. 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 (7). The results show that these modifications do not have an effect on the qualitative results.

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

4 The Role of the Regulatory Environment

The results so far indicate that financial institutions lead by overconfident CEOs were riskier prior to the financial crisis and decreased risk-taking towards the level of firms with non-overconfident CEOs during and after the crisis – a period characterized by stricter regulation. This is consistent with a tightening of regulatory standards limiting the scope for overconfident CEOs to take additional risks. To deliver further evidence for this hypothesis and to preclude general crisis effects, I further analyze the role of the regulatory environment in the following.

4.1 Analysis

To further examine the role of the regulatory environment, I divide the sample into two groups of financial institutions differing in the degree of exposure to regulation after the financial crisis. The first group includes smaller depository institutions ($< 10bn$ in total assets) and non-depository institutions.[21] Depository institutions, in general, are overseen by depository regulators such as the Federal Reserve, the Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation (FDIC), or the National 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

[21] 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).

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.

The second group includes larger financial institutions which comprise both depository institutions ($> 10bn$ in total assets) and non-depository financial institutions if they hold a bank holding company status or are designated by the FSOC to be subject to enhanced regulation. During and after the financial crisis, these financial institutions were subject to *enhanced regulation* and stress testing. 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 risk management as part of the enhanced regulation, among other measures, might have contained the scope of overconfident CEOs to take additional risks.

To estimate the heterogeneous effect of overconfidence under the different regulatory environments, I re-estimate the fixed effects model in Equation (2) interacted with a binary variable for the regulatory status of the financial institution as described above. Thereby, the unregulated financial institutions serve as the base category. If regulation is indeed the mechanism behind the decline, one would expect the post-crisis decrease in overconfidence-induced risk to be driven by the regulated financial institutions.

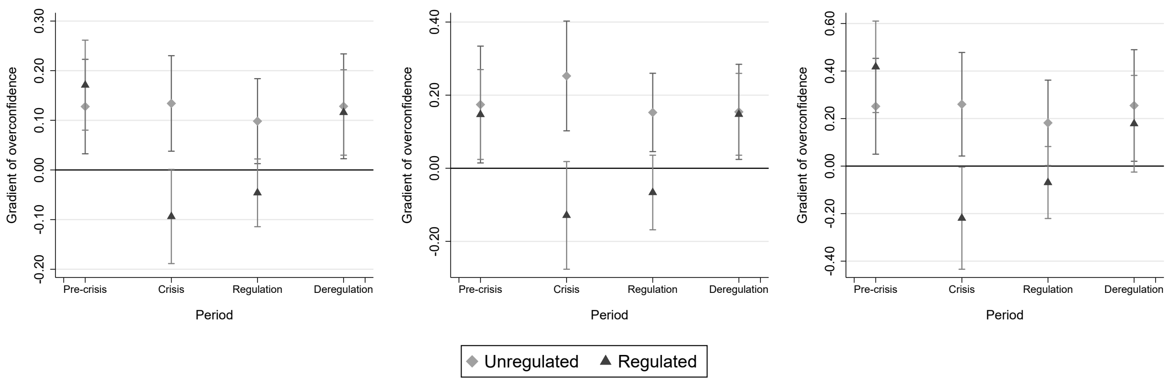
The gradients for overconfidence shown in Figure 3, with the corresponding estimates in Table 8, confirm the conjunction as outlined above. The decrease in overconfidence-induced risk during the period of stricter regulation is entirely driven by financial institutions subject to enhanced regulation. The result that unregulated financial institution remain unaffected supports the hypothesis that the regulatory intervention is the mechanism behind the decline in risk-taking during the period of stricter regulation.

4.2 Discussion

The previous results are consistent with enhanced regulation being the explanation for the additional decrease in risk-taking at financial institutions with overconfident CEOs.

Figure 3: The role of regulation – Dynamic results

This figure shows the gradient of overconfidence, which is the linear combination of β_0 and β_j for each year period j in the OLS estimation of Equation (2), 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. Hubert-White heteroskedasticity consistent standard errors are clustered at the firm level. *Pre-crisis* indicates the years 2000-2006, *crisis* the years 2007-2009, *regulation* the years 2010-2017, and *deregulation* the years 2018-2019.



