

A Service of

ZBШ

Leibniz-Informationszentrum Wirtschaft Leibniz Information Centre for Economics

Haufler, Andreas; Kassner, Bernhard

Working Paper Matching for Risk-Taking: Overconfident Bankers and Government-Protected Banks

CESifo Working Paper, No. 11336

Provided in Cooperation with: Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Haufler, Andreas; Kassner, Bernhard (2024) : Matching for Risk-Taking: Overconfident Bankers and Government-Protected Banks, CESifo Working Paper, No. 11336, CESifo GmbH, Munich

This Version is available at: https://hdl.handle.net/10419/305578

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



WWW.ECONSTOR.EU



Matching for Risk-Taking: Overconfident Bankers and Government-Protected Banks

Andreas Haufler, Bernhard Kassner



Impressum:

CESifo Working Papers ISSN 2364-1428 (electronic version) Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute Poschingerstr. 5, 81679 Munich, Germany Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de Editor: Clemens Fuest https://www.cesifo.org/en/wp An electronic version of the paper may be downloaded • from the SSRN website: www.SSRN.com

- from the RePEc website: <u>www.RePEc.org</u>
- from the CESifo website: <u>https://www.cesifo.org/en/wp</u>

Matching for Risk-Taking: Overconfident Bankers and Government-Protected Banks

Abstract

We set up a simple theoretical model in which banks with varying degrees of government support are matched with CEOs that have different degrees of overconfidence. The channel through which the matching occurs is the share of bonus payments offered by banks in their profit-maximizing contracts. This yields a sequence of hypotheses: banks with more government support incentivize their CEOs more and this disproportionately attracts overconfident CEOs. In equilibrium this in turn leads to an assortative matching between overconfident managers and banks with a larger bailout probability. We then test the hypotheses derived from this model for U.S. data spanning both the Great Financial Crisis and the Covid Crisis. Our results confirm the hypotheses from our theoretical model for normal years, but not during crises and periods of enhanced regulation. In normal years, therefore, overconfident bankers are indeed matched with government-protected banks, with cumulative effects on the degree of risk-taking.

JEL-Codes: G210, G280, H320.

Keywords: matching, overconfidence, incentive contracts.

Andreas Haufler Seminar for Economic Policy LMU Munich / Germany Andreas.Haufler@econ.lmu.de Bernhard Kassner Seminar for Economic Policy LMU Munich / Germany Bernhard.Kassner@econ.lmu.de

September 2024

Paper presented at workshops and conferences in Berlin and Nicosia. We thank conference participants and in particular Jocelyn Tapia Stefanoni and Chen Sun for helpful comments. We also thank Minh Ngoc Truong for excellent research assistance. Financial support from the German Research Foundation through CRC TRR 190 is gratefully acknowledged.

1 Introduction

Starting with the bankruptcy of Lehman Brothers in September 2008, the global financial crisis caught financial professionals and policymakers by surprise. Despite a buildup of systemic risks and fragility long before the peak, financial professionals were overly optimistic in their forcasts and policymakers were overly confident that no government bailout would be necessary until shortly before the event. This indicates that biased beliefs played a critical role in the buildup of the global financial crisis (Gennaioli and Shleifer, 2018). More recently, the failure of the Silicon Valley Bank in March 2023 similarly originated in biased beliefs and an underestimation of interest rate risks in a period where interest rates were rapidly rising after a long period of zero interest rates (Bloomberg, 2023).

The psychology of financial top executives has long been an important topic in the finance literature. While overconfidence is a frequently observed behavior even in the general population, it is particularly pronounced among high-earning top executives, who have experienced success in their previous career and attribute this success largely to their own abilities (Gervais and Odean, 2001; Goel and Thakor, 2008; Billett and Qian, 2008). As a result, CEOs are significantly more optimistic than the overall population (Graham et al., 2013). In crisis times, this overconfidence is likely to backfire, however. Ho et al. (2016), for example, have demonstrated that banks with overconfident CEOs weakened their lending standards prior to the 2007-2009 financial crisis, and performed significantly worse in the crisis, as compared to their non-overconfident counterparts. Taken together, overconfident CEOs overestimate their ability to run a bank and overestimate the likelihood of a high outcome, while underestimating the probability of failure.

A further cause of risk-taking that may be equally important are implicit or explicit government guarantees for banks and other financial institutions. One important form of government guarantees is deposit insurance, which is meant to avoid bank-runs in crisis times. However, this policy instrument has also been shown to systematically increase moral hazard and risk-taking by the protected banks (Demirgüç-Kunt and Detriagiache, 2002). The forced removal of explicit government guarantees for German savings banks caused these banks to significantly reduce their credit risk, indicating that public guarantees are associated with substantial moral hazard (Gropp et al., 2014). More recently, the focus has been on systemically important financial institutions (SIFIs). Ueda and Weder di Mauro (2013) quantify the value of the implicit subsidies for SIFIs, which arise from the possibility of bailouts. They find substantial subsidy-driven reductions in the cost of capital for SIFIs, which increased further during the financial crisis.

In this paper, we bring together these two strands in the literature, which have so far been almost completely separated.¹ We ask whether the risk-increasing effects of CEO

¹Lee et al. (2020) find that CEO overconfidence has increased systemic risk in the buildup of the

overconfidence on the one hand, and of government guarantees on the other, accumulate via a matching process in which overconfident CEOs are systematically attracted to government-protected banks. The mechanism through which this assortative matching occurs are bonuses and other incentive payments. These bonus payments are well-known to stimulate risk-taking, exploiting the banks' limited liability (Bhagat and Bolton, 2014, Efing et al., 2015). Moreover, incentive payments are particularly attractive for overconfident managers, who overestimate their probability of success and therefore the likelihood of receiving the bonus. This in turn allows rational banks and their shareholders to 'exploit' this overconfidence by adjusting their compensation structure and increasing the share of incentive pay.²

To study these issues, we first set up a simple theoretical model that connects overconfident mangers and government-protected banks via incentive contracts.³ Banks of different size choose combinations of bonus payments and fixed pay to hire managers with different levels of overconfidence. Government support is rising in bank size, causing larger - and better protected - banks to use steeper incentive contracts. These steeper incentive contracts are in turn more attractive for more overconfident bank managers, which overvalue the probability of receiving the bonus. In this framework, we derive four hypotheses: (*i*) overconfident managers take more risk; (*ii*) government-protected banks pay higher bonus shares; (*iii*) overconfident managers receive higher bonus shares in equilibrium; and (*iv*) overconfident managers are matched in equilibrium with government-protected banks.

We then test these four hypotheses empirically using the option-exercising behavior of managers to measure overconfidence (Malmendier and Tate, 2005, 2008). We derive the degree of government protection from the U.S. G-SIB scores, which determine the degree of systemic importance of U.S. financial institutions. Our regression results confirm the hypotheses from our theoretical model, but only for periods outside of (financial and Covid-related) crises, and only in periods of moderate regulation. In these years, banks with more government support incentivize their CEOs more and this disproportionately attracts overconfident CEOs. In equilibrium this in turn leads to an assortative matching between overconfident managers and banks with a larger bailout probability. The same correlations are not confirmed in crises and in periods of enhanced regulation, however, during which overconfident CEOs do not behave differently from non-overconfident CEOs.

Section 2 sets up our theoretical model linking overconfidence of CEOs and government support to banks in a model where banks optimizing the compensation structure of CEOs. From this model we derive the main hypotheses of our analysis. Section 3 presents the

global financial crisis. This paper does not incorporate the effect of government guarantees, however.

²See Gervais et al. (2011) and De la Rosa (2011) for theoretical analyses. Humphery-Jenner et al. (2016) provide empirical evidence for this positive relationship between overconfidence and the share of incentive pay.

 $^{^{3}}$ Our model draws on the framework of optimal incentive pay developed by Besley and Ghatak (2013). Their model has been extended by Hakenes and Schnabel (2014) to study the effects of bailout expectations, and by Gietl and Kassner (2020) to incorporate overconfidence.

data used in the empirical analysis and the regression results that test the theoretical propositions. Section 4 concludes.

2 Theory

2.1 Model setup

We consider a model where managers with heterogeneous degrees of overconfidence are matched with banks of varying size. There is a continuum of banks, indexed by *i*, which differ in their level of organizational quality, ϕ_i . Effectively we envisage banks as being composed of identical divisions and the number of these divisions, n_i , determines the size of the bank. Running a larger bank imposes costs that are convex in banks size, n_i , but the cost profiles differ across banks given the parameter ϕ_i . In each bank's optimum, bank size will therefore be a monotone function of its organizational quality, $n_i(\phi_i)$, with $dn/d\phi > 0$. Importantly, the organizational quality of a bank affects only its equilibrium size, but not the profitability of each division. The latter depends only on the characteristics of the bank's CEO. Bank size matters only indirectly for each division's profits, because it affects the level of government support that the bank can expect.⁴

There is a continuum of bank managers (CEOs), indexed by m, who differ in their level of overconfidence θ_m , with $0 \leq \theta_m < 1.^5$ Each manager m is matched to one bank i. Manager types m are observable to banks. A manager m employed in bank i chooses the risk level q_{im} of the bank's operations, the same in all the n divisions of bank i. We assume that the (net) outcomes of a division's operations are exogenously fixed in each of three different states of the world, with the risk-taking choice q_{mi} affecting the probabilities that each state occurs (Besley and Ghatak, 2013). Higher risk-taking increases the probability of a high outcome, but also increases the probability of the low state, leading to bank default. Overconfident CEOs overestimate their ability to run a bank and thus overestimate the likelihood of a high outcome, while underestimating the probability of failure.

Specifically, in the high state the exogenous return to a representative division of each bank is R + X, with R, X > 0, whereas in the intermediate state it is R. In the low state the bank defaults and has default costs $\gamma \theta_m$. These default costs are rising in the overconfidence level of the bank's manager, for example because overconfident managers take fewer precautions and this leads to higher costs to the bank when hit by an adverse event. This model element corresponds to empirical evidence that overconfident managers

⁴Empirical support for our setting comes from Huber (2021), who finds that M&A-driven increases in bank size in postwar Germany were not associated with increases in profitability or efficiency, but did lead to more risky credit operations of the enlarged banks.