However, the results could also be consistent with a higher exposure to the financial crisis and, thus, higher losses for those financial institutions subject to enhanced regulation. Hence, those financial institutions could have learned from the adverse experience and contain the scope of their CEO. To test this hypothesis, I analyze the exposure to the financial crisis by estimating the following cross-sectional model using OLS:

$$exp_{i,\tau} = \alpha + \beta_1 \mathbb{1}[regulated = 1]_i + \boldsymbol{\gamma'} \boldsymbol{X_{i,2006}} + \varepsilon_i, \tag{4}$$

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.[22] Standard errors are adjusted

[22]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 return on

Table 8: The role of 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 $t-1$, $\mathbb{1}[crisis = 1]_{i,t}$ is an indicator variable for the crisis period from 2007 to 2009, $\mathbb{1}[regulation = 1]_{i,t}$ for the period from 2010 to 2017, and $\mathbb{1}[deregulation = 1]_{i,t}$ for the period from 2018 to 2019. 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) $ln(\sigma_t)$	(2) $beta_t$	(3) $ln(mse_t)$
OC_{t-1}	0.128***	0.174**	0.252**
	(0.048)	(0.081)	(0.102)
$crisis_t \times OC_{t-1}$	0.00632	0.0782	0.00855
	(0.070)	(0.103)	(0.151)
$reg_t \times OC_{t-1}$	-0.0294	-0.0216	-0.0699
	(0.065)	(0.093)	(0.136)
$dereg_t \times OC_{t-1}$	0.000528	-0.0201	0.00327
	(0.067)	(0.097)	(0.149)
$OC_{t-1} \times regulated_t$	0.0431	-0.0272	0.166
	(0.066)	(0.102)	(0.140)
$crisis_t \times OC_{t-1} \times regulated_t$	-0.271***	-0.354***	-0.645***
	(0.091)	(0.131)	(0.201)
$reg_t \times OC_{t-1} \times regulated_t$	-0.188**	-0.192*	-0.417**
	(0.080)	(0.113)	(0.174)
$dereg_t \times OC_{t-1} \times regulated_t$	-0.0555	0.0206	-0.243
	(0.091)	(0.130)	(0.206)
Observations	2448	2448	2448
Clusters	238	238	238
Mean	-3.94	1.19	-8.35
adjusted R^2	0.85	0.61	0.82
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

for heteroskedasticity.

The results in Table 9 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 significant larger share of write-offs (column (2)) nor a lower net income (column (3)) during the crisis. The share of mortgage loans in total lending show 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 were not significantly more exposed to the financial crisis than the other financial institutions. Hence, this mechanism

assets are only calculated for financial institutions observed in each of the crisis years.

Table 9: Regulated financial institutions – Crisis exposure

This table presents the regression results of the OLS estimation of the cross-sectional model in Equation (4) 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 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)
$regulated_t$	-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
Controls	Yes	Yes	Yes	Yes

is unlikely to explain the observed decrease in overconfidence-induced risk-taking.

5 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 during and after the financial crisis. Moreover, the results in Section 4 show that the decline is consistent with regulation affecting the scope of overconfident CEOs. The so far employed stock market-based risk measures, however, capture a wide range of factors. Ho et al. (2016) show that financial institutions with overconfident CEOs eased lending standards prior to the financial crisis. Hence, it is likely that the lending behavior has changed differently. 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 credit-worthiness 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 extend mortgages, I link the 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 in 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 which were active for at least half a year in a respective calender 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 which 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 credit-worthiness of the borrower. I winsorize the loan-to-income ratio at the 0.01% and 99.99% level 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 do not change qualitatively.

[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:

$$\begin{aligned} y_{i,b,m,t} = \alpha_0 &+ \beta_0 \mathbb{1}[overconfidence = 1]_{b,t-1} + \beta_1 OC_{b,t-1} \times \mathbb{1}[crisis = 1]_{b,t} \\ &+ \beta_2 OC_{b,t-1} \times \mathbb{1}[regulation = 1]_{b,t} + \beta_3 OC_{b,t-1} \times \mathbb{1}[deregulation = 1]_{b,t} \\ &+ \eta_0 lti_{i,b,m,t} + \eta_1 lti_{i,b,m,t} \times \mathbb{1}[crisis = 1]_{,t} \\ &+ \eta_2 lti_{i,b,m,t} \times \mathbb{1}[regulation = 1]_{b,t} + \eta_3 lti_{i,b,m,t} \times \mathbb{1}[deregulation = 1]_{b,t} \\ &+ \lambda_0 OC_{b,t-1} \times lti_{i,b,m,t} + \lambda_1 OC_{b,t-1} \times \mathbb{1}[crisis = 1]_{b,t} \times lti_{i,b,m,t} \\ &+ \lambda_2 OC_{b,t-1} \times \mathbb{1}[regulation = 1]_{b,t} \times lti_{i,b,m,t} \\ &+ \lambda_3 OC_{b,t-1} \times \mathbb{1}[deregulation = 1]_{b,t} \times lti_{i,b,m,t} \\ &+ \boldsymbol{\gamma' X_{b,t}} + \boldsymbol{\delta' X_{i,t}} + \alpha_i + \alpha_b + \alpha_m + \mu_t + \alpha_m \times \mu_t + \epsilon_{i,b,m,t}, \end{aligned} \tag{5}$$

where $y_{i,b,c,t}$ is a binary that equals one if a loan application of borrower 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 $t-1$, $\mathbb{1}[crisis = 1]_{b,t}$ is an indicator variable for the crisis period, $\mathbb{1}[regulation = 1]_{b,t}$ for the period from 2010 to 2017, $\mathbb{1}[deregulation = 1]_{b,t}$ for the period from 2018 to 2019, $lti_{i,b,m,t}$ is the loan-to-income ratio of borrower i at bank b for a property in MSA m in year t. Furthermore, α_i denotes borrower fixed effects (i.e. gender, race, and ethnicity) as well as loan characteristics such as, in the full specification, loan type (insured loans), property type, occupancy, loan amount, and spread, α_b denotes bank holding company fixed effects, α_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 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 and the spread. The standard errors are clustered at the bank holding company level to allow for within-bank correlation of residuals. I estimate Equation (5) using OLS.

Coefficients β_j denote how the likelihood to approve loans varies with overconfidence and could also reflect general demand effects. Coefficient η_j denotes the general effect of the loan-to-income ratio on the likelihood to approve a loan varying with period j. A positive coefficient indicates a riskier loan. The coefficients of interest, λ_j, show how the marginal effect of overconfident CEOs on the likelihood to approve a loan varies with bor-

Table 10: Overconfidence and approval of mortgage applications

This table presents the regression results of the OLS estimation of the loan-level estimation in Equation (5) for the years 2004 to 2019. The dependent variable is a binary variable which is one of a mortgage application of borrower i at financial institution b in 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 $t-1$, $\mathbb{1}[crisis = 1]_{b,t}$ is an indicator variable for the crisis period, $\mathbb{1}[regulation = 1]_{b,t}$ for the period from 2010 to 2017, and $\mathbb{1}[deregulation = 1]_{b,t}$ for the period from 2018 to 2019. $lti_{i,b,m,t}$ is the loan-to-income ratio of borrower 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: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

	(1) approve	(2) approve	(3) approve	(4) approve	(5) approve
$OC_{b,t-1}$	0.117**	0.125**	0.119**	0.119**	0.118**
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
$crisis_t \times OC_{b,t-1}$	-0.00291	0.00164	0.0266	0.0243	0.0257
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
$reg_t \times OC_{b,t-1}$	-0.103*	-0.126**	-0.155***	-0.149***	-0.148***
	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
$dereg_t \times OC_{b,t-1}$	-0.134	-0.142*	-0.140*	-0.133*	-0.133*
	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)
lti_t	-0.0150***	-0.0154***	-0.0240***	-0.0262***	-0.0266***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$crisis_t \times lti_t$	0.00205	0.00319	0.00805	0.00836	0.00859
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$reg_t \times lti_t$	0.0129***	0.0119***	0.0167***	0.0174***	0.0177***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$dereg_t \times lti_t$	0.00623	0.00694	0.0131***	0.0133***	0.0137***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$OC_{b,t-1} \times lti_t$	0.0110*	0.0117**	0.0134**	0.0135**	0.0139**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$crisis_t \times OC_{b,t-1} \times lti_t$	-0.0130	-0.0130	-0.0187**	-0.0186**	-0.0189**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$reg_t \times OC_{b,t-1} \times lti_t$	-0.0151**	-0.0160**	-0.0158**	-0.0162**	-0.0164**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$dereg_t \times OC_{b,t-1} \times lti_t$	-0.00391	-0.00443	-0.00597	-0.00606	-0.00639
	(0.01)	(0.01)	(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	0.16	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 controls	No	No	No	Yes	Yes
Loan FE	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes	Yes
MSA x Year FE	No	Yes	Yes	Yes	Yes