⁵The restriction $\theta_m < 1$ is needed to ensure that the bank's optimal bonus choice is well defined; see Section 2.3 below.

state	payoff	true probability	perceived probability
		(shareholders)	(managers)
high	R + X	βq_{im}	$\beta q_{im}(1+\theta_m)$
medium	R	$(1 - q_{im})$	$(1-q_{im})$
low	$-\gamma \theta_m [1 - v_i(n)]$	$q_{im}(1-\beta)$	$q_{im}[1 - \beta(1 + \theta_m)]$

 Table 1: Bank division payoffs in different states

do worse in crisis years, as shown by Ho et al. (2016).

In the low state, the representative division of a bank receives a negative payoff. We assume that the outcomes of all divisions in a given bank *i* are perfectly correlated and hence the probability of failure of an individual division is the same as the probability of failure of the entire bank. If a bank defaults, there is a probability v_i that the bank is bailed out by the government.⁶ The probability of a bailout $v_i(n_i)$ is rising in the size of the bank. This corresponds to the "too-big-to-fail" phenomenon that governments are more likely to save large banks, in order to avoid the potentially severe consequences for other banks and firms that are associated with large bank defaults. We will provide further evidence for the positive relationship between bank size and bailout probability in the empirical analysis below. From the banks' perspective, the expected payoff in the low state is therefore $-\gamma \theta_m (1 - v_i)$. The shareholders of each bank correctly evaluate the true probability of each state, in contrast to managers. The state-dependent payoffs for each division and the associated probabilities, both the true ones and the ones perceived by overconfident agents, are summarized in Table 1.

As Table 1 shows, the rate at which higher risk-taking increases the likelihood of the high state is parameterized by $1 > \beta > 0$. For any given level of β , the likelihood of the high state and the likelihood of the low state *both* increase with the manager's risk-taking q_{im} , while the likelihood of the medium state falls by the corresponding amount. Overconfident individuals of type θ_m perceive a higher effectiveness of their risk-taking on the likelihood of a high outcome, as given by the factor $(1 + \theta_m)$, and simultaneously underestimate the probability of default. To ensure that all probabilities are positive, we restrict parameters such that $q_{im} < 1$ for all managers in all banks, and $\beta(1 + \theta_m) < 1$ for all manager types m.

Banks compensate and incentivize their managers of type m with a combination of a bonus payment, payable only in the event of a high state, and a fixed payment. Banks are unable to punish managers in the event of a low state. We account for different bank sizes by assuming that a manager (CEO) who runs a bank with n divisions receives n times the bonus payment and n times the fixed wage of a CEO who runs a bank with only one division. This ensures that the share of incentive payments in total pay is structurally

⁶These bailouts are exogenous in the present analysis. For models in which optimal bailouts are endogenized, see Niepmann and Schmidt-Eisenlohr (2013), or Haufler (2021).

(i.e., for fixed θ_m) the same for all CEOs in our model, consistent with the empirical evidence presented in Edmans et al. (2009). Moreover, the total earnings of managers are increasing - linearly, for analytical simplicity - in the size of the bank that they run. Finally, for the matching process, we assume that there are as many banks as there are managers, so that the market for bank managers clears. Moreover, the matching process is perfect and frictionless and matchings are formed so as to maximize joint output (Gabaix and Landier, 2008; Bandiera et al., 2015).

We consider a three-stage game. In the first stage, banks of different size, and accordingly with different bailout probabilities v_i , are matched with managers with different degrees of overconfidence. In the second stage, bank shareholders incentivize CEOs by choosing the combination of bonus pay and fixed salary so as to maximize bank profits. In the third stage, overconfident managers choose the risk level q_{im} so as to maximize their perceived expected utility. We solve the game by backward induction.

2.2 Stage 3: Risk choice

Our model setup ensures that we can analyze all decisions at the level of a representative bank division, which can be part of a larger or a smaller bank *i*. Decisions at the division level are affected only by the overconfidence level θ_m of the bank's CEO, not by the organizational structure of the bank.

In stage 3, a manager of type m chooses the same risk level q_{im} in each division of their bank, based on their private costs and benefits. The manager's monetary reward comes from their total compensation *per division*, consisting of the fixed payment F_{im} and the expected bonus payment z_{im} .⁷ While the true likelihood of receiving the bonus is βq_{im} , a manager of type m perceives a probability of receiving the bonus of $\beta q_{im}(1 + \theta_m)$ (see Table 1), and makes their choices based on this perceived probability. On the cost side, risk-taking involves psychological costs of seeking out risk-taking opportunities above a 'natural' or benchmark level, which is here normalized to zero (see Besley and Ghatak, 2013). For analytical tractability, we assume that this cost function is quadratic and given by $c(q_{im}) = \mu(q_{im})^2/2$.

Managers maximize their *perceived* utility per division, which is denoted by \hat{u} . Utility per division is the difference between perceived monetary rewards and psychological costs (in monetary equivalents). Managers differ only in their level of overconfidence, but not in their psychological costs of risk-taking. A manager of a bank with n divisions faces the same psychological costs in each division. Hence a manager of type m maximizes

$$\hat{u}_{im} = \beta q_{im} (1 + \theta_m) z_{im} + F_{im} - \frac{\mu q_{im}^2}{2}.$$
(1)

⁷Hence the total compensation of a manager of a bank with n divisions is $n(z_{im} + F_{im})$.

This leads to the optimal risk-taking choices

$$q_{im}^* = \frac{\beta(1+\theta_m)z_{im}}{\mu}.$$
(2)

Hence, the bonus payment z_{im} incentivizes all managers to take higher risks, in order to benefit from a higher probability of receiving the bonus. Moreover, this effect is stronger for more overconfident managers, because they overestimate the likelihood of attaining the high state, and hence of obtaining the bonus. We summarize in:

Hypothesis 1: More overconfident bank managers choose higher levels of risk-taking, for any given level of bonus payment.

2.3 Stage 2: Banks' contract choices

The shareholders of a bank of type i with manager m maximize the profits of each division, i.e. the sum of expected returns in the different states of the world, net of all (divisionspecific) payments to the manager.⁸ In contrast to the manager, the bank's shareholders use the true probabilities of each state in their maximization problem. Using Table 1 yields each bank's division profit as

$$\pi_{im} = \beta q_{im} \left(R + X - z_{im} \right) + (1 - q_{im}) R - (1 - \beta) q_{im} \gamma \theta_m [1 - v_i(n)] - F_{im}.$$
 (3)

The two components of manager compensation, the bonus z_{im} and the fixed salary F_{im} are linked by the division-specific participation constraint of each manager that the perceived utility in (1) must be equal or larger to a (division-specific) reservation utility \bar{u} , which is the same for all manager types m.⁹ This determines the fixed wage per division of manager m as a function of their bonus payment:

$$F_{im} = \bar{u} - \frac{\beta q_{im} (1+\theta_m) z_{im}}{2}.$$
(4)

Equation (4) shows that for any given bonus payment z_{im} , a more overconfident manager (with a higher level of θ_m) will receive a lower fixed wage per division, while still meeting their reservation utility. Even when adding the higher bonus, more overconfident managers receive a lower total expected compensation, when the latter is measured by

⁸We take the banks' financing decisions, in particular the shares of equity and deposit financing, as exogenous. In reality, deposits are insured and therefore implicitly subsidized by governments, but the subsidy share is the same for all banks and therefore not relevant for our matching model. We can therefore treat each division's financing costs as a lump-sum that does not affect any of our results.

⁹Again, the CEO of a bank of size n has the reservation utility \bar{u} for each division of their bank. This captures higher opportunity costs of running a larger bank and ensures that their total compensation in equilibrium is $n(z_{im} + F_{im})$; see footnote 7.

the true probability of receiving the bonus. The "exploitation" of managers' overoptimism by unbiased shareholders is a general result in the literature on overconfidence (De la Rosa, 2011; Gervais et al., 2011). Empirical evidence for this result is presented by Humphery-Jenner et al. (2016), who show that firms indeed tailor their incentive contracts to individual behavioral traits such as overconfidence. This feature is incorporated in our matching model.

Differentiating the division profits in (3) with respect to z_{im} , and using the manager's optimal risk choice (2) and the fixed wage expression (4), gives a reduced form expression for the optimal bonus payment:

$$z_{im}^* = \frac{\Omega_{im}}{\beta(1-\theta_m)}, \qquad \Omega_{im} \equiv \beta X + (\beta-1)R - (1-\beta)\gamma\theta_m(1-v_i). \tag{5}$$

All parameters in the term Ω_{im} , which represents the net return to bonus incentives from the shareholders' perspective, are exogenous. We assume that these parameters are such that Ω_{im} is positive for all manager types m. Given that $\theta_m < 1$ (see footnote 5), all managers are then paid a positive bonus in equilibrium. Higher bailout probabilities $v_i(n)$ reduce the costs of managerial risk-taking from the bank's perspective, and therefore incentivize banks to pay higher bonuses.¹⁰ We summarize in:

Hypothesis 2: Bonus compensation z_{im} is rising in the level of government support v_i .

Are more overconfident managers always paid a higher bonus? Differentiating (5) with respect to θ_m yields

$$\frac{\partial z_{im}}{\partial \theta_m} = \frac{1}{\beta(1-\theta_m)} \left[\frac{\Omega_{im}}{(1-\theta_m)} - (1-\beta)\gamma(1-v_i) \right].$$
(6)

The first term in the squared bracket on the RHS of (6) is positive under our above assumptions. As more overconfident managers value the bonus more, paying higher bonuses (and reducing the fixed payment) is a way for banks to save on total expected compensation. The second term in the squared bracket is negative, however, as the bonus incentivizes more risk-taking and more overconfident bankers induce higher losses in the low state. Therefore, the bonus payment is rising in the overconfidence level m only when the parameter γ is not too large, so that the higher profits caused by overconfidence in the good state dominate the negative consequences of overconfidence in the case of failure. We will develop a formal condition ensuring that (6) is positive in the next section.