rower 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 10. Column (1) shows the results when only controlling for bank and borrower characteristics and firm, MSA, and year fixed effects as in the baseline analysis. Column (2) includes MSA times year fixed effects. Column (3) and column (4) include additional loan characteristics respectively. Column (5) excludes all observations where a parent-subsidiary relationship was not existent for the entire calender yea. The results across all specifications suggest that banks with an overconfident CEO have a significantly higher likelihood of approving a loan (β_1) 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 (see Ho et al., 2016). After the financial crisis, approval rates were reduced at financial institutions with overconfident CEOs. 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 $0.0174 * (1.79 - 0.77) = 0.0177$ or 1.77 percentage points using the point estimate from the 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, banks with overconfident CEOs are less likely to approve a loan with a higher loan-to-income ratio as compared to their counterparts. Again, the coefficients suggest a convergence across banks with overconfident CEOs and non-overconfident CEOs.

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. After the crisis converged towards the behavior of banks with non-overconfident CEOs by tightening lending standards.

6 Conclusion

Managerial overconfidence takes an important role in the risk-taking behavior of financial institutions. This paper, however, shows that 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 lending standard, the analysis reveals that risk at firms with overconfident CEOs and risk at firms with non-overconfident CEOs converged after the crisis. This holds for aggregate risk measures as well as individual loan approval rates. The results are driven by financial institutions subject to enhanced regulation. Since these financial institutions did not suffer more from the financial crisis, this is consistent with the post-crisis regulatory environment being successful in reducing the risk-taking of overconfident CEOs. This is further supported by the finding that when repealing parts of the post-crisis regulation, overconfidence-induced risk-taking re-emerges. Taken together, the analysis shows that managerial overconfidence increases risk-taking in times of regulatory forbearance, such as the decade before the financial crisis or after deregulation. In times of regulatory scrutiny, such as the period during and after the financial crisis, overconfident CEOs are more constrained in their actions. Thus, it is less feasible for an overconfident CEO to take additional risk.

Notwithstanding that this paper documents changes in the relationship between overconfidence and risk-taking in general after the financial crisis, it remains silent about the actual mechanism of the additional decrease in risk-taking. Thereby, two channels could potentially be important. First, regulation targeting corporate governance of systemically important financial institutions. The DFA, for example, mandates chief risk officers and risk committees for large financial firms depending on the size of the financial institution. Second, a change in the compensation scheme of managers. Since overconfident CEOs overestimate the probability of positive outcomes, they overvalue bonus payments and could, thus, be more influenced by a decrease in incentive compensation (e.g. Gietl and Kassner, 2020; Goel and Thakor, 2008).[25] Eliciting specific channels of the additional decrease in risk-taking at large banks after the financial crisis is, therefore, an interesting avenue for future research.

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[25] 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 deductability 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 $t-1$, $\mathbb{1}[crisis = 1]_{i,t}$ is an indicator variable for the crisis period from 2007 to 2009, $\mathbb{1}[regulation = 1]_{i,t}$ for the period from 2010 to 2017, and $\mathbb{1}[deregulation = 1]_{i,t}$ for the period from 2018 to 2019. 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, column (4) 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: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	Baseline	Imputed OC	Robust OC	Gender & Tenure	Delta & Vega	Excess compensation	Exercisable options	Predicted wealth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$ln(\sigma_t)$	$ln(\sigma_t)$	$ln(\sigma_t)$	$ln(\sigma_t)$	$ln(\sigma_t)$	$ln(\sigma_t)$	$ln(\sigma_t)$	$ln(\sigma_t)$
OC_{t-1}	0.167***	0.167***	0.167***	0.174***	0.179***	0.167***	0.167***	0.148***
	(0.034)	(0.034)	(0.034)	(0.037)	(0.035)	(0.034)	(0.034)	(0.035)
$crisis_t \times OC_{t-1}$	-0.140***	-0.140***	-0.140***	-0.141***	-0.127***	-0.139***	-0.139***	-0.146***
	(0.047)	(0.047)	(0.047)	(0.048)	(0.048)	(0.047)	(0.047)	(0.048)
$reg_t \times OC_{t-1}$	-0.132***	-0.132***	-0.132***	-0.134***	-0.119***	-0.132***	-0.132***	-0.126***
	(0.042)	(0.042)	(0.042)	(0.043)	(0.042)	(0.042)	(0.042)	(0.044)
$dereg_t \times OC_{t-1}$	-0.0482	-0.0484	-0.0482	-0.0488	-0.0446	-0.0483	-0.0479	-0.0424
	(0.045)	(0.045)	(0.045)	(0.045)	(0.052)	(0.045)	(0.045)	(0.046)
Observations	2448	2447	2448	2385	1871	2448	2447	2448
Clusters	238	238	238	230	216	238	238	238
Mean	-3.94	-3.94	-3.94	-3.93	-3.90	-3.94	-3.94	-3.94
adjusted R^2	0.85	0.85	0.85	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)	(2)	(3)	(4)
	$ln(networth_t)$	$ln(networth_t)$	$ln(networth_t)$	$ln(networth_t)$
$ln(income_t)$	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 $t-1$, $\mathbb{1}[crisis = 1]_{i,t}$ is an indicator variable for the crisis period from 2007 to 2009, $\mathbb{1}[regulation = 1]_{i,t}$ for the period from 2010 to 2017, and $\mathbb{1}[deregulation = 1]_{i,t}$ for the period from 2018 to 2019. 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: $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