We can now use (2), (4) and (5) in (3) to obtain a reduced-form expression for the

¹⁰Efing et al. (2015) show for a sample of Austrian, German and Swiss banks that higher incentive pay was significantly correlated with more risk-taking in the period preceding the 2007/08 financial crises. They also find that pre-crisis incentive pay was too high to represent an optimal trade-off between higher yield and risk.

division profits of a bank i when hiring a manager of type m:

$$\pi_{im}^* = \frac{\Omega_{im}^2 (1 + \theta_m)}{2\mu (1 - \theta_m)} + R - \bar{u}$$
(7)

The optimized division profits in (7) form the basis for our ensuing matching analysis.

2.4 Stage 1: Matching

We first ask how optimal division profits in (7) change with the manager's overconfidence level θ_m . Differentiating gives

$$\frac{\partial \pi_{im}^*}{\partial \theta_m} = \frac{\Omega_{im} \Delta}{\mu (1 - \theta_m)}, \qquad \Delta \equiv \left[\frac{\Omega_{im}}{(1 - \theta_m)} - (1 + \theta_m)(1 - \beta)\gamma(1 - v_i) \right]. \tag{8}$$

The ambiguity in (8) is similar, but not identical, to that in equation (6): more overconfident managers receive a lower expected total compensation, as measured by true probabilities, and this increases division profits by the first term in Δ . On the other hand, more overconfident managers cause more damage in the low state; this is the negative second term in Δ .¹¹ If γ is sufficiently low to ensure that more overconfident managers receive higher bonuses, the first effect in Δ dominates the second and hence more overconfident managers also increase banks' profits.

Using the definition of Ω_{im} in (5), the condition for $\Delta > 0$ in (8) yields

$$\Delta > 0 \quad \Leftrightarrow \quad \gamma < \frac{\beta X + (\beta - 1)R}{(1 - \beta)(1 - v_i)[1 + \theta_m(1 - \theta_m)]} . \tag{9}$$

It is straightforward to show that when condition (9) is met, this is sufficient (but not necessary) for the derivative in (6) to be positive. We summarize in

Hypothesis 3: If condition (9) is met, then more overconfident bank managers (with higher θ_m) receive a higher bonus share z_{im} , and they increase banks' profits.

Finally, we ask how heterogeneous banks and managers are matched in equilibrium. Larger banks have a larger probability v_i of being bailed out, and this is the only relevant heterogeneity at the division level. Since the number of divisions n of each bank is exogenous, bank size does not directly enter into the matching process (but only indirectly via the size-dependent bailout probability). Matching overconfident managers with larger banks is profitable, if and only if the bank's division profits are supermodular in θ_m and

¹¹The difference between the second terms in the squared brackets of (6) and (8) arises from the fact that overconfidence must increase division profits *net* of the bonus, and the latter increases with higher overconfidence.

 v_i , i.e. if the second cross-derivative $\partial^2 \pi_{im}^* / (\partial \theta_m \partial v_i)$ is positive:

$$\frac{\partial^2 \pi_{im}^*}{\partial \theta_m \partial v_i} = \frac{(1-\beta)\gamma}{\mu (1-\theta_m)^2} \left[\theta_m \Delta + \frac{1+\theta_m (1-\theta_m)}{(1-\theta_m)} \,\Omega_{im} \right]. \tag{10}$$

For $0 < \theta_m < 1$, equation (10) is indeed unambiguously positive whenever $\Delta > 0$ holds. This leads to our last hypothesis:

Hypothesis 4: If condition (9) is met, then more overconfident managers are matched in equilibrium with larger banks, which receive a higher level of government support.

The result in Hypothesis 4 is easily explained. More overconfident managers have lower expected total compensation costs for all banks, but they also cause larger losses in the low state. Since government protection applies precisely in the low state, it is particularly important for banks that employ highly overconfident managers. Moreover, if the only difference between banks is their size, and if larger banks receive higher government support in equilibrium ("too-big-to-fail"), then matching larger banks with more overconfident managers will be privately profitable in equilibrium. Larger banks will then take more risks than their smaller counterparts for two distinct reasons. First, they hire more overconfident managers, who take more risk even in the absence of other differences (H1). Second, larger banks receive more government support, which increases bonus compensation from H2, and this in turn further incentivizes risk-taking (H3).

Note that the matching equilibrium that arises in our model differs in several respects from standard matching models between heterogeneous workers and firms. Standard models match more productive workers with larger and more productive firms, which pay them higher wages in equilibrium (e.g. Gabaix and Landier, 2008; Eeckhout and Kircher, 2018). Moreover, more talented workers receive a higher share of incentive pay (Bandiera et al., 2015). In our framework, more overconfident workers are not generally more productive in (true) expected value terms, and for given levels of government support.¹² However, they receive a higher share of their total compensation as incentive pay. At the same time, all banks are equally productive at the division level in our setting, and the only difference lies in varying levels of (implicit) government support, which favors large firms. In this sense, firms that are more profitable post-transfer (and only post-transfer) are matched with managers whose higher risk-taking incentives increase the effective level of government support.

 $^{^{12}}$ This is in line with the finding of Kaplan et al. (2022) that overconfidence, as conventionally measured, is negatively related to managerial ability.

3 Empirical analysis

In this section, we take the theoretical hypotheses derived in the previous section to the data and test whether we can observe the predicted relationships.

3.1 Data

We use detailed data for the U.S. financial sector for the years 2000 to 2022. Balance sheet data for U.S. financial institutions is obtained via *Compustat Annual North America*. We only keep financial institutions headquartered in the U.S. and drop all firms for which we observe gaps in the data. We want to focus on the traditional financial sector and, thus, only keep financial institutions with Standard Industrial Code (SIC) 6000 to 6282, excluding classification 6282. This leaves us with 1.629 firms and 20.067 firm-year observations. We complement this data with executive compensation data from *Execucomp Annual Compensation* and data on daily stock returns from the *Center for Research in Security Prices (CRSP)*. Keeping only observations that intersect all three databases, we arrive at a base sample of 295 firms and 3.994 firm-year observations.

Further, we only keep observations where the fiscal year coincides with the calendar year to avoid that timing issues affect the results. We drop government-sponsored enterprises, since these are inherently different in nature from the remaining firms. Last, we only keep firms for which we observe at least three observations in the data. The final sample amounts to 3.572 firm-year observations and 249 distinct firms.

3.2 Variables

3.2.1 Overconfidence

The first main variable in our empirical analysis is managerial overconfidence. The literature proposes different measures of overconfidence. However, the revealed-beliefs approach using the option exercising behavior of managers, first introduced by Malmendier and Tate (2005), has become standard. The idea behind the option-based approach can be sketched as follows. Through their contract, the value of the CEO's human capital is tied to the firm. Since they are usually contractually detained from taking short positions with respect to the firm, CEOs have limited possibilities to address this under-diversification. To diversify, rational and risk-averse CEOs should exercise stock options, which they receive as part of their compensation package, as soon as their value exceeds a certain, rational benchmark. Therefore, if CEOs do *not* diversify their risks in this way, this may signal that they hold overly optimistic beliefs about their firm's success, and hence about their ability as a CEO.

We consider a CEO as overconfident when they postpone to exercise exercisable options that were at least 100% 'in the money', i.e., the stock price is at least twice as high as the strike price. Using 100% as the cutoff follows previous literature and ensures that only highly overconfident CEOs are classified as overconfident (Campbell et al., 2011).¹³ To not capture inattentive behavior, this behavior has to be observed at least twice during tenure. The CEO is then classified as overconfident for the entire period of their tenure, to capture the underlying behavioral trait.¹⁴

Malmendier and Tate (2005, 2008) also discuss alternative explanations for the observed late-exercising of options, but conclude that overconfidence is the most consistent explanation. Moreover, a high correlation between the option-based measure and a pressbased measure of overconfidence, which classifies CEOs according to their portrayal in the press, also supports the measure (Hirshleifer et al., 2012). Finally, Kaplan et al. (2022) have more recently used detailed personality assessments of CEOs, which provide evidence that the option-based measure indeed reflects overconfident behavior. Taken together, these results provide strong evidence that late exercising behavior is a good proxy for CEO overconfidence.

3.2.2 Bailout probability

Our second core variable is the bailout probability of a financial institution. Following our theoretical model, this bailout probability is connected to the bank's systemic importance. Bailout probabilities are determined by government guarantees, which usually are implicit and therefore not directly observable. To construct a proxy for such implicit guarantees we use the U.S. Global Systematically Important Banks (G-SIB) scores, which assess the degree of systemic importance of financial institutions in the U.S. and are based on data from FR Y-15 Snapshots Reports.¹⁵ All banks with more than \$50 billion in assets are required to file these reports, which contain five main risk categories: size, interconnectedness, complexity, cross-jurisdictional activity, and short-term wholesale-funding. These categories encompass a total of ten risk variables that are used to construct the G-SIB scores. The underlying assumption for using these scores in our analysis is that a financial institution with a higher systemic score also enjoys larger implicit guarantees, and therefore has a higher bailout probability.¹⁶

These systemic scores are available for the years 2017 to 2022 and for the 24 largest financial institutions in our sample, yielding 112 firm-year observations. Given this low

¹³Since we only have aggregate data available for the option portfolios of CEOs prior to 2006, we follow earlier studies in constructing the overconfidence measure based on the average degree of moneyness of the CEO's option portfolio in a given year (see Ho et al., 2016; Campbell et al., 2011).

¹⁴If a CEO switches between firms in the observed period, all tenures are taken into account. Observations with zero options or a value of exercisable, unexercised options of zero are treated as non-overconfident. In contrast, 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.

 $^{{\}rm ^{15}See\ https://www.financial$ $research.gov/bank-systemic-risk-monitor.}$

¹⁶An alternative would be to follow Gropp et al. (2011) and calculate the difference between standalone credit ratings and overall credit ratings of financial institutions. These ratings are scarce in our sample, however, and they do not provide enough variation over time.

number of directly observed scores, and given that we cannot construct these scores due to lack of data, we have to extrapolate these scores based on other observations in our data. While the underlying measures are not collected from smaller banks, it is reasonable to assume that they are closely linked to the balance sheet data available to us, given that they encompass the same elements. Hence, we use the correlation between the observed scores and the available balance sheet data to extrapolate the G-SIB scores to the remaining banks in our sample. To trace out the variables that are predictive of the observed scores, we run a LASSO on the entire balance sheet data and pick those variables that have the highest explanatory power in the sample for which we observe systemic scores.¹⁷

Running the LASSO on the subsample with the observed systemic scores yields 40 predictive variables and an adjusted R-squared of .9958.¹⁸ While the LASSO yields all remaining variables with a non-zero coefficient, it also yields statistically non-significant coefficients. We exclude all statistically insignificant coefficients and obtain a set of 18 predictive balance sheet variables (see Tables A.3 and A.4 in the appendix). These remaining variables are closely related to the risk variables that are used to construct the G-SIB scores.

In the next step we predict the systemic scores for all other observations in our sample, based on the derived model. The results are shown in Figure 1. The left panel shows the fit between our predicted scores and the actual observed scores from the Federal Reserve, with an R-squared of .9943. The right panel of Figure 1 shows the relationship between the size of banks (total assets) and our predicted scores for the entire sample. Even though size is not among the variables used to predict the systemic score, the graph shows a clear, positive correlation between the systemic score and the size of financial institutions and, thus, their systemic importance.

We now have derived an indicator for the systemic importance of a financial institution, and hence for the degree of implicit guarantees this institution receives. To test the assumption that these systemic scores are positively correlated with bailout probabilities, we follow Gropp et al. (2011) and use Fitch stand-alone and overall credit ratings to calculate a proxy for the bailout probability that is reflected by the ratings. For this we transform the rating notches into default probabilities using the transition matrix for the U.S. non-financial sector provided by Fitch.¹⁹ A lower rating on the rating scale

¹⁷LASSO is a shrinkage estimator with the objective to choose those variables with the highest predictive power for the dependent variable from the set of all possible control variables. It does so by estimating a penalized regression, which minimizes the sum of squared residuals and a penalty term for the sum of the coefficients. We implement this via cross-validation, i.e., the estimator partitions the data into different folds of training and testing data and selects the penalty term that minimizes the out-of sample prediction error in the testing data.

¹⁸The cross-validation of the model is performed on 10 folds with an optimal penalty parameter of 2.28.

¹⁹We use the transition matrix for non-financial firms since the default probabilities of financial firms would themselves be affected by the bailout probability of financial institutions. Thus, the observed default probabilities in the transition matrices for financial firms are underestimated.



Figure 1: Systemic scores for financial institutions.

The left panel shows the correlation between the systemic scores observed in the data and the systemic scores as predicted by the LASSO model. The right panel shows the correlation between total assets and the predicted systemic scores in the full sample.

corresponds to a higher realized historic default rate. If the default probability for the stand-alone rating is higher than the default probability for the overall rating, which takes into account potential external support, this indicates a positive probability that this institutions receives external aid. We then regress this measure for the bailout probability on the predicted systemic scores in a logistic regression.²⁰ Table 2 shows that the systemic scores are highly positively correlated with the bailout probability. This confirms our underlying assumption that systemically important institutions can expect a higher level of (implicit or explicit) government support.

In a last step, we transform the predicted systemic scores into bailout probabilities using the coefficient from the logistic regression in Table 2. This is essentially a logistictransformation of the systemic scores, which ensures that they are bound between zero and one. This has the advantage that we do not need to assume a linear relationship between the systemic scores and the bailout probability in the subsequent analysis. This follows the observation that banks with medium to low scores have a bailout probability close to zero, whereas the bailout probability of banks with medium to high scores approaches one. Figure 2 shows this non-linear relationship.

²⁰We restrict this regression analysis to the firm-year observations for which both Fitch credit ratings and systemic scores from the Federal Reserve are available (104 observations). This avoids that measurement errors in the predicted scores affect our analysis.

Logistic reg	ression		Number of	obs =	104	
				Wald $chi2(1$.) =	14.70
				$\text{Prob} > \text{chi}^2$	2 =	0.0001
Log pseudo	likelihood	= -48.967	7627	Pseudo R2	=	0.1778
bailout probability	Coef.	Rob. Std. Err.	z	P > z	95% Conf	. Interval
predicted systemic score	.00454	.00118	3.83	0.000	.00222	.00686
constant	-2.525	.425	-5.95	0.000	-3.357	-1.693

 Table 2: Predicted systemic scores and bailout probabilities

This table presents the results of regressing the bailout probability pr on the predicted systemic score using a logistic regression in the subsample of banks for which we observe the actual systemic score. Heteroscedasticity-robust standard errors are used.

3.2.3 Incentive compensation

The third main measure in our analysis is incentive compensation. *Execucomp* offers detailed data on incentive payments and other salary components. These are, however, expost observations of realized values that depend on many factors such as firm performance, the achievement of personal goals, or other circumstances. Hence they do not reflect the true incentive component that was contractually agreed upon when hiring the CEO. The latter data is confidential, and is therefore not observable. Nevertheless, we can use the observed realized values of incentive pay to construct a measure for the incentive component that is independent of the performance of the firm. We argue that this is good proxy for the incentive component in the actual hiring contract.

To do so, we regress the observed incentive payment in year t for a CEO at bank i on a vector of variables that are related to firm performance. We follow Humphery-Jenner et al. (2016) in their choice of the explaining variables as far as they are available to us. These are the age of the CEO, the ownership share of the CEO, the bank's return on assets, book leverage, annualized stock returns, cash-flow, liquidity ratios, and the size of the executive board. We also include the lags of all performance-related variables as well as year and firm fixed effects. The dependent variable is the sum of all non-equity incentive components recorded in *Execucomp*: these are bonus payments, long-term incentive payments, and other non-equity performance pay (see Table A.2 in the appendix for precise definitions).

From this regression, we then calculate the predicted incentive component. This is the incentive compensation that would on average have been paid according to the performance parameters in the entire sample of financial institutions, taking into account fixed firm characteristics and time trends in wage setting. We then calculate the ratio of the observed realized incentive compensation over this predicted incentive compensation to



Figure 2: Predicted systemic scores and predicted bailout probabilities

This figure presents the mapping that arises from the regression in Table 2 that transforms the predicted systemic scores in a bailout probability between 0 and 100%.

obtain a measure of excessive incentive compensation. If this measure is above one, the CEO received a higher incentive compensation in this year as compared to what would have been paid on average for the combination of performance parameters.²¹

Table 3 compares this measure of excessive compensation for overconfident (Group 1) and non-overconfident CEOs (Group 0). The measure is close to one for the latter group, which suggests that contracts for non-overconfident CEOs do not have above-average incentive components. In contrast, the measure is 4.7 for overconfident CEOs (Group 1), indicating a strong excess incentive component for this group. Since we are ultimately interested in the year of hiring the CEO, and to reduce noise, we take the average across all observations of the CEO within the same firm as our measure of the incentive component. We argue that this component reflects the incentive share that was contractually agreed.

3.2.4 Control variables

We include further control variables in the main analysis in Section 3.3. When estimating the relationship between overconfidence and the incentive component, and the matching of CEOs to financial institutions, we use the age of the CEO, the ownership share of the CEO, return on assets, book leverage, the market-to-book ratio, annualized stock returns, cash-flows, the liquidity ratio, and the size of the executive board. These variables are similar to the vector of controls used to construct the measure of the incentive component.

 $^{^{21}}$ Note that this is not the average of actual levels of incentive compensation, but only that part of it which can be explained systematically by the performance variables. See Correa and Lel (2016) for a similar procedure in the context of excessive CEO pay.

Group	Obs	Mean Std. Err. Std.		Std. Dev.	[95% Cor	nf. Interval]
0 (non-overconfident)	1,785	1.12094	.0761732	3.218261	.9715415	1.270338
1 (overconfident)	875	4.736797	2.590464	76.62696	3474596	9.821054
combined	2,660	2.310366	.8539672	44.04352	.6358593	3.984874
diff		-3.615858	1.816594		-7.177939	0537765
diff = mean(0) - mean(0)			deį	t = -1.99 grees of freed	$905 \ om = 2658$	
Ha: diff < 0 Pr(T < t) = 0.0	Ha: $Pr(T >$	diff $! = 0$ > $ t) = 0.04$.66	Ha: difference $Prob(T > t)$	f > 0 = 0.9767	

Table 3: Excessive incentive compensation for overconfident / non-overconfident CEOs

This table presents the results from a t-test on the difference in the excessive incentive compensation component betwen overconfident and non-overconfident CEOs. The excessive compensation component is calculated as observed incentive payment over predicted incentive payment. This pediction is based on the relationship between the incentive component and various variables related to firm performance.

When estimating the effect of overconfidence on risk-taking, we use a different vector of controls, following previous econometric analyses in the literature. Here we additionally include size (logarithm of total assets), the deposit ratio, and the year-end stock price, but we do not include the CEO's age, their ownership share, and the bank's cash-flow and annualized returns. Table A.1 in the appendix shows which controls are employed in the tests of the different hypotheses.

Table 4 presents the descriptive statistics of the main variables used in the analysis. It shows that around one third of the observations relate to an overconfident CEO. Moreover, incentive payments vary widely across CEOs, with the p75/p25 ratio being close to 8.

To conclude our description of the data, Figure 3 summarizes the development over time for four of our core variables. These trends reveal several interesting patterns. The upper left panel shows that the share of overconfident CEOs has significantly fallen during the last two decades, from close to 40% in the early 2000s before the financial crisis to around 30% in the period after the financial crisis. The increase in the first years of the sample and the decrease in the last years are caused by a sample effect, as we only observe CEOs in this period for a shorter period of time. As such, these CEOs are less likely to be classified as overconfident under our approach (see section 3.2.1).²² This sample effect can, however, not explain the drop in the share of overconfident CEOs in the years immediately following the financial crisis. The upper right panel shows that the average systemic importance of the financial institutions in the U.S. financial sector has simultaneously increased during this period, in response to the financial crisis and

 $^{^{22}\}mathrm{In}$ Section 3.4 we carry out a robustness test to assess whether these 'short-tenure' CEOs affect our results.

	mean	sd	p25	p50	p75	count
overconfidence	0.329	0.470	0.000	0.000	1.000	3572
volatility	0.023	0.014	0.015	0.019	0.026	3495
size	9.469	1.782	8.426	9.247	10.442	3572
return on assets	0.013	0.129	0.007	0.011	0.015	3568
book leverage	9.813	8.440	7.387	9.257	11.345	3535
market-to-book	2.210	7.014	1.074	1.489	2.156	3494
liquidity ratio	0.096	0.130	0.025	0.046	0.106	3572
deposit ratio	0.614	0.281	0.577	0.725	0.801	3391
size of exec. board	5.609	1.135	5.000	5.000	6.000	3572
incentive compensation	1296.158	1979.449	199.946	664.572	1540.000	3572
annualized returns	0.128	0.374	-0.030	0.132	0.311	3495
cash-flow	0.088	3.088	0.043	0.076	0.127	3076
ownership share of CEO	0.019	0.124	0.001	0.004	0.011	3449

Table 4: Descriptive statistics

This table shows the descriptive statistics of the variables used in the analysis. The data is from Compustat, Execucomp, and CRSP.

to the consolidation of financial institutions that followed it. The lower two panels show the development of the average incentive payment on the left, and of the average fixed salary on the right. Both took a dip in the financial crisis, with the decline being more pronounced for incentive pay. After the crisis, both types of compensation rose back up and meanwhile exceed their pre-2007 levels. However, the ratio of incentive pay to fixed pay remains lower at the end of our sample period, as compared to the pre-crisis period in the early 2000s.

3.3 Analysis

In the following, we will test the four theoretical hypotheses developed in Section 2.

3.3.1 Overconfidence and risk-taking

The theoretical model rests on the important assumption that overconfident CEOs increase risk-taking at financial institutions for any given level of incentive compensation (Hypothesis 1). There have been numerous studies in the literature that examine the relationship between CEO overconfidence and risk-taking. For example Ho et al. (2016) show that financial institutions with overconfident CEOs took higher risks before financial crises and performed worse during financial crises. Kassner (2023) examines the relationship between CEO overconfidence and risk-taking in a dynamic setting. He finds that overconfident CEOs took more risk than non-overconfident CEOs in the period before the 2007-2009 financial crises, behaved similarly to non-overconfident CEOs in the post-crisis



Figure 3: Development of core variables over time

This figure shows the development of the share of overconfident CEOs, the bailout probability, the incentive payments, and the base salary over time.

period of strict regulation, and again took more risk than non-overconfident CEOs once regulation was relaxed after 2018.²³

For the purposes of our matching analysis, we use a similar econometric model as in Kassner (2023), but additionally include the incentive component to control for the level of incentive compensation. We regress the standard deviation of daily stock returns, i.e., the volatility of the firm, on overconfidence interacted with year dummies along with a vector of controls and firm and year fixed effects using OLS. Standard errors are clustered at the firm level. The coefficients of the interactions between the year dummies and the overconfidence dummy yield the gradient of overconfidence, that is, the additional volatility at firms with overconfident CEOs. Figure 4 presents these gradients of CEO overconfidence on banks' risk-taking, as measured by the standard deviation of daily stock returns in a given year, for each year in our sample period 2000-2022. The results show that there was a statistically significant correlation between CEO overconfidence and risk in the pre-crisis years 2000-2006. However, this relationship is not different from zero

 $^{^{23}}$ Similarly, Banerjee et al. (2015) show that economy-wide regulation through the Sarbanes-Oxley Act in 2002 significantly disciplined the behavior of overconfident CEOs.



Figure 4: Relationship between overconfidence and risk

This figure shows the gradient of overconfidence in the regression of risk (standard deviation of daily stock returns) on the overconfidence dummy interacted with the year dummies. We include a vector of control variables that is composed of size (logarithm of total assets), return on assets, book leverage, the market-to-book ratio, the liquidity ratio, the size of the executive board, the deposit ratio, and the year-end stock price, as well as firm and year fixed effects. Standard errors are clustered at the firm level. The sample size is N=2,931.

during the Great Financial Crisis (2007-2009), and during periods of stricter financial regulation (Dodd-Frank Act 2010-2017). With deregulation starting in 2018, the positive relationship between risk and overconfidence reappears, with a notable interruption in the years of the Covid Crisis (2020-2021).

Based on these findings, we define three distinctive periods for our subsequent analysis: (i) the period in which there is a positive relationship between CEO overconfidence and risk-taking (2000-2006, 2018-2019, 2022); (ii) crisis years in which this relationship is zero (2007-2009, 2020-2021); and (iii) periods of strict financial regulation in which the relationship is also zero (2010-2017). Column (1) in Table 5 shows the static representation of Figure 4 using an indicator variable representing the three periods defined above. On average, financial institutions with overconfident (*OC*) CEOs had a 6% higher standard deviation of daily stock returns, and this effect is significant at the 10% level.²⁴ This confirms Hypothesis 1, but only for non-crisis years that were not characterized by enhanced regulation. We will label these 'normal years' in the following. Our model in Section 2, and our main hypotheses, apply to these periods. In contrast, the effect of CEO overconfidence decreases towards zero during both crisis periods, and in periods of strict regulation. The latter finding shows that tight regulation following the financial crisis has been effective in counteracting the fundamental economic incentives on which our analysis is focused.

3.3.2 Matching between overconfident CEOs and banks

For our following tests of Hypotheses 2 to 4, we focus only on CEO turnovers. This is because we want to capture the relationship between government protection for banks and CEO overconfidence at the time of hiring a CEO. Hence, we only keep the first year of tenure of each CEO. This reduces the sample to 310 observations. Since some of the control variables have missing values, the effective sample will be smaller, depending on the specification of the model. Given this low number of observations, we cannot carry out a dynamic analysis. Therefore, we use the indicator variable representing the three periods differing in the relationship between CEO overconfidence and risk as described above. The results for testing Hypotheses 2 to 4 are summarized in Table 5.

H2: Bonus compensation and government support

Hypothesis 2 states that bonus compensation is rising in the level of government support. This should, however, only be the case when the stakeholders of the bank can assume that risk-taking can be affected via incentives, and therefore in normal years. During periods of strict financial regulation, this may not be the case due to exogenous constraints on

 $^{^{24}{\}rm The}$ effect is significant at the 5% level when influential observations in the data are removed. See Section 3.4 and Table A.5 in the appendix.

	H1	H	[2	H	H3	
	(1)	(2)	(3)	(4)	(5)	(6)
	Volatility	Incentive	Incentive	Incentive	Incentive	ÒĆ
OC_t				0.989^{**}	0.679	
				(0.442)	(0.489)	
$OC \times crisis$				-1 1/18	-0 753	
				(0.766)	(0.600)	
				(0.700)	(0.000)	
$OC_t \times regulated period$				-0.824	-0.923	
				(0.534)	(0.582)	
				(0.001)	(0.002)	
OC_{t-1}	0.0587^{*}					
	(0.031)					
	~ /					
$OC_{t-1} \times crisis$	-0.0672^{*}					
	(0.041)					
	0.0010*					
$OC_{t-1} \times regulated period$	-0.0618*					
	(0.036)					
$\mathcal{D}T_{\pm -1}$		0.0665***	0.0473***			0.254^{**}
$F \cdot t = 1$		(0.015)	(0.017)			(0.105)
		(0.010)	(0.011)			(01200)
$pr_{t-1} \ 1 \times crisis$		-0.0294	-0.0176			-0.282**
		(0.020)	(0.023)			(0.132)
		× ,				· · · ·
$pr_{t-1} \times regulated \ period$		-0.0388**	-0.0185			-0.291***
		(0.017)	(0.017)			(0.109)
Observations	2931	253	233	255	234	204
R^2	0.563	0.139	0.363	0.0927	0.336	
$Pseudo - R^2$						0.285
Clusters	218	151	144	151	144	127
Controls	Yes	No	Yes	No	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	firm-level					

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

Table 5: Main results of the analysis

This table presents the main empirical results of the analysis. In column (1) we regress the natural logarithm of the daily stock return volatility on the overconfidence dummy interacted with the three different periods as described in Section 3.3.1. In columns (2) and (3) we regress the natural logarithm of the incentive component on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In columns (4) and (5) we regress the natural logarithm of the incentive component on the overconfidence dummy interacted with the three different periods as described in Section 3.3.2. In columns (4) and (5) we regress the natural logarithm of the incentive component on the overconfidence dummy interacted with the three different periods as described in Section 3.3.2. In column (6) we regress the overconfidence dummy on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In column (6) we regress at the firm level, which are reported in parentheses. Columns (1) to (5) use OLS, column (6) a logistic regression.

risk-taking. Moreover, during such periods the use of incentive compensation might itself be restricted. In the U.S., for example, both the Dodd-Frank Act and the Troubled Asset Relief Programme (TARP) imposed restrictions on bonus payments to CEOs. Therefore, we expect a positive relationship between government support and incentive compensation primarily in 'normal', non-crisis years with moderate regulation.

We test this hypothesis by regressing our measure for the contractual incentive component on our measure of the bailout probability (pr). We interact the bailout probability with the indicator variable reflecting the three periods differing in the relationship between CEO overconfidence and risk-taking. We estimate the model using OLS, with and without a vector of controls. We cluster standard errors on the firm level. For normal years, columns (2) and (3) in Table 5 show a highly significant (1% level) positive relationship between the bailout probability and the incentive component. This positive relationship is still present in crisis years and in years of strict regulation, but it is weaker during these periods.²⁵ In sum, our empirical analysis therefore confirms that government-protected banks do indeed incentivize higher risk-taking by offering contracts with a larger bonus component.

H3: CEO overconfidence and incentive payments

According to Hypothesis 3, banks pay higher incentive shares if their CEOs are overconfident. Overconfident managers, who overestimate their probability of success, are willing to take higher risks for a given incentive payment, and they accept a lower total compensation by overestimating the expected value of their incentive payment. However, as Hypothesis 3 states, this relationship holds only when the damage caused by overconfident managers in the low state (as parameterized by γ) is not too large. Hence, we expect again that the positive relationship in Hypothesis 3 appears primarily in normal years where bank failure is not a primary concern for the bank's stakeholders.

We test this hypothesis by regressing our measure for the contractual incentive component on our binary overconfidence variable. We again interact the indicator with the period dummy. We estimate different models including and excluding control variables using OLS and cluster standard errors on the firm level. The results are given in columns (4) and (5) of Table 5. They show that, in normal years, overconfident CEOs are incentivized more than non-overconfident CEOs. This relationship is statistically significant at the 5% level when control variables are absent (column (4)). It remains positive when control variables are added, but loses its statistical significance given the high standard errors (column (5)). In contrast, the relationship is close to zero in crisis years, or periods

²⁵Comparing columns (2) and (3) shows that the R^2 measure increases significantly when controls are added. This is due primarily to the control variables *liquidity ratio*, market-to-book ratio, and age of *CEO*, which are all associated with bonus payments. The same role of controls applies in column (5) that tests H3.

of strict regulation. In sum, Hypothesis 3 is only weakly confirmed by our regression analysis. Previous literature focusing explicitly on this hypothesis has, however, found convincing evidence to support it (see, e.g., Humphery-Jenner et al., 2016).

H4: Matching of overconfident CEOs

Finally, we come to our main hypothesis that overconfident CEOs are matched, in equilibrium, with government protected banks (Hypothesis 4). Again, this relationship should only hold in periods where there is a positive relationship between overconfidence and risk-taking and when the damage in the 'bad' state caused by overconfident managers is not too large. Hence, we expect this assortative matching primarily in normal years, absent crises and years of enhanced regulation.

We test this hypothesis by regressing the binary overconfidence variable on our measure for the bailout probability, interacted with the period indicator in a logistic framework. We include the standard control variables and cluster standard errors on the firm level. For normal years, column (6) in Table 5 shows a positive relationship between the bailout probability of a bank and the overconfidence level of its CEO that is significant at the 5% level. In crisis periods, and in periods of enhanced regulation, the relationship is instead zero and the assortative matching stated in Hypothesis 4 does not occur.

Taken together, the results from the empirical analysis support the hypothesis derived from our theoretical model for normal years. They show that banks with larger government support, as reflected by a higher bailout probability, incentivize their CEOs more. This attracts overconfident CEOs who overestimate their probability of success and are therefore more likely to accept higher-powered incentive contracts. In equilibrium this in turn leads to an assortative matching between overconfident managers and banks with a larger bailout probability. Importantly, however, these relationships do not hold in crisis periods, and in periods of strict financial regulation. In these periods our basic hypothesis that overconfident CEOs take more financial risks (Hypothesis 1) is violated.

3.4 Robustness tests

In this section, we assess the robustness of the baseline results in several ways. First, we identify and address influential observations in the data. Influential observations are those that exert a strong impact on the estimated coefficients and, thus, on the predicted values of the model. To detect such observations, we use DFFITS, a diagnostic measure that evaluates the influence of individual data points on the fitted values by quantifying the change in predicted values when a specific observation is excluded. A high DFFITS value suggests that an observation significantly influences the regression model's predictions,

potentially flagging it as influential.²⁶ The results, presented in Table A.5 in the appendix, indicate that removing these influential observations does not qualitatively change the results.

We further assess the robustness of our findings concerning the overconfidence measure. As pointed out in Section 3.2 and illustrated in Figure 3, our measure may not accurately reflect overconfidence towards the beginning and the end of the sample, where we observe CEOs only for a short period of time and, thus, CEO tenures are shorter by definition. Therefore, we exclude CEOs from the analysis if they are observed for less than five years at either end of the sample. Figure B.1 in the appendix shows the change in the share of overconfident CEOs. The results presented in Table A.6 in the appendix show that our findings remain robust to this adjustment, despite decreasing the sample substantially.

Last, we test an alternative hypothesis for our Hypothesis 4. Overconfident CEOs might have had a stronger track record in the past due to unobserved characteristics that are correlated with overconfidence. As such, they might sort into larger banks where they can expect higher total earnings. As larger banks have a higher bailout probability, the bailout probability might not necessarily be the driver behind the matching between overconfident CEOs and these banks. To test this, we re-estimate Hypothesis 4 substituting size for bailout probability and also using both measures simultaneously. Table A.7 in the appendix presents these results, with both measures standardized to have mean zero and standard deviation one for comparability. The findings indicate that when each measure is included separately, the bailout probability has a larger coefficient. When both are included, the coefficient of the bailout probability remains positive, and it exceeds the size coefficient in magnitude.²⁷ Thus, even after controlling for size, there remains a positive correlation between bailout probability and CEO overconfidence.

4 Conclusion

In this paper we have shown that there is a positive assortative matching between overconfident CEOs and government-protected banks in normal years, absent crises and enhanced regulation. Banks that expect a higher bailout probability due to their systemic relevance attract more overconfident CEOs by means of above-average bonus shares, given their larger risk appetite. Hence the moral hazard problem of government-protected banks that has been stressed in the previous literature is exacerbated by the hiring of managers who overestimate their probability of success and accordingly take excessive risks.

²⁶To identify only the most influential observations, we apply a threshold of $4 \times \sqrt{((e(dfm)+1)/e(N))}$, where dfm are the degrees of freedom, N is the number of observations and e is the exponential function. This threshold is a heuristic that adjusts for both model complexity and sample size, ensuring a balance between detecting influential data points and avoiding over-flagging in larger datasets.

²⁷We note, however, that the significance of both coefficients diminishes. This is likely to be attributed to the small sample size.

These findings underscore the incentive problems arising in systemically relevant banks which can expect to be protected in times of crisis. As the withdrawal of this protection is not credible, the remaining option is to regulate these banks tightly, in order to minimize their risks of default. Our analysis has also shown that stricter regulation is able to prevent overconfident managers from taking excessive risks, and it also breaks the link between the degree of government protection for banks and the hiring of overconfident CEOs. This offers additional support for the Basel III regulation requiring systemically important banks to hold extra equity buffers – as well as higher leverage ratios, as is planned under the new Basel IV framework.

From our methodological perspective, our analysis is among the few studies that use data on the degree of government protection for banks to empirically analyze the effects of the implicit bailout guarantees. To gain an improved understanding for the incentives of the affected banks, it is important to improve the database on the systemic importance of individual banks. The U.S. Global Systemically Important Banks (G-SIB) database could serve as a blueprint to develop a similar database for European banks.

Appendix

A Additional Tables

	H1	H2	H3	H4
Dependent variable	Volatility	Incentive	Incentive	Overconfidence
Age of CEO		\checkmark	\checkmark	\checkmark
Ownership Share of CEO		\checkmark	\checkmark	\checkmark
Annualized Stock Returns		\checkmark	\checkmark	\checkmark
Cash-Flows		\checkmark	\checkmark	\checkmark
Return on Assets	\checkmark	\checkmark	\checkmark	\checkmark
Book Leverage	\checkmark	\checkmark	\checkmark	\checkmark
Market-to-Book Ratio	\checkmark	\checkmark	\checkmark	\checkmark
Liquidity Ratio	\checkmark	\checkmark	\checkmark	\checkmark
Size of Executive Board	\checkmark	\checkmark	\checkmark	\checkmark
Size (Log Total Assets)	\checkmark			
Deposit Ratio	\checkmark			
Year-End Stock Price	\checkmark			
Incentive Component	\checkmark			

 Table A.1: List of control variables in the analysis

This table shows which of the control variables are used in the different hypotheses.

Variable	Definition 1992-2005	Definition change from
Non stock based Co	mongation	2006
solory	Dollar value of the annual	No chango
Salal y	base salary paid during the	No change.
	fiscal year	
bonus	Dollar value of the annual	ExecuComp retains vari-
bonus	bonus paid during the fiscal	able name BONUS but
	vear. The amount of cash or	it should be BONUS(R)
	non-cash unrestricted com-	since elements of BONUS
	pensation received during	are included in the new
	the fiscal year, if subject to	variable noneq_incent,
	performance criteria not in	with BONUS(R) now
	excess of one year and/or if	confined to annual non-
	contingent only on contin-	performance payments
	ued employment.	while noneq_incent is
		contingent on achieving
		performance targets, often
		extending beyond one year.
ltip	Cash payment under long-	Discontinued and replaced
	term incentive plan that	by noneq_incent.
	may include restricted stock	
	(or stock "units") tied to	
	performance criteria such as	
	cash flow or EPS over a	
	period of more than one	
	year (usually three years).	
	If only restricted stock is	
	given, company can opt to	
nonog ingent	disclose htp under rstkgrift.	Now variable Paparta
noneq_mcent		amount of all non oquity
		componential non-equity
		vear that is triggered by
		attainment of performance
		target(s) defined by the
		incentive compensation
		plan. noneq_incent ex-
		cludes stock-based pay.
		differentiating it from Itip
		but similar to elements of
		BONUS.

Table A.2: Compensation variable definitions in Execucomp

This table presents the variable definitions for incentive compensation in the *Execucomp* database. The table is taken from Hopkins and Lazonick (2016), p.40f.

				Numl	per of obs	112
					F(40, 71)	655.71
					$\mathbf{Prob} > \mathbf{F}$	0.0000
				I	R-squared	0.9973
				Adj I	R-squared	0.9967
				F	loot MSE	15.332
Systemic score	Coef.	Std. Err.	t	$\mathbf{P} > t $	[95% Conf.	Interval]
sociother_ind	-0.0102	0.0064	-1.63	0.107	-0.0234	0.0023
che_ind	0.0003	0.0001	2.63	0.010	0.0001	0.0005
dlc_ind	0.0002	0.0016	0.10	0.924	-0.0034	0.0039
dltp_ind	-0.0002	0.0002	-1.09	0.363	-0.0006	0.0002
dvint_ind	0.0003	0.0018	0.14	0.889	-0.0033	0.0038
exre_ind	0.0028	0.0012	2.43	0.018	0.0005	0.0052
fate_ind	0.0081	0.0020	4.03	0.000	0.0041	0.0120
fiao_ind	-0.0002	0.0000	-4.19	0.000	-0.0003	-0.0005
hedge_ind	0.0130	0.0042	3.14	0.003	0.0047	0.0212
ivstch_ind	0.0008	0.0016	0.53	0.600	-0.0023	0.0040
lqpl1_ind	-0.0012	0.0014	-0.87	0.386	-0.0039	0.0015
msa_ind	-0.0009	0.0005	-1.69	0.094	-0.0019	0.0001
nim_ind	0.0196	0.0052	3.78	0.000	0.0094	0.0298
nrtxtnps_ind	0.0028	0.0019	1.49	0.141	-0.0010	0.0066
oancf_ind	0.0007	0.0014	0.51	0.610	-0.0021	0.0036
optdr_ind	-0.0039	0.0016	-2.49	0.016	-0.0070	-0.0008
optfvgr_ind	0.3669	0.0839	4.38	0.000	0.1997	0.5342
reunr	0.0604	0.0243	2.49	0.015	0.0121	0.1087
spipv_ind	-0.0112	0.0045	-2.49	0.015	-0.0202	-0.0022
stkco_ind	0.0024	0.0018	1.29	0.200	-0.0013	0.0060
$\mathrm{txdc}_{-\mathrm{ind}}$	0.0052	0.0024	2.15	0.035	0.0004	0.0100
$txds_ind$	0.0156	0.0023	6.82	0.000	0.0111	0.0202
txdnb_ind	0.0062	0.0026	2.41	0.019	0.0010	0.0114
ca_fs	0.0194	0.0067	2.90	0.005	0.0061	0.0327
capr1_fs	15.8669	1.6254	9.76	0.000	12.6394	19.0944
cfo_fs	2.8176	0.4903	5.75	0.000	1.8466	3.7885
fate_fs	-0.1534	0.1134	-1.35	0.180	-0.3783	0.0715
fca_fs	0.0661	0.0198	3.35	0.001	0.0267	0.1055
idis_fs	0.0091	0.0032	2.87	0.005	0.0029	0.0153
intano_fs	0.0685	0.0193	3.54	0.001	0.0301	0.1070
ivs_fs	-0.0614	0.0208	-2.95	0.004	-0.1027	-0.0201
pstkr_fs	0.2086	0.0521	4.00	0.000	0.1052	0.3119
sc_fs	-0.2665	0.0522	-5.10	0.000	-0.3702	-0.1628
ssnp_fs	0.3011	0.0894	3.37	0.001	0.1236	0.4785
tdslg_fs	-0.0706	0.0200	-3.52	0.001	-0.1103	-0.0310
tdst_fs	0.0003	0.0000	4.21	0.000	0.0002	0.0005
tf_fs	-0.0631	0.0273	-2.31	0.023	-0.1173	-0.0089
xintd_fs	0.0618	0.0233	2.65	0.010	0.0153	0.1082
_cons	-98.5280	17.4518	-5.65	0.000	-133.3762	-63.7298

Table A.3: The full LASSO model

This table shows the results of the full model that is chosen by the LASSO approach, leaving out variables with a coefficient of zero. The cross-validation of the model is performed on 10 folds with an optimal penalty parameter of 2.28. Variable definitions can be found in *Compustat*. The suffixes $_ind$ denote the industrial data view and $_fs$ the financial data view.

				Numl	per of obs	112
					F(40, 71)	1071.37
					$\mathbf{Prob} > \mathbf{F}$	0.0000
				I	R-squared	0.9952
				Adj I	R-squared	0.9943
				F	loot MSE	17.862
Systemic score	Coef.	Std. Err.	t	$\mathbf{P} > t $	[95% Con	f. Interval]
che_ind	0.000260	0.000030	8.72	0.000	0.000200	0.000319
fate_ind	0.048076	0.006366	7.56	0.000	0.035416	0.060736
fiao_ind	-0.008462	0.003308	-2.56	0.012	-0.015039	-0.001885
ivstch_ind	0.002574	0.001053	2.44	0.017	0.000483	0.004664
nim_ind	0.084570	0.014272	5.93	0.000	0.056178	0.112962
$optdr_ind$	0.018239	0.008037	2.27	0.025	0.002269	0.034209
$optfvgr_ind$	2.238189	1.561692	1.43	0.048	6.229249	2.866262
reunr	0.075162	0.033677	2.23	0.027	0.008201	0.142124
ca_fs	0.033398	0.014843	2.25	0.027	0.003929	0.062867
$capr1_fs$	1.420325	0.629417	2.26	0.026	0.168168	2.672482
cfo_fs	2.940167	0.471719	6.23	0.000	2.002892	3.877442
fate_fs	-0.141794	0.096073	-1.48	0.141	-0.332686	0.049097
fca_fs	0.109462	0.036568	2.99	0.004	0.036757	0.182167
pstkr_fs	0.137513	0.053719	2.56	0.012	0.030789	0.244237
sc_fs	-0.200652	0.051787	-3.87	0.000	-0.303413	-0.097891
tdst_fs	0.004591	0.001202	3.82	0.000	0.002200	0.006982
tf_fs	0.080428	0.016120	4.99	0.000	0.048370	0.112487
xtindf_fs	0.100378	0.020145	4.98	0.000	0.060173	0.140583
_cons	-118.1835	16.5149	-7.16	0.000	-150.9772	-85.3897

Code	Description
che_ind	Cash and Short-Term Investments
$fate_ind$	Property, Plant, and Equipment - Machinery and Equipment at Cost
fiao_ind	Financing Activities - Other
ivstch_ind	Short-Term Investments - Change
nim_ind	Net Interest Margin
$optdr_ind$	Dividend Rate - Assumption (%)
$optfvgr_ind$	Options - Fair Value of Options Granted
reunr	Retained Earnings - Unrestricted
ca_fs	Customers' Acceptance
$capr1_fs$	Risk-Adjusted Capital Ratio - Tier 1
cfo_fs	Commissions and Fees - Other
fate_fs	Property, Plant, and Equipment - Machinery and Equipment at Cost
fca_fs	Foreign Exchange Income (Loss)
pstkr_fs	Preferred/Preference Stock - Redeemable
sc_fs	Securities In Custody
$tdst_fs$	Trading/Dealing Account Securities - Total
tf_fs	Trust Fees
xintd_fs	Interest Expense - Long-Term Debt

Table A.4: The lean LASSO model

This table shows the results of the lean model after all insignificant variables are dropped. Variable definitions can be found in *Compustat*. The suffixes $_ind$ denote the industrial data view and $_fs$ the financial data view.

	H1		H	I2	H	[3	H	I4
	(1) Vola	(2) tility	(3) Ince	(4) ntive	(5) Ince	(6) ntive	(7) C	(8) OC
OC_t					$0.679 \\ (0.489)$	$0.646 \\ (0.480)$		
$OC_t \times crisis$					-0.753 (0.600)	-0.671 (0.583)		
$OC_t \times regulated period$					-0.923 (0.582)	-0.871 (0.584)		
OC_{t-1}	$\begin{array}{c} 0.0587^{*} \\ (0.031) \end{array}$	$\begin{array}{c} 0.0619^{**} \\ (0.031) \end{array}$						
$OC_{t-1} \times crisis$	-0.0672^{*} (0.041)	-0.0771^{**} (0.039)						
$OC_{t-1} \times regulated period$	-0.0618^{*} (0.036)	-0.0763^{**} (0.034)						
pr_{t-1}			$\begin{array}{c} 0.0473^{***} \\ (0.017) \end{array}$	$\begin{array}{c} 0.0417^{***} \\ (0.015) \end{array}$			0.254^{**} (0.105)	0.250^{**} (0.105)
$pr_{t-1} \ 1 \times crisis$			-0.0176 (0.023)	-0.00964 (0.020)			-0.282^{**} (0.132)	-0.283^{**} (0.134)
$pr_{t-1} \times regulated period$			-0.0185 (0.017)	-0.0143 (0.015)			-0.291^{***} (0.109)	-0.286^{***} (0.108)
Observations	2931	2917	233	226	234	227	204	200
R^2	0.563	0.567	0.363	0.377	0.336	0.330		
$Pseudo - R^2$							0.285	0.259
Clusters	218	215	144	142	144	142	127	126
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	firm-level	firm-level						

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

Table A.5: Robustness of main results to outliers in the data

This table presents the baseline empirical results in the respective first column, and the respective second column excludes influential observations as identified by DFFITS, diagnostics meant to show how influential a point is in a linear regression. The threshold is set to $4 \times \sqrt{((e(df_m) + 1)/e(N))}$. In columns (1) and (2) we regress the natural logarithm of the daily stock return volatility on the overconfidence dummy interacted with the three different periods as described in Section 3.3.1. In columns (3) and (4) we regress the natural logarithm of the incentive component on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In columns (5) and (6) we regress the natural logarithm of the incentive set described in Section 3.3.2. In column (7) and (8) we regress the overconfidence dummy on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In column (7) and (8) we regress the overconfidence dummy on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In column (7) and (8) we regress the overconfidence dummy on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In column (7) and (8) we regress the overconfidence dummy on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In column (7) and (8) we regress the overconfidence dummy on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In column (7) and (8) a logistic regression.

	H	[1	H	H2	H	[3	H4	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Vola	tility	Ince	ntive	Ince	ntive	0	С
OC_t					$\begin{array}{c} 0.679 \\ (0.489) \end{array}$	$\begin{array}{c} 0.430\\ (0.559) \end{array}$		
$OC_t \times crisis$					-0.753 (0.600)	-0.562 (0.695)		
$OC_t \times regulated period$					-0.923 (0.582)	-0.624 (0.672)		
OC_{t-1}	$\begin{array}{c} 0.0587^{*} \\ (0.031) \end{array}$	$\begin{array}{c} 0.0795^{**} \\ (0.033) \end{array}$						
$OC_{t-1} \times crisis$	-0.0672^{*} (0.041)	-0.109^{**} (0.044)						
$OC_{t-1} \times regulated period$	-0.0618^{*} (0.036)	-0.0800** (0.038)						
pr_{t-1}			$\begin{array}{c} 0.0473^{***} \\ (0.017) \end{array}$	$\begin{array}{c} 0.0774^{***} \\ (0.028) \end{array}$			0.254^{**} (0.105)	0.202^{**} (0.088)
$pr_{t-1} \ 1 \times crisis$			-0.0176 (0.023)	-0.0543 (0.035)			-0.282^{**} (0.132)	-0.283 (0.268)
$pr_{t-1} \times regulated period$			-0.0185 (0.017)	-0.0480^{*} (0.028)			-0.291^{***} (0.109)	-0.246^{**} (0.099)
Observations	2931	2682	233	143	234	169	204	140
R^2	0.563	0.573	0.363	0.407	0.336	0.345		
$Pseudo - R^2$	210	204		0.0		110	0.285	0.258
Clusters	218	206	144	98	144	112	127	97
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	firm-level	firm-level						

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

Table A.6: Robustness of main results to 'short-tenure' CEOs

This table presents the baseline empirical results in the respective first column, and the results excluding the first and last CEO per firm with less than five years of tenure in the respective second column. In columns (1) and (2) we regress the natural logarithm of the daily stock return volatility on the overconfidence dummy interacted with the three different periods as described in Section 3.3.1. In columns (3) and (4) we regress the natural logarithm of the incentive component on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In columns (5) and (6) we regress the natural logarithm of the incentive section as described in Section 3.3.2. In columns (7) and (8) we regress the overconfidence dummy on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In columns (7) and (8) we regress the overconfidence dummy on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In columns (7) and (8) we regress the overconfidence dummy on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In columns (7) and (8) we regress the overconfidence dummy on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In columns (7) and (8) we regress the overconfidence dummy on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In all specifications we cluster standard errors at the firm level, which are reported in parentheses. Columns (1) to (6) use OLS, columns (7) and (8) a logistic regression.

	(1)	(2)	(3)	(4)
	OC	OC	OC	OC
pr_{t-1}	2.186^{**}		1.595^{*}	1.085
	(0.907)		(0.932)	(1.194)
	× /		()	× /
$pr_{t-1} \ 1 \times crisis$	-2.426^{**}		-2.112^{*}	-0.979
	(1.134)		(1.264)	(1.266)
	. ,			. ,
$pr_{t-1} \times regulated \ period$	-2.510^{***}		-2.101^{**}	-1.716
	(0.939)		(0.930)	(1.265)
$size_{t-1}$		1.357^{**}	0.519	0.897
		(0.542)	(0.387)	(0.822)
$size_{t-1} \ 1 \times crisis$		-1.739^{**}		-1.365
		(0.760)		(0.989)
$size_{t-1} \times regulated period$		-0.946		-0.197
		(0.582)		(0.870)
Observations	204	204	204	204
R^2				
$Pseudo - R^2$	0.285	0.291	0.296	0.307
Clusters	127	127	127	127
Controls	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Fixed effects				

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

Table A.7: Testing an alternative explanation for Hypothesis 4

This table tests for an alternative explanation for Hypothesis 4. In column (1) we regress the overconfidence dummy on the proxy for the bailout probability interacted with the three different periods as described in Section 3.3.2. In column (2) we use size instead of the bailout probability. In column (3) we add size to column (1). In column (4) we also interact size with the period dummies. For comparability purposes, bailout probability and sizes are standardized to mean zero and standard deviation one. In all specifications we use a logistic regression and cluster standard errors at the firm level, which are reported in parentheses.

B Additional Figures



Figure B.1: Development of overconfidence over time

This figure shows the development of the share of overconfident CEOs over time. The left panel shows the share in the original sample and the right panel the share in the sample when excluding CEOs with less than five years of tenure at either end of the sample.

References

- Bandiera, O., Guiso, L., Prat, A., Sadun, R. (2015). Matching firms, managers, and incentives. *Journal of Labor Economics* 33, 623-681.
- Bandiera, O., Prat, A., Hansen, S., Sadun, R. (2020). CEO behavior and firm performance. Journal of Political Economy 128, 1325-1369.
- Banerjee, S., Humphery-Jenner, M., Nanda, V. (2015). Restraining overconfident CEOs through improved governance: Evidence from the Sarbanes-Oxley Act. *Review of Financial Studies 28*, 2812-2858.
- Besley, T., Ghatak, M. (2013). Bailouts and the optimal taxation of bonus pay. American Economic Review Papers & Proceedings 103, 163-167.
- Bhagat, S., Bolton, B. (2014). Financial crisis and bank executive incentive compensation. Journal of Corporate Finance 25, 313-341.
- Billett, M., Qian, Y. (2008). Are overconfident CEOs born or made? Evidence of selfattribution bias from frequent acquirers. *Management Science* 53, 1037-1051.
- Bloomberg (2023). SVB's 44 hour collapse was rooted in treasury bets during pandemic. https://www.bloomberg.com/news/articles/2023-03-10/svb-spectacularlyfails-after-unthinkable-heresy-becomes-reality
- Campbell, C., Gallmeyer, M., Johnson, S., Rutherford, J., Stanley, B. (2011). CEO optimism and forced turnover. *Journal of Financial Economics* 101, 695-712.
- Chen, J., Song, K. (2013). Two-sided matching in the loan market. *International Journal* of Industrial Organization 31, 145-152.
- Correa, R., Lel, U. (2016). Say on pay laws, executive compensation, pay slice, and firm valuation around the world. *Journal of Financial Economics 122*, 500-520.
- De la Rosa, L.E. (2011). Overconfidence and moral hazard. *Games and Economic Behavior* 73, 429-451.
- Demirgüç-Kunt, A., Detriagiache, E. (2002). Does deposit insurance increase banking system stability? An empirical investigation. Journal of Monetary Economics 49, 1373-1406.
- Edmans, A., Gabaix, X., Landier, A. (2009). A multiplicative model of optimal CEO incentives in market equilibrium. *Review of Financial Studies* 22, 4881-4917.
- Edmans, A., Gabaix, X. (2016). Executive compensation: A modern primer. Journal of Economic Literature 54, 1232-1287.

- Eeckhout, J., Kircher, P. (2018). Assortative matching with large firms. *Economet*rica 86, 85-132.
- Efing, M., Hau, H., Kampkötter, P., Steinbrecher, J. (2015). Incentive pay and bank risktaking: Evidence from Austrian, German, and Swiss banks. *Journal of International Economics 96*, S123-S140.
- Gabaix, X., Landier, A. (2008). Why has CEO pay increased so much? *Quarterly* Journal of Economics 123, 49-100.
- Gennaioli, N., Shleifer, A. (2018). A crisis of beliefs: Investor psychology and financial fragility. Princeton University Press.
- Gervais, S., Odean, T. (2001). Learning to be overconfident. *Review of Financial Studies 14*, 1-27.
- Gervais, S., Heaton, J.B., Odean, T. (2011). Overconfidence, compensation contracts, and capital budgeting. *Journal of Finance 66*, 1735-1777.
- Gietl, D., Kassner, B. (2020). Managerial overconfidence and bank bailouts. *Journal of Economic Behavior and Organization 179*, 202-222.
- Goel, A., Thakor, A. (2008). Overconfidence, CEO selection, and corporate governance. Journal of Finance 63, 2737-2784.
- Graham, J., Campbell, H., Puri, M. (2013). Managerial attitudes and corporate actions. Journal of Financial Economics 109, 103-121.
- Gropp, R., Gruendl, C., Guettler, A. (2014). The impact of public guarantees on bank risk-taking: Evidence from a natural experiment. *Review of Finance 18*, 457-488.
- Gropp, R., Hakenes, H., Schnabel, I. (2011). Competition, risk-shifting, and public bail-out policies. *Review of Financial Studies* 24, 2084-2120.
- Grossman, G. (2013). Heterogeneous workers and international trade. *Review of World Economics 149*, 211-245.
- Hall, B., Murphy, K. (2002). Stock options for undiversified executives. Journal of Accounting and Economics 33, 3-42.
- Hakenes, H., Schnabel, I. (2014). Bank bonuses and bailouts. Journal of Money, Credit and Banking 46, 259-288.
- Haufler, A. (2021). Regulatory and bailout decisions in a banking union. Journal of Banking and Finance 133, 106300.

- Hirshleifer, D., Low, A., Teoh, S.H. (2012). Are overconfident CEOs better innovators? Journal of Finance 67, 1457-1498.
- Ho, P.-H., Huang, C., Lin, C., Yen, J. (2016). CEO overconfidence and financial crisis: Evidence from bank lending and leverage. *Journal of Financial Economics 120*, 194-209.
- Hopkins, M., Lazonick, W. (2016). The mismeasure of mammon: Uses and abuses of executive pay data. Institute for New Economic Thinking Working Paper No. 49.
- Huber, K. (2021). Are bigger banks better? Firm-level evidence from Germany. *Journal* of Political Economy 129, 2023-2066.
- Humphery-Jenner, M., Lisic, L., Nanda, V., Silveri S.D. (2016). Executive overconfidence and compensation structure. *Journal of Financial Economics* 119, 533-558.
- Kaplan, S., Sorensen, M., Zakolyukina, A. (2022). What is CEO overconfidence? Evidence from executive assessments. *Journal of Financial Economics* 145, 409-425.
- Kassner, B. (2023). Taming overconfident CEOs through stricter financial regulation. CRC 190 Discussion Paper No. 375. Munich and Berlin.
- Lee, J.-P., Lin, E., Lin, J., Zhao, Y. (2020). Bank systemic risk and CEO overconfidence. The North American Journal of Economics and Finance 54, 100946.
- Malmendier, U., Tate, G. (2005). CEO overconfidence and corporate investment. Journal of Finance 60, 2661-2700.
- Malmendier, U., Tate, G. (2008). Who makes acquisitions? CEO overconfidence and the market's reaction. *Journal of Financial Economics* 89, 20-43.
- Malmendier, U. (2015). Behavioral CEOs: The role of managerial overconfidence. Journal of Economic Perspectives 29, 37-60.
- Niepmann, F., Schmidt-Eisenlohr, T. (2013). Bank bailouts, international linkages, and cooperation. American Economic Journal: Economic Policy 5, 270-305.
- Ueda, K., Weder di Mauro, B. (2013). Quantifying structural subsidy values for systemically important financial institutions. Journal of Banking and Finance 37, 3830-3842.