	Baseline (1) $ln(\sigma_t)$	Tobin's Q (2) $ln(\sigma_t)$	Stock return (3) $ln(\sigma_t)$	Board size (4) $ln(\sigma_t)$	Competition (5) $ln(\sigma_t)$
OC_{t-1}	0.167***	0.167***	0.154***	0.168***	0.167***
	(0.034)	(0.034)	(0.044)	(0.034)	(0.034)
$crisis_t \times OC_{t-1}$	-0.140***	-0.137***	-0.153***	-0.140***	-0.140***
	(0.047)	(0.047)	(0.052)	(0.047)	(0.047)
$reg_t \times OC_{t-1}$	-0.132***	-0.133***	-0.130***	-0.132***	-0.132***
	(0.042)	(0.042)	(0.048)	(0.042)	(0.042)
$dereg_t \times OC_{t-1}$	-0.0482	-0.0535		-0.0492	-0.0468
	(0.045)	(0.045)		(0.045)	(0.044)
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 $t-1$, $\mathbb{1}[crisis = 1]_{i,t}$ is an indicator variable for the crisis period from 2007 to 2009, $\mathbb{1}[regulation = 1]_{i,t}$ for the period from 2010 to 2017, and $\mathbb{1}[deregulation = 1]_{i,t}$ for the period from 2018 to 2019. 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 CEOs who were in office both in 2006 and in 2010, column (5) only keeps financial institutions which are in the sample over the entire sample period, column (6) omits the last year of each CEO's tenure, and column (7) 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: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

	Baseline	WLS	Industry	Non-turnover	Attrition	Last year	First year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$ln(\sigma_t)$	$ln(\sigma_t)$	$ln(\sigma_t)$	$ln(\sigma_t)$	$ln(\sigma_t)$	$ln(\sigma_t)$	$ln(\sigma_t)$
OC_{t-1}	0.167***	0.169***	0.155***	0.140**	0.184***	0.168***	0.184***
	(0.034)	(0.056)	(0.032)	(0.070)	(0.050)	(0.035)	(0.035)
$crisis_t \times OC_{t-1}$	-0.140***	-0.170***	-0.121***	-0.107*	-0.288***	-0.129***	-0.120**
	(0.047)	(0.062)	(0.046)	(0.063)	(0.079)	(0.047)	(0.049)
$reg_t \times OC_{t-1}$	-0.132***	-0.136**	-0.123***	-0.130**	-0.167**	-0.123***	-0.140***
	(0.042)	(0.066)	(0.038)	(0.058)	(0.066)	(0.043)	(0.042)
$dereg_t \times OC_{t-1}$	-0.0482	-0.0716	-0.0166	-0.0651	-0.0443	-0.0379	-0.0543
	(0.045)	(0.072)	(0.045)	(0.065)	(0.057)	(0.045)	(0.045)
Observations	2448	2448	2448	1139	669	2251	2255
Clusters	238	238	238	113	35	238	237
Mean	-3.94	-4.04	-3.94	-3.87	-4.00	-3.95	-3.94
adjusted R^2	0.85	0.94	0.77	0.88	0.89	0.85	0.86
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes