Regulating the Overconfident: Financial Regulation in the Presence of Overconfidence

Department of Economics
Ludwig-Maximilians-Universität München

Bernhard Arnold Kassner

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Regulating the Overconfident: Financial Regulation in the Presence of Overconfidence

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Bernhard Arnold Kassner

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Referent:	Prof. Dr. Andreas Haufler
Korreferent:	Prof. Dr. Florian Englmaier
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Preface

What would I eliminate if I had a magic wand? Overconfidence.

—Daniel Kahneman, *The Guardian*, July 18, 2015

With the bankruptcy of Lehman Brothers on September 14, 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 forecasts and policymakers overly confident that no government bailouts would be necessary still shortly before the event. This indicates that beliefs played an important role in the buildup of the global financial crisis of 2007/2008 (Gennaioli and Shleifer, 2018). This is endorsed by a survey conducted by the University of Chicago in October 2017 that asked a panel of leading economists in the U.S. and Europe to rank the factors that contributed to the 2008 global financial crisis. Of the twelve possible answers, "underestimated risks" was ranked second immediately after "flawed financial sector regulation and supervision" (University of Chicago, 2017). This is echoed in the recent failure of Silicon Valley Bank (SVB) on March 10, 2023, which originated in an underestimation of interest rate risks and the associated insufficient hedging (see Bloomberg, 2023).

Such underestimation of risks can be attributable to overconfidence, a pervasive and potent bias in human judgment (Kahneman, 2011; Mannes and Moore, 2013).[1] From a theoretical standpoint, overconfidence can influence individuals' risk-taking choices in two ways: First, it leads to underestimating potential risks associated with future cash flows and overestimating the probability of success (e.g., Hackbarth, 2008). Second, it results in overestimating the precision of private noisy signals (e.g., Gervais et al., 2011). In line with the theory, several empirical and experimental studies focusing on the individual level show that overconfidence affects risk-taking decisions of individuals (e.g., Camerer and Lovallo, 1999; Barber and Odean, 2001; Chuang and Lee, 2006;

[1] Overconfidence is a general term that encompasses three different phenomena: overestimation (thinking you are better than you are), overplacement (thinking your performance is better than that of others), and overprecision (thinking your knowledge is more accurate than it is) (Moore and Healy, 2008; Moore and Schatz, 2017).

Glaser and Weber, 2010; Nosic and Weber, 2010; Broihanne et al., 2014).

According to the psychology literature, individuals are in general prone to overconfidence (e.g., Taylor and Brown, 1988). However, there are several reasons why overconfidence is even more prevalent among executives. Among others, these include sorting, position of ultimate control, the nature of abstract and high-skilled tasks, and incentives related to performance in these tasks (Malmendier and Tate, 2005b; Malmendier et al., 2011). Furthermore, Goel and Thakor (2008) argue that overconfidence increases the likelihood of promotions, as overconfident managers tend to show higher performance. In line with these arguments, Graham et al. (2013) empirically show that CEOs are significantly more optimistic than the lay population.

Since overconfidence matters for risk-taking decisions at the individual level and is particularly prevalent among managers, and considering the important role of managers in corporate decision-making (Bertrand and Schoar, 2003), it is clear that managerial overconfidence matters for corporate outcomes. The literature shows that overconfident CEOs tend to overinvest when internal funds are abundant (Malmendier and Tate, 2005a) and to make worse investment decisions (Malmendier and Tate, 2008). Furthermore, the literature finds that CEO overconfidence is related to the choice of debt maturity, risk management, dividend policy, and forecasting (e.g., Deshmukh et al., 2013; Graham et al., 2013; Adam et al., 2015; Hribar and Yang, 2016). On the other hand, some studies have also found positive effects of overconfidence on firms such as increased innovation, which can increase the firm's value while also increasing stock return volatility (Galasso and Simcoe, 2011; Hirshleifer et al., 2012). There is also evidence that CEOs and their personality traits significantly impact firm outcomes in the financial sector. Ho et al. (2016) show that financial firms with overconfident CEOs tend to adopt riskier strategies, which led to worse outcomes during the financial crisis. Moreover, financial firms with overconfident CEOs also tend to invest more in real estate, perform worse during financial crisis (Ma, 2015), and are perceived to be riskier due to higher variation in daily stock returns (Niu, 2010). Additionally, CEO overconfidence has been found to increase systemic risk in the buildup of the global financial crisis (Lee et al., 2020).

Given the strong evidence for the nexus between managerial overconfidence and risk-taking and the contribution of overconfidence to the global financial crisis, holistic financial regulation requires a better understanding of overconfidence and the effects it has on risk-taking in order to address its adverse effects. This dissertation contributes to this understanding by examining how overconfidence affects decision-making and how financial regulation can mitigate negative consequences of overconfidence. Chapters 1 and 2 contribute to the behavioral economics and psychology literature by providing new (experimental) evidence on the effects of overconfidence on belief formation and the financial and political behavior of individuals. Chapter 1 extends the evidence that overconfidence leads to an underreaction to new information and, thus, to an underestimation of the relative precision of noisy public signals, i.e., relative to the precision of the prior belief. Chapter 2 shows that overconfident individuals make larger forecast errors in financial markets, diversify their portfolios less, and tend to hold more extreme political views. Chapter 3 then turns to managerial overconfidence in the financial sector in a theoretical framework. The principal-agent model proposes that banks exploit the managers' overconfidence, causing excessive risk-taking in equilibrium. This is amplified by government guarantees and necessitates an intervention in banker pay. Chapter 4 complements the theoretical findings and provides empirical evidence that overconfidence increases risk in the financial sector and that stricter financial regulation can mitigate these effects. Since all four chapters are based on individual essays, they can be read independently. In the following, I briefly review the literature to which each chapter adds before summarizing the main results of each chapter.

Chapter 1, which is co-authored work with Ciril Bosch-Rosa and Muhammed Buluty (Bosch-Rosa et al., 2023), adds to the general understanding of deviations from rational belief formation, such as limited attention to taxes (e.g., Chetty et al., 2009; Taubinsky and Rees-Jones, 2018), inattention in finance (e.g., Hirshleifer et al., 2009), or inadequate reactions to monetary policy announcements (Coibion et al., 2021b), and to the understanding of the effects of overconfidence on belief formation (e.g., Moore and Healy, 2008). While the benchmark theory assumes perfectly rational Bayesian decision-makers, which use all available information to make decisions, the accumulated empirical evidence challenges this assumption and shows both under- and overreaction to information (Coibion and Gorodnichenko, 2015; Enke et al., 2020; Bordalo et al., 2023; Maćkowiak et al., 2023). Rational inattention, conceptualized by Sims (2003) as a constraint on the ability to process information, and individual cognitive biases, such as overconfidence (Moore and Healy, 2008; Moore and Schatz, 2017), are prominent explanations for the failure of the Bayesian benchmark.

The literature so far only examined these two potential explanations separately. To examine potential interactions between these two underlying mechanisms, in Chapter 1 we first develop a tractable model of belief updating with overprecise agents. Agents form posterior beliefs about an uncertain fundamental based on the available information. Thereby, they deliberately choose how attentive they are to the information which affects the noise of the signal. Furthermore, agents are overconfident and incorrectly assess the precision of their prior beliefs (overprecision). The model shows that both inattention and overprecision lead to an underreaction to new information. However, the model also predicts that overprecise agents are more sensitive to changes in information processing costs. We then test the predictions of the model in a pre-registered randomized information provision experiment on inflation expectations, where the information processing costs and the informativeness of the signal are exogenously varied. Additionally, we measure overprecision of subjects using the Subjective Error Method of Bosch-Rosa et al. (2021). In line with the theory, we find that both an increase in cognitive information processing costs and overprecision lead to less updating. Moreover, the results point toward a negative interaction between rational inattention and overprecision, implying that overprecision increases the sensitivity of agents to an increase in information processing costs.

Given that overprecision is heterogeneously distributed in the population, these findings indicate that information provision policies might not be well-targeted in the presence of overconfidence. From a policy perspective, these results suggest that reducing information processing costs, i.e., the complexity of information, makes information provision more efficient in two ways: i) it mechanically reduces rational inattention by reducing information processing costs and ii) it reduces the distortion that overprecision creates in belief formation. Reducing information processing costs, for example by simplifying texts or messages, is less complex than debiasing the population, i.e., removing the bias itself, which requires a deep understanding of the distribution of overprecision in the population.

With Chapter 2, which is co-authored work with Steffen Ahrens and Ciril Bosch-Rosa (Bosch-Rosa et al., 2021), we contribute to the understanding of the consequences of overconfidence concerning the behavior of individuals. The behavioral economics literature shows that overconfidence distorts individuals' behavior in many ways. It leads to underinsurance (Grubb, 2015), large distortions in corporate decisions (Ben-David et al., 2013; Moore et al., 2015), under-diversification of portfolios (Goetzmann and Kumar, 2008), excessive trading (Barber and Odean, 2001), and systematic forecast errors (Deaves et al., 2019). Moreover, there is evidence that overconfidence affects the political behavior of individuals, which ranges from ideological extremism and strong partisan identification (Ortoleva and Snowberg, 2015a,b; Stone, 2019) to an increased susceptibility to "fake news" (Thaler, 2023).

The existing literature relies on complicated and indirect measures of overprecision. This chapter contributes to the understanding of the effects of overprecision on the financial and political behavior of a representative population[2] by introducing a new measure to measure overprecision, the "Subjective Error Method." This method

[2]Most of the existing literature on overprecision relies on university students (e.g., Alpert and Raiffa, 1982) or special pools of subjects, e.g, finance professionals (Glaser and Weber, 2007) or IT professionals (McKenzie et al., 2008).

consists of two questions: i) a question with a numerical answer and ii) an estimate of the distance to the correct answer. In other words, we ask the individuals for their absolute expected error. By contrasting this subjective error to the true error, we get a direct measure of overprecision. Applying this measure to a representative sample of the German population, we test several predictions from the theoretical literature. In line with the theory we find that overprecision is positively correlated with forecasting errors and negatively correlated with portfolio diversification, as suggested by Odean (1998) and Barber and Odean (2000). Moreover, we find that overprecision is positively correlated with ideological extremeness, as suggested by Ortoleva and Snowberg (2015b). The results from a companion survey further show that overprecision is a personality trait that is consistent within individuals across different domains. Taken together, our results show that overprecision is a personality trait that affects behavior across different domains.

Having established consequences of overconfidence on belief formation and individual behavior in Chapters 1 and 2, Chapter 3 then turns to the effects of overconfidence on risk-taking in the financial sector and adds to the literature on the optimal taxation and regulation of banker compensation. Hackbarth (2008) and Gervais et al. (2011) theoretically propose that overconfident managers tend to take higher risks. This is backed by empirical evidence showing that overconfident managers tend to make worse investment decisions (Malmendier and Tate, 2008) or engage in higher risk-taking (Ho et al., 2016). The literature on the taxation and regulation of banker compensation shows that a bonus tax is progressive in the size of the government (Besley and Ghatak, 2013) and that there can be either a 'race to the bottom' or a 'race to the top' in bonus taxation with mobile managers and government guarantees (Gietl and Haufler, 2018). Concerning non-tax regulatory measures, the literature finds that bonus caps are welfare-increasing if bailout expectations are sufficiently large (Hakenes and Schnabel, 2014) and that a combination of clawback rules and restrictions on the curvature of pay can implement socially optimal risk choices (Thanassoulis and Tanaka, 2018).

Chapter 3, which is co-authored work with Daniel Gietl (Gietl and Kassner, 2020), adds to the existing literature by combining managerial overconfidence and limited liability in a joint theoretical framework by incorporating two principal-agent problems based on Besley and Ghatak (2013) and Hakenes and Schnabel (2014). The first principal-agent problem is between the government and the bank, which is due to government guarantees, and the second is between the bank and the manager, which is due to private effort and risk-taking costs. The model further encompasses managerial overconfidence in form of an overestimation of the returns to risk-taking. The analysis delivers three results: i) managerial overconfidence always necessitates an intervention into banker pay, even if shareholders internalize the bailout costs, ii) the optimal bonus tax increases in overconfidence, if returns to risk-taking are positive, and iii) overconfident bankers and banks with large government guarantees match in equilibrium.

Taken together, the results suggest that managerial overconfidence justifies bonus taxes in systemically important institutions. Bonus taxation can decrease risk-shifting incentives caused by public guarantees. Further, it can prevent the exploitation of managerial overconfidence, due to the managers' overvaluation of the utility derived from bonuses, and mitigate the matching between overconfident managers and systemically important financial institutions.

Chapter 4, based on single-authored work (Kassner, 2023), then complements the theoretical findings from Chapter 3 by empirically analyzing the effects of stricter financial regulation on risk-taking of overconfident CEOs in the financial sector. The empirical corporate finance literature shows that CEO overconfidence affects investment and merger decisions (e.g., Malmendier and Tate, 2005a, 2008), the choice of debt maturity (e.g., Landier and Thesmar, 2009; Graham et al., 2013; Huang et al., 2016), risk management (Adam et al., 2015), dividend policy (Deshmukh et al., 2013), merger decisions (Malmendier and Tate, 2008), forecasting (Hribar and Yang, 2016), and innovation (Galasso and Simcoe, 2011; Hirshleifer et al., 2012). For the financial sector, there is evidence for higher risk-taking at firms with overconfident CEOs before financial crises and worse performance during financial crises (Niu, 2010; Ma, 2015; Ho et al., 2016). Turning to the regulation of overconfident CEOs, Banerjee et al. (2015) show that the Sarbanes-Oxley Act (SOX) in 2002 substantially improved the behavior of overconfident CEOs. Cheffins (2015), however, argues that this corporate governance movement did not affect CEOs of firms in the financial sector.

With Chapter 4, I contribute to the existing literature by examining the effect of stricter financial regulation on the risk-taking behavior of overconfident CEOs in the financial sector. For this empirical analysis, I draw on detailed financial data for listed firms in the U.S. financial sector for the years 1999 to 2019. CEO overconfidence is measured using a revealed beliefs measure based on their option exercising behavior. I first document a decrease in overconfidence-induced risk, i.e., the additional risk at financial institutions with overconfident CEOs, during the period of stricter regulation after the global financial crisis. Once large parts of the regulation are repealed, however, overconfidence-induced risk-taking increases again. Then, I attribute this observed decline to stricter financial regulation by distinguishing two groups of financial institutions differing in the degree of regulation. The results show that the observed decline in overconfidence-induced risk-taking is only observable for financial institutions subject to enhanced regulation.

The results in this chapter underline that CEO overconfidence necessitates financial regulation that not only strengthens the capital adequacy of financial institutions (i.e., capital requirements) but also reduces risk-taking incentives, strengthens corporate governance, and promotes transparency to address the behavior of individual decision-makers.

At the core of all four chapters are biased beliefs in the form of overconfidence. Based on theoretical, experimental, and empirical evidence, this dissertation concludes that overconfidence significantly affects individual decision-making by influencing belief formation and ultimately the behavior of individuals. Moreover, it shows both theoretically and empirically that overconfidence increases risk-taking in the financial sector, which can be addressed by financial regulation. This provides evidence that there is room for policymakers. The results suggest that instead of debiasing individuals' beliefs and thereby reducing overconfidence, financial regulation that decreases risk-taking incentives and increases oversight and transparency is effective in mitigating the adverse effects of overconfidence. While the theoretical model proposes that regulation targeting risk-taking incentives should specifically be targeted toward overconfident individuals, the empirical evidence suggests that non-targeted oversight successfully reduced overconfidence-induced risk-taking. Last, by providing information and research on potential risks in the financial sector in an easier-to-understand format, not only policymakers but also economists can contribute to mitigating the adverse effects of overconfidence in combination with rational inattention.

Chapter 1

Overconfidence and Rational Inattention in Belief Formation

This chapter is based on co-authored work with Ciril Bosch-Rosa and Muhammed Bulutay. See Bosch-Rosa et al. (2023) for the full reference.

1.1 Introduction

Beliefs are fundamental in economic decision-making. The rational benchmark theory assumes Bayesian decision-makers who optimally use all available information to update their information set. However, this framework is at odds with the empirical evidence as individuals are often inattentive to information (Maćkowiak et al., 2023).[1] This inattentiveness can lead to suboptimal behavior, including underreaction to changes in taxation (Chetty et al., 2009; Taubinsky and Rees-Jones, 2018) or the failure to react adequately to monetary policy announcements (Coibion et al., 2021b).

A prominent explanation for such deviations from the full attention Bayesian benchmark is rational inattention. Sims (2003) conceptualizes rational inattention as a constraint on the information-processing capacity of individuals. Because information is costly to process, individuals need to -optimally- decide how much attention they pay to new information trading off its costs and benefits. This theory has become a very effective tool to explain a variety of economic phenomena such as the slow adjustment of prices to nominal shocks (Woodford, 2001; Sims, 2003), the long-lasting unemployment after the recent financial crisis (Acharya and Wee, 2020), migration flows (Bertoli et al., 2020), financial contagion (Mondria and Quintana-Domeque, 2013), or game theoretical puzzles (Alaoui and Penta, 2022).[2]

However, individual biases can also explain the observed failure of the Bayesian updating benchmark and complement rational inattention. Some examples of such biases include limited cognitive ability (D'Acunto et al., 2021; Bosch-Rosa and Corgnet, 2022) or economic literacy (Burke and Manz, 2014). More recently, the literature has pointed to overprecision as a potent and pervasive bias that impacts how individuals process information (Kahneman, 2011; Moore et al., 2015; Moore, 2022). Overprecision, is a type of overconfidence in which agents perceive their information to be more precise than it actually is and can explain excessive trading (Barber and Odean, 2001), the formation of systematic forecasting errors in finance (Deaves et al., 2019), political extremism (Ortoleva and Snowberg, 2015b), or the prevalence of "fake news" (Thaler, 2023). Compared to rationally inattentive individuals, non-rationally inattentive but overprecise individuals take all information available into consideration. However, be-

[1] While inattention to information is associated with an underreaction to new information, there is also evidence that individuals can overreact to information. The empirical and theoretical literature point toward a wide range of reasons to explain under- or overreaction including limited information (Coibion and Gorodnichenko, 2015), inattention (Maćkowiak et al., 2023), associative recall or similarity-induced interference (Enke et al., 2020; Bordalo et al., 2023). These findings are not limited to a specific group of people. A variety of decision-makers including consumers, firms, and professional forecasters are shown to exhibit these deviations (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020; Born et al., 2021).

[2] See Maćkowiak et al. (2023) for an overview of this literature.

cause they perceive their prior belief to be more precise than it actually is, overprecise individuals imperfectly update their information given the available information.[3]

Importantly, even if both rational inattention and overprecision lead to informational underreaction, their underlying causes are different. Any deviations from the Bayesian benchmark under rational inattention are deliberate. In contrast, overprecision is an individual bias that occurs during information processing. This fundamental difference has important implications for our epistemological understanding of how individuals form beliefs. Moreover, rational inattention and overprecision are not mutually exclusive, but most likely occur simultaneously. Hence, there is scope for an interaction between both phenomena. This would add another layer of heterogeneity in the way that individuals react to changes in information processing costs and, therefore, to how they react to information provision policies.

To our knowledge, despite being entwined concepts, the literature has always studied rational inattention and overprecision separately. To fill in this gap, we develop a tractable model that incorporates both rational inattention and overprecision. Agents receive a noisy signal about an uncertain fundamental for which they hold a prior belief and form a posterior belief. Overprecision leads agents to overestimate the precision of their prior beliefs.[4] Inattention generates a noisy perception of the public signal whereby agents choose the level of this noise, i.e., how much attention they want to pay to the signal. Since paying attention is costly, they choose the optimal amount of attention upon deliberating the costs and benefits. The results show that both rational inattention and overprecision lead agents to underreact to new information. More importantly, the joint analysis of overprecision and rational inattention allows us to disentangle these two effects and show that there is an interaction between both phenomena which results in more overprecise agents being more sensitive to changes in the marginal cost of information processing. This is for two reasons. First, because overprecise agents have extremely precise prior beliefs, it will require a more precise signal and, hence, much higher effort to update it. Second, since overprecise agents underestimate the benefit of updating, any change in the marginal cost of information has a stronger effect on them.

As an example, consider an individual who has a prior belief about the effect of a new vaccine and faces new evidence from clinical trials. If the individual is overprecise

[3]Note that here we are agnostic about the underlying reasons for overprecision. However, Moore (2022) claims that overprecision can be the result of individuals not being aware of all the ways they can be wrong. Hence, the lack of cognitive capacity and, therefore, rational inattention could be one explanation.

[4]Note that while overprecise and precise individuals appear identical, the implications differ. Individuals with a more precise prior, e.g., due to better knowledge, react optimally. However, overprecise individuals with the same prior precision underreact to new information.

(e.g., because she has been subject to biased news sources as in Ortoleva and Snowberg (2015b)), she overestimates the precision of her prior belief, making her reluctant to update her beliefs because it takes more effort to update a precise prior. Similarly, if the individual is rationally inattentive since the costs of processing the new information are high (e.g., because the new evidence uses complex statistical methods), she will be less likely to update her beliefs even if the evidence is strong. On its own, each of these effects would make the individual underreact to new information. However, since overprecision distorts the trade-off between the costs and benefits of processing new information, it makes the individual more sensitive to processing costs. In other words, an overprecise individual is more likely to dismiss the new information as relatively unimportant and decide to ignore the new clinical trials if processing costs are high.

This interaction between overprecision and rational inattention points to an additional layer of systematic heterogeneity in the effects that a change in information processing costs can have on the general population. Instead of debiasing the general population to improve the effectiveness of information provision policies, our result shows that by reducing the costs of information processing, i.e., the complexity of information, part of the underreaction to new information driven by overprecision can be mitigated. This makes information provision more efficient in two aspects. First, it reduces rational inattention due to information processing constraints and therefore reduces underreaction in general. Second, it further reduces the underreaction to information caused by overprecision, making the reaction to new information more homogeneous in the population.[5]

To test the predictions from our model, we implement a pre-registered randomized information provision experiment in the Bundesbank's Online Panel on Households.[6] In this experiment, we first elicit the respondents' prior beliefs about the one-year ahead inflation rate in Germany. We then randomly assign respondents to an *active control*, an *easy* condition, or a *hard* condition. In *active control*, respondents receive information that is not related to current inflation, while in *easy* and *hard*, respondents are informed about the most recent realized inflation rate, differing in the presentation of the information. The difference between the easy and hard treatment is the cognitive cost of processing the inflation information. While in *easy* the realized inflation is clearly expressed in a short text, in *hard*, the relevant information is embedded in a long text which increases the cost of processing information. In all cases, after reviewing the information, respondents are asked again for their beliefs about next year's inflation rate (i.e., their revised posterior). To measure the degree of overprecision of subjects,

[5]A concrete example could be the decision of central banks to provide their inflation report in a simplified manner to reduce the attention costs through improving readability (Haldane et al., 2020).

[6]The experiment along with the analysis plan are preregistered (see AsPredicted #87400).

we use the Subjective Error Method (Bosch-Rosa et al., 2021).

In line with the predictions from the model, the results of our experiment show that an increase in cognitive costs leads to less updating. Moreover, we find that overprecision increases the respondents' weight on the prior belief when forming their posterior beliefs and, hence, also leads to less updating as predicted by the model. Most importantly, as predicted by our model, the results point toward a negative interaction between overprecision and rational inattention. This implies that overprecise agents are more sensitive to an increase in the cost of information processing, and reinforces the importance of studying rational inattention as a phenomenon that takes place in complex environments and not as an isolated characteristic of information processing.

Our project relates to the literature that studies deviations from rational belief formation. This literature ranges from limited attention to taxes (e.g., Chetty et al., 2009; Taubinsky and Rees-Jones, 2018) to inattention in finance (e.g., Hirshleifer et al., 2009). Moreover, it relates to the literature providing explanations for the observed deviations in attention, which ranges from rational inattention (e.g., Fuster et al., 2020) to the effects of overconfidence on belief formation (e.g., Moore and Healy, 2008). We add to the existing literature by combining two explanations of limited attention in information processing. Combining the two frictions in a single model provides a novel insight for belief updating. Specifically, we find that interventions that aim at reducing cognitive costs turn out to be heterogeneous in the population, depending on the distribution of overconfidence.

Moreover, by testing our prediction through an information provision experiment, we contribute to the growing literature of survey experiments regarding expectation formation (Fuster and Zafar, 2022; Haaland et al., 2023). The prior literature has highlighted the importance of engaging the broader public for the effectiveness of unconventional monetary policy (Coenen et al., 2017; Haldane et al., 2020) but has also shown that even major policy announcements do not lead to the effect they are designed to generate (Coibion et al., 2020, 2021b). Our project emphasizes an understudied dimension of information updating, and complements the existing theoretical literature on overconfidence in macroeconomics (Born et al., 2021; Reis, 2021) with a new model and accompanying micro evidence.

This chapter proceeds as follows: in Section 1.2, we present our theoretical model and derive the testable hypotheses. In Section 1.3, we outline the design of our information provision experiment and present the data. This is followed by the empirical analysis in Section 1.4. The last section concludes.

1.2 Model

1.2.1 Preliminaries

We start from a standard Bayesian updating framework where agent i has a prior belief about the state of the uncertain fundamental θ. These beliefs are assumed to be normally distributed with mean $\mu_{\theta,i}$ and variance $\sigma^2_{\theta,i}$. We introduce individual overprecision ω_i which leads agents to perceive their prior beliefs as more informative than they really are and, therefore, to underestimate the variance such that $f(\omega_i) = \tilde{\sigma}^2_{\theta,i}$ with $f' < 0$ and $f(0) = \sigma^2_{\theta,i}$. In other words, the higher the degree of overprecision of an agent, the lower the perceived variance of her prior beliefs whereas for a perfectly calibrated agent ($\omega_i = 0$) the perceived variance of prior beliefs is equal to the true variance of such beliefs.[7]

Agents receive a noisy public signal x_j on the fundamental from the information source j of the form

$$x_j = \theta + \epsilon_j,$$

where $\epsilon_j \sim N(0, \sigma^2_{\epsilon,j})$. Inattention to the signal is modeled following Fuster et al. (2020) by an additional individual specific noise term ψ_i, such that individual i perceives the signal as

$$s_{i,j} = x_j + \psi_i,$$

where ψ_i is assumed to be normally distributed as $N(0, \sigma^2_{\psi,i})$. Agents decide how attentive they want to be to information by choosing the level of additional noise (i.e., by choosing $\sigma^2_{\psi,i}$).

In this setup, the posterior belief of individual i can be written as the weighted average of the signal and the prior mean

$$E[\theta|s_{i,j}] = \beta_{i,j} \cdot (\theta + \epsilon_j + \psi_i) + (1 - \beta_{i,j}) \cdot \mu_{\theta,i}, \tag{1.1}$$

where the weight on signal (or updating) can be expressed as the ratio of variances

$$\beta_{i,j} = \frac{\tilde{\sigma}^2_{\theta,i}}{\tilde{\sigma}^2_{\theta,i} + \sigma^2_{\epsilon,j} + \sigma^2_{\psi,i}}. \tag{1.2}$$

The weight on the signal shows that for an overprecise individual (lower $\tilde{\sigma}^2_{\theta,i}$), all else equal, the prior is more resistant to change. Hence, it takes more effort in the form of smaller additional noise $\sigma^2_{\psi,i}$ to achieve the same updating rate as for individuals that correctly asses their prior.

[7] We remain agnostic to the source of over- or underprecision but measure it empirically.

1.2.2 Optimal Updating

Inattention to information expressed as the additional noise $\sigma^2_{\psi,i}$ is modeled as the choice variable of the individual. To solve the model, we follow Fuster et al. (2020) by assuming (i) a payoff function that is negatively related to the quadratic forecast error and (ii) a processing cost function that depends on the entropy of displayed information as in Sims (2003). Accordingly, individuals maximize

$$\mathbb{E}_\theta\left[\mathbb{E}_s\left[-\phi(\theta - E[\theta|s_{i,j}])^2\right]\right] - d(\sigma^{-2}_{\psi,i}) = -\phi\sigma^2_{\theta|s_i} - d(\sigma^{-2}_{\psi,i}) \tag{1.3}$$

by choosing $\sigma^2_{\psi,i}$. The first term refers to the disutility that arises from an inaccurate posterior belief, with ϕ reflecting a scaling parameter that measures the incentive to hold an accurate posterior. The second term refers to the cost of paying attention to the signal. Following the literature on rational inattention, we assume that information costs are related to the expected reduction in uncertainty, measured by the Shannon entropy

$$\begin{aligned} d(\sigma^{-2}_{\psi,i}) &= g(H(x_j) - H(x_j|s_{i,j})) \\ &= g\left(\frac{1}{2}ln\left(\frac{\sigma^2_{x,j}}{\sigma^2_{x,j|s}}\right)\right) = g\left(\frac{1}{2}ln\left(1 + \frac{\sigma^2_{\theta,i} + \sigma^2_{\epsilon,j}}{\sigma^2_{\psi,i}}\right)\right). \end{aligned}$$

A common approximation is to assume that the function g is linearly related to the expected reduction in uncertainty such that $d(\sigma^{-2}_{\psi,i}) = \lambda\frac{1}{2}ln\left(1 + \frac{\sigma^2_{\theta,i}+\sigma^2_{\epsilon,j}}{\sigma^2_{\psi,i}}\right)$. In this case, the parameter λ reflects the marginal cost of attention (Maćkowiak et al., 2023).[8]

Using the expression for the weight on the signal in Equation (1.2) and the definition of the Gaussian posterior variance, one can rewrite Equation (1.3) as

$$-\phi(1 - \beta_{i,j})\tilde{\sigma}^2_{\theta,i} - \lambda\frac{1}{2}ln\left(\frac{1}{1 - \beta\frac{\tilde{\sigma}^2_{\theta,i}+\sigma^2_{\epsilon,j}}{\tilde{\sigma}^2_{\theta,i}}}\right). \tag{1.4}$$

From Equation (1.4) it becomes apparent, that overprecise respondents underestimate the marginal benefit of updating due to a lower perceived prior variance. At the same time, overprecise respondents overestimate the marginal costs of updating.

One can solve the maximization problem in Equation (1.4) and rewrite the optimal weight on the signal j under rational inattention (RI) and overprecision (OP) as

$$\beta^{RI/OP}_{i,j*} = max\left\{0, \frac{\tilde{\sigma}^2_{\theta,i}}{\tilde{\sigma}^2_{\theta,i} + \sigma^2_{\epsilon,j}} - \frac{\lambda}{2\phi\tilde{\sigma}^2_{\theta,i}}\right\}. \tag{1.5}$$

[8] In the next section, we describe the experimental design that exogenously shifts this parameter.

Both parameters ϕ and λ are defined in the set of non-negative real numbers and can be heterogeneous in the cross-section. Note that the first part of Equation (1.5) is the standard Bayesian variance ratio of prior and signal which is mechanically distorted by overprecision. The second part is an additional behavioral effect that directly stems from the cost-benefit trade-off and is also affected by overprecision. In the Full-Attention Bayesian updating (FABU) benchmark, attention is not a costly resource and individuals are optimally precise such that $\lambda = 0$ and $\tilde{\sigma}^2_{\theta,i} = \sigma^2_{\theta,i}$ (i.e., $\omega_i = 0$). The optimal level of updating in this benchmark is simply equal to the relative precision of the prior

$$\beta^{FABU}_{i,j*} = \frac{\sigma^2_{\theta,i}}{\sigma^2_{\theta,i} + \sigma^2_{\epsilon,j}}.$$

The optimal level of attention in the presence of processing constraints and overprecision, signified by the choice variable $\sigma^2_{\psi,i}$, can be shown as

$$\sigma^{2*}_{\psi,i} = \left(2\frac{\phi}{\lambda} \frac{(\tilde{\sigma}^2_{\theta,i})^2}{\tilde{\sigma}^2_{\theta,i} + \sigma^2_{\epsilon,j}} - 1 \right)^{-1} \left(\tilde{\sigma}^2_{\theta,i} + \sigma^2_{\epsilon,j} \right) \tag{1.6}$$

for the case of an interior solution of Equation (1.5), i.e., $\frac{\lambda}{\phi} < 2\tilde{\sigma}^2_{\theta,i} \frac{\tilde{\sigma}^2_{\theta,i}}{\tilde{\sigma}^2_{\theta,i} + \sigma^2_{\epsilon,j}}$, and $\sigma^{2*}_{\psi,i} = \infty$ otherwise. In the first case, the cost-to-benefit ratio is sufficiently small to ensure attention is paid to the signal. In the second case, the costs are too high compared to the benefits of paying attention. In this case, no attention is paid to the signal and the weight on the signal is zero. Note that the more overprecise individuals are, the lower this cost-benefit ratio threshold is.

The Gaussian prior belief and signal allow us to write the posterior precision as

$$\frac{1}{\tilde{\sigma}^2_{\theta|s,i}} = \frac{1}{\tilde{\sigma}^2_{\theta,i}} + \frac{1}{\sigma^2_{\epsilon,j} + \sigma^2_{\psi*,i}},$$

which in return allows us to express the change in precision after the new information as

$$\frac{1}{\tilde{\sigma}^2_{\theta|s,i}} - \frac{1}{\tilde{\sigma}^2_{\theta,i}} = \frac{1}{\sigma^2_{\epsilon,j} + \frac{\tilde{\sigma}^2_{\theta,i} + \sigma^2_{\epsilon,j}}{2\frac{\phi}{\lambda}\frac{(\tilde{\sigma}^2_{\theta,i})^2}{\tilde{\sigma}^2_{\theta,i} + \sigma^2_{\epsilon,j}} - 1}}. \tag{1.7}$$

We can derive several predictions using the optimal updating rate specified in Equation (1.5). The first is that increasing the precision of the signal (i.e., decreasing $\sigma^2_{\epsilon,j}$) leads to an increase in the updating rate. This effect is standard to Bayesian belief updating and driven by the variance ratio of prior and signal. The second is that when facing new information, more overprecise individuals update their beliefs less. This result is driven by two effects: i) a 'mechanical' effect since overprecision affects the variance ratio of prior and signal and ii) a 'behavioral' effect that is due to the cost-benefit trade-off. Third, the higher the costs of attention ($\Delta\lambda > 0$), the lower the updating of individuals. Finally, the model predicts an interaction between overprecision and rational inattention. While higher attention costs result in less updating, this effect is amplified by overprecision. That is, more overprecise individuals are more susceptible to changes in the marginal cost of attention. Intuitively, overprecision distorts the cost-benefit trade-off as overprecision leads to an overestimation of the marginal benefit and an underestimation of the marginal costs of information. And, thus, overprecise individuals are more sensitive to changes in the marginal costs of information processing.

Mathematically, these predictions can be represented by the following derivations:

$$\frac{\partial \beta_{i,j*}}{\partial \sigma^2_{\epsilon,j}} = -\frac{\tilde{\sigma}^2_{\theta,i}}{(\tilde{\sigma}^2_{\theta,i} + \sigma^2_{\epsilon,j})^2} < 0 \tag{1.8}$$

$$\frac{\partial \beta_{i,j*}}{\partial \omega_i} = f' \cdot \left[\frac{\sigma^2_{\epsilon,j}}{(\sigma^2_{\epsilon,j} + \tilde{\sigma}^2_{\theta,i})^2} + \frac{\lambda}{2\phi(\tilde{\sigma}^2_{\theta,i})^2} \right] < 0 \tag{1.9}$$

$$\frac{\partial \beta_{i,j*}}{\partial \lambda} = -\frac{1}{2\phi \cdot \tilde{\sigma}^2_{\theta,i}} < 0 \tag{1.10}$$

$$\frac{\partial}{\partial \omega_i}\left(\frac{\partial \beta_{i,j*}}{\partial \lambda}\right) = f' \cdot \frac{1}{2\phi \cdot (\tilde{\sigma}^2_{\theta,i})^2} < 0 \tag{1.11}$$

1.3 Experimental Design

To test the theoretical predictions from the model, we implemented an information provision experiment in the November 2021 wave of the Bundesbank Online Panel Households (BOP-HH). The BOP-HH is a monthly online survey representative of the adult population (age>16) in Germany, which is ongoing since 2019. It elicits households' expectations about a variety of topics such as the expected development of the inflation rate, individual income, or property prices in Germany (Beckmann and Schmidt, 2020). Our experiment consists of four stages.

First Stage: In the first stage of the experiment we elicit the respondents' beliefs about the one-year ahead inflation rate in Germany. These beliefs are elicited in two ways: a point prediction of the inflation rate over the next 12 months and a distribution of inflation expectations with a probabilistic forecast question where respondents assign probabilities to potential inflation realizations.[9] We denote the answer to these questions as respondents' "prior beliefs." We will use the point prediction of the inflation rate as prior expectation ($prior_i$).

Second Stage: In the second stage of the experiment, we randomly assign respondents to three equally sized groups ($j \in \{0, 1, 2\}$). Respondents in each group receive a piece of information. The first group ($j = 0$), which we call *active control*, receives information on the population growth rate in Germany over the last 30 years (i.e., 4.3%). This information should not shift respondents' short-run inflation expectations. However, because the number provided in this treatment is similar in size to the number provided in the *easy* ($j = 1$) and *hard* ($j = 2$) treatments, it allows us to control for any experimental priming or numerical anchoring side effects of providing a numerical cue in our treatments (Haaland et al., 2023). Respondents in the *easy* and *hard* treatments receive information about the last announced annual inflation rate in Germany (i.e., 4.5%). In both cases, this information should lead respondents to update their information in case their prior beliefs are off the fundamental.[10] However, the text with which we provide this information differs across both treatments. While respondents in *easy* receive a concise text which contains the signal, those in *hard* receive a long text which contains information about the German Statistical Office (Destatis) that is providing the inflation estimates (see Table A.1.1 in the appendix for the text in each treatment).[11]

The random allocation to different treatment conditions allows us to identify the causal effects of two variables on beliefs. On the one hand, we exogenously decrease the signal's noise level $\sigma^2_{\epsilon,j}$ in the treatment conditions compared to the *active control* group (i.e., $\sigma^2_{\epsilon,0} > \sigma^2_{\epsilon,1} \approx \sigma^2_{\epsilon,2}$) by providing a signal that is more informative for the fundamental than the long-term population growth rate (i.e., the last inflation rate). On the other hand, by changing the length of the text without shifting the signal value or the signal source, we exogenously shift the cost of attention λ_j across the two treatment groups. Since the text length and structure are almost identical in the *active control* and *easy* treatments, we have $\lambda_0 \approx \lambda_1 < \lambda_2$. Therefore, we can identify the effects of rational inattention on beliefs by comparing the updating of beliefs in the *easy* and *hard* treatments, which we elicit in the third stage.

[9] For the specific formulation of all the questions, see the documentation of the Bundesbank Online Panel — Households (BOP-HH) (Deutsche Bundesbank, 2021).

[10] Past experiments corroborate this statement (e.g., Cavallo et al., 2017).

[11] The information about Destatis is a copy and paste of the Wikipedia entry for this state institution.

Third Stage: In the third stage, we again ask respondents for their forecast of inflation in Germany over the next twelve months. To avoid confusing respondents by asking the same question twice, we follow Coibion et al. (2021a) and elicit inflation expectations by asking respondents to report three points: the highest likely inflation, the most likely inflation, and the lowest likely inflation. This three-point elicitation allows us to vary the format of our question while at the same time permitting us to calculate the variance of the respondent's beliefs. We call the elicited beliefs of respondents at this stage the "posterior beliefs." We will use the answer to the most likely inflation as posterior expectation ($posterior_i$).

Fourth Stage: Finally, in the fourth stage, we measure respondents' individual degree of overprecision. To do so, we use the Subjective Error Method (SEM) (Bosch-Rosa et al., 2021). This method consists of a two-step procedure. First, respondents are asked a question with a numerical answer (e.g. How long is the Nile River?) and then they are asked to estimate how large the mistake they made in their answer to the numerical question is.[12] In other words, respondents are asked to estimate their *subjective error*. By comparing the reported subjective error to the true error, one can get a measure of overprecision on this specific question. Formally, denote the answer of respondent i to question j as $a_{i,j}$, her subjective error for question j as $se_{i,j}$, and the true answer to the question as ta_j, then the measure of overprecision for respondent i for question j is:

$$error_{i,j} = |a_{i,j} - ta_j|, \tag{1.12}$$

$$overprecision_{i,j} = error_{i,j} - se_{i,j}, \tag{1.13}$$

where equation (1.12) measures the absolute realized true error ($error_{i,j}$) of respondent i to question j. In equation (1.13), the difference between the subjective error ($se_{i,j}$) and the realized true error ($error_{i,j}$) of respondents i to question j is then calculated. Note that here the direction of the difference matters. A respondent who underestimates her subjective error (i.e., $error_{i,j} > se_{i,j}$) is considered to be *overprecise*, while a respondent who overestimates her subjective error (i.e., $error_{i,j} < se_{i,j}$) is *underprecise*. Finally, those respondents who correctly guess their subjective error (i.e., $error_{i,j} = se_{i,j}$) are considered to be perfectly calibrated for that question. By repeating this procedure over multiple questions and aggregating for each individual, one can get an aggregate measure of overprecision for each individual. Bosch-Rosa et al. (2021) show that this procedure delivers an internally consistent measure that is consistent within individuals

[12] A more sophisticated way of asking this question would be to ask respondents to report their estimated *absolute* error.

across domains and that significantly correlates with overprecise behavior as postulated by the theoretical literature.

We implement this measure of overprecision by asking respondents five questions on different historical events which took place no more than 100 years ago (e.g., the year in which Lady Diana died). Figure A.2.1 in the appendix shows the distribution of the answers to each of the five questions. In Figure A.2.2 in the appendix, we plot the true error against the subjective error, whereby every observation above the 45-degree line represents an overprecise answer. For each of the events, we calculate the difference between the true error and the subjective error. We then aggregate the five calculated differences to an aggregate measure of overprecision using the simple mean.

1.4 Results

1.4.1 Survey Characteristics

Our experiment is administered to a cross-section of 1,913 individuals. As pre-registered, we drop respondents (i) who give the right answer to at least four of the five questions and expect to make zero error for these questions,[13] (ii) who answer less than four of the double-questions in the SEM questionnaire, and (iii) who do not answer the prior belief or posterior belief questions. These exclusion criteria leave us with 1,348 subjects in the main analysis with observations in all necessary variables.[14]

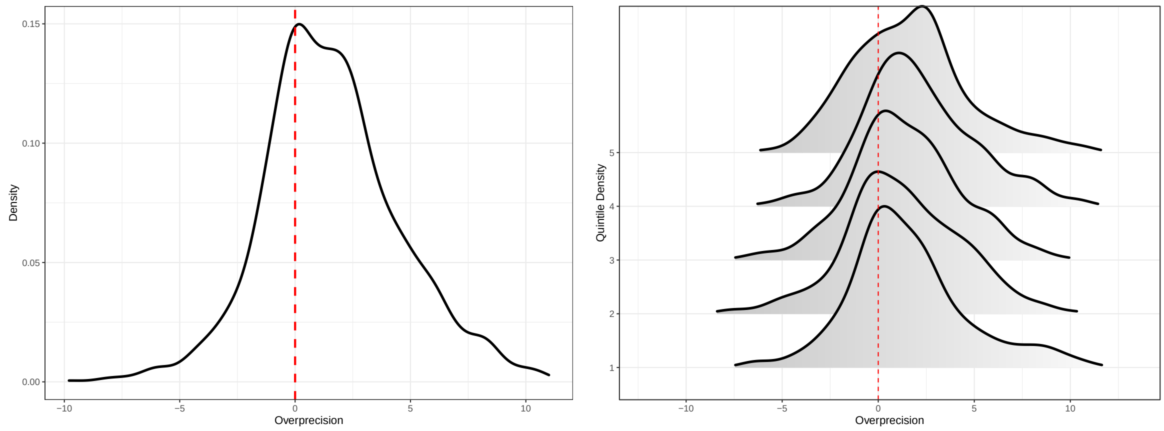
Following Bosch-Rosa et al. (2021), we construct an aggregate measure of overprecision for each respondent (op_i) by taking the mean of each measure of overprecision across the five history questions. In Figure 1.1a we plot the resulting distribution of overprecision in the sample. Most respondents are overprecise (68%), with most of the mass being close to being perfectly calibrated (i.e., an overprecision of 0, marked with a vertical red line).

To get a sense of how our measure of overprecision is associated with the confidence of respondents on the accuracy of their inflation expectations, we relate it to the respondents' prior precision. We define $priorprecision_i$ as one over the variance of the reported distribution on inflation expectations before the treatment.[15] In Figure 1.1b we divide respondents into quintiles based on $priorprecision_i$, and plot the density of

[13] We assume such respondents used a search engine to find the answers to the questions.

[14] Of the 1,913 individuals in the sample, 1,766 answered both the point estimates for prior and posterior inflation expectations. Since the overprecision questionnaire was placed at the very end of the survey and not enforced, only 1,348 respondents answered at least three of these questions and were not excluded based on our pre-registered restrictions.

[15] The variance of inflation expectations is measured with the same procedure as in Coibion et al. (2022) by fitting a generalized beta distribution for each respondent.



(a) This figure shows the density of overprecision op_i, which is the average overprecision for each respondent i across all questions j. Note that this figure is trimmed at the 0.5% and 99.5% percentile.

(b) This figure shows the density of the overprecision of respondents (op_i) for each quintile of prior precision in the sample. Note that op_i is trimmed at the 0.5% and 99.5% percentile.

Figure 1.1: Distribution of overprecision

op_i for each quintile. The figure shows that with increasing prior precision, the mass shifts towards the right of the overprecision distribution. Hence, those subjects who gave narrower distributions of their pre-treatment beliefs of inflation expectations are also more overprecise according to our measure.

Along with the variables on inflation expectations specified in Section 1.3, the survey also collects various personal characteristics of the respondents (i.e., gender, age, income, etc.). Table 1.1 summarizes the main variables along with demographic characteristics for the sample.[16]

1.4.2 Empirical Strategy

Starting from Equation (1.1) of the theoretical model, the respondents' updating rate upon information provision, which is the weight on the signal $\beta_{i,j}$, can be estimated regressing the posterior belief on the prior belief, assuming Gaussian priors and signals (Coibion et al., 2018). For the simplest case, consider the following regression equation:

$$posterior_i = a + b \cdot prior_i + \varepsilon_i, \tag{1.14}$$

where $posterior_i$ is the posterior inflation expectation of individual i, $prior_i$ is the prior inflation expectation of individual i, and ε_i is the random error term.

In this regression, the estimated coefficient $\hat{b}$ would be the estimated weight the respondent puts on her prior belief and hence, represent $1 - \beta_{i,j} = 1 - \frac{\tilde{\sigma}^2_{\theta,i}}{\tilde{\sigma}^2_{\theta,i} + \sigma^2_{\epsilon,j}} + \frac{\lambda}{2\phi\tilde{\sigma}^2_{\theta,i}}$,

[16]Note that most of the personal characteristics are provided as categorical variables and, thus, not reported in Table 1.1. See Table A.1.2 in the appendix for a full list of variables used in this study.

Table 1.1: Summary statistics of selected variables

This table presents the summary statistics of the sample used in the analysis. Note that the table excludes categorical variables. For a detailed description of the variables see Table A.1.2 in the appendix.

	mean	sd	p1	p25	p50	p75	p99
prior	5.450	6.537	1.0	3.0	4.0	5.5	35.0
posterior	5.418	6.428	1.0	3.0	4.5	5.5	27.0
overprecision (op)	1.593	3.367	-6.6	-0.3	1.4	3.4	10.0
age	54.596	15.138	20.0	44.0	56.0	67.0	80.0
gender (female=1)	0.463	0.499	0	0	0	1	1
N	1348						

where $\beta_{i,j}$ denotes the updating rate. Linearizing the regression equation with respect to the parameters by applying Taylor approximations, as shown in Appendix A.3, we derive the following empirical specification for our specific case:

$$\begin{aligned} posterior_i = a_0 &+ \sum_{j=1}^{2} a_j \cdot \mathbb{1}\{i \in Treat_j\} \\ + b_0 \cdot prior_i &+ \sum_{j=1}^{2} b_j \cdot \mathbb{1}\{i \in Treat_j\} \cdot prior_i \\ + c_0 \cdot sop_i &+ \sum_{j=1}^{2} c_j \cdot \mathbb{1}\{i \in Treat_j\} \cdot sop_i \\ + d_0 \cdot prior_i \cdot sop_i &+ \sum_{j=1}^{2} d_j \cdot \mathbb{1}\{i \in Treat_j\} \cdot prior_i \cdot sop_i \\ &+ \mathbf{X}' \cdot \delta + \varepsilon_i \end{aligned}, \tag{1.15}$$

where $\mathbb{1}\{i \in Treat_j\}$ is an indicator variable that takes the value one if the individual is in treatment group $j \in \{1, 2\}$, whereby 1 refers to the *easy* information condition and 2 to the *hard* information treatment condition, sop_i refers to the standardized overprecision measure for individual i as measured by the SEM, and $\mathbf{X}$ is a vector of control variables.

Assuming Bayesian updating, the weight placed on the signal by individual i in treatment group $j \in \{0, 1, 2\}$, on average, can be calculated as one minus the weight on the prior (see Equation 1.1). Empirically, this corresponds to

$$\hat{\beta}_{i,j} = 1 - (\hat{b}_0 + \hat{b}_j + \hat{d}_0 \cdot sop_i + \hat{d}_j \cdot sop_i). \tag{1.16}$$

This estimate should lie between 0 and 1, where values close to 0 imply the absence of updating (i.e., no weight is placed on the signal) and values close to 1 imply almost

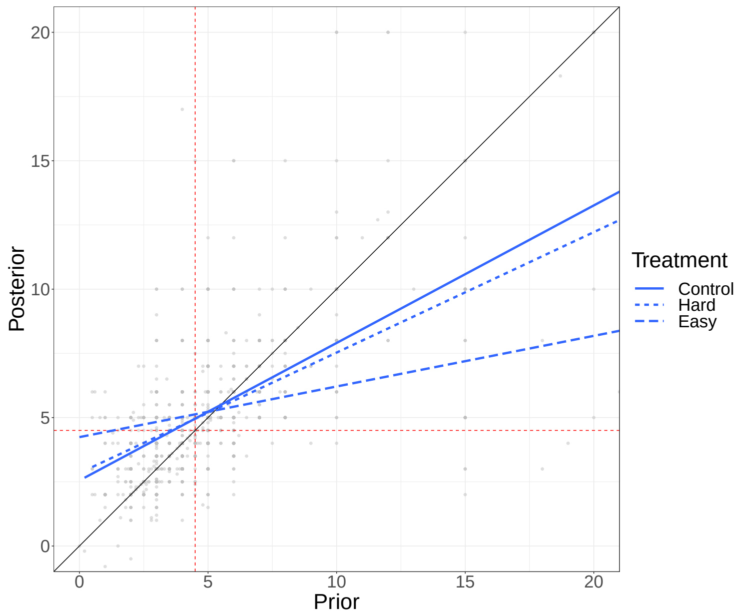


Figure 1.2: Prior against posterior expectations

This figure plots prior against posterior expectations. The graph includes a 45-degree line (black) and linear fits (blue) for each of the three experimental conditions. The dotted lines (red) indicate the signal (4.5% in treatments, 4.3% in control). Gray dots in the background reflect the full data set. The horizontal axis is cropped at a maximum of 20 for readability.

full updating. We denote the average updating rate for the entire sample in a given treatment condition j as $\hat{\beta}_j$.

From Equation (1.16) we can derive expressions corresponding to the theoretical predictions in Section 1.2. The average effect of an increase in the informativeness of the signal as in Equation (1.8) can be calculated as $\hat{\beta}_1 - \hat{\beta}_0 = -(\hat{b}_1 + \hat{d}_1 \cdot s\bar{o}p_1)$. The isolated effect of an increase in cognitive costs as in Equation (1.10) can be derived as $\hat{\beta}_2 - \hat{\beta}_1 = -(\hat{b}_2 + \hat{d}_2 \cdot s\bar{o}p_2 - (\hat{b}_1 + \hat{d}_1 \cdot s\bar{o}p_1))$. $s\bar{o}p_j$ is the average level of overprecision in treatment group j. For the remainder of the analysis, we assume that $s\bar{o}p_0 = s\bar{o}p_1 = s\bar{o}p_2$ given the randomization of the treatment.

1.4.3 Posterior Beliefs

In this section, we analyze how information provision affects posterior beliefs depending on the format of the information and overprecision of respondents.

Figure 1.2 plots the prior inflation expectations against the posterior inflation expectations for each of the three groups. A 45° line would imply that the information provided does not shift expectations while a horizontal line at 4.5 would imply that the information fully shifts expectations to the provided data point. The slopes of the blue regression lines reflect the weight on the prior and, hence, one minus the slopes of the blue regression lines the updating rate specified in Equation (1.16) for each treatment. The results show that respondents revise their beliefs towards the signal in the *active control* treatment (solid blue line) despite the absence of inflation-relevant information. Such revision reflects potential anchoring (Tversky and Kahneman, 1974) or question format effects. Moreover, despite not directly linked to inflation, population growth might still contain indirect information for the development of long-term inflation expectations.

Importantly, both the *hard* (dotted blue line) and *easy* (dashed blue line) regression slopes are flatter than the active control treatment and closer to the horizontal 4.5 line. This implies that providing respondents with last month's inflation rate shifts their posterior beliefs towards the value of the signal beyond any potential anchoring effects. Moreover, in line with our predictions, the effect of the signal is stronger in the *easy* treatment than in the hard *treatment*, which is reflected in a flatter slope for the *easy* treatment. Despite aligning with the prediction of our model, the graphical analysis does not take into account the effects of overprecision.

To empirically test the full set of our predictions, we estimate Equation (1.15) using OLS with robust standard errors and Huber-robust regressions as pre-registered. The results are shown in Table 1.2. Column (1) shows the estimates without control variables and columns (2) and (3) report the results with a set of control variables including age, gender, income (categorical), education (categorical), a dummy variable that takes the value one if the individual lived in Eastern Germany before the reunification, and region fixed effects.[17] In Appendix A.3, we provide a linearization of our theoretical model in Equation (1.1) that maps the theoretical model to the linear regression model.

In Table 1.3, we translate these estimates into updating rates across treatment conditions. From these updating rates, we can derive the first set of our results. We reject the null hypothesis that providing a more informative signal does not change the updating rate, i.e., $\hat{\beta}_0 - \hat{\beta}_1 = 0$ (difference $\hat{\beta}_0 - \hat{\beta}_1 = -0.28$; one-sided p-value= 0.02),[18] in line with the predictions from our model. On the contrary, we fail to reject the null hypothesis that providing a more informative signal in a more complex format does not change the updating rate, i.e., $\hat{\beta}_0 - \hat{\beta}_2 = 0$ (difference $\hat{\beta}_0 - \hat{\beta}_2 = -0.04$; one-sided p-value: 0.40), which suggests that the cognitive cost in the *hard* treatment is relatively high and, therefore, canceling out the effect of providing a more informative signal. However, as predicted by our model, we find a significant difference in the updating rate after a more informative signal between the *hard* and *easy* treatment, i.e., $\hat{\beta}_2 - \hat{\beta}_1 = -0.24$ (one-sided p-value= 0.04), which means that an increase in cognitive costs, keeping the

[17] Despite randomizing respondents across treatment groups, we need to control for potential confounders of overprecision.

[18] Since we preregistered directional hypotheses, we report one-sided p-values for all directional hypotheses.

Table 1.2: Estimation results

This table presents the estimation results of Equation (1.15) with OLS (first two columns) and Huber-robust (third column) regressions. R^2 in the last column refers to the pseudo-R^2. Robust standard errors in parentheses. Stars indicate significance: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Dependent variable: *posterior*	OLS (1)	OLS (2)	Huber (3)
$treat_1 \quad (a_1)$	1.424**	1.347**	0.920
	(0.691)	(0.683)	(0.619)
$treat_2 \quad (a_2)$	0.113	0.202	0.536
	(0.674)	(0.647)	(0.791)
$prior \quad (b_0)$	0.482***	0.455***	0.581***
	(0.098)	(0.097)	(0.130)
$treat_1 \times prior \quad (b_1)$	-0.287**	-0.277**	-0.145
	(0.144)	(0.139)	(0.145)
$treat_2 \times prior \quad (b_2)$	-0.034	-0.034	-0.080
	(0.147)	(0.142)	(0.190)
$sop \quad (c_0)$	-1.267***	-1.366***	-0.874***
	(0.254)	(0.252)	(0.318)
$treat_1 \times sop \quad (c_1)$	1.378	1.392*	0.443
	(0.856)	(0.832)	(0.660)
$treat_2 \times sop \quad (c_2)$	1.163**	1.143**	0.585
	(0.478)	(0.445)	(0.769)
$sop \times prior \quad (d_0)$	0.273***	0.283***	0.210***
	(0.069)	(0.067)	(0.070)
$treat_1 \times sop \times prior \quad (d_1)$	-0.340	-0.329	-0.122
	(0.214)	(0.209)	(0.154)
$treat_2 \times sop \times prior \quad (d_2)$	-0.216*	-0.215**	-0.142
	(0.115)	(0.106)	(0.189)
$constant \quad (a_0)$	2.812***	3.838***	1.721**
	(0.481)	(1.382)	(0.839)
N	1348	1348	1348
adj. R^2	0.22	0.23	
pseudo R^2			0.25
Controls	No	Yes	Yes

informativeness of the signal constant, leads to a significant decrease in the updating rate. This leads to our first set of results:

<u>Result 1:</u> *Respondents update their beliefs upon receiving publicly available information (i.e., the last announced inflation rate). This aligns with the theoretical prediction in Equation 1.8.*

Table 1.3: Estimates for weight on signal/updating rate

This table presents the estimates for weight on signal/updating rate (β_j) in different treatment conditions. The last column reports the p-values from one-sided t-tests against the value 0.

	Coefficient	Estimate (SE)	p-value
Weight on signal $\bar{\hat{\beta}}_j$			
Active control	$1-(b_0+s\bar{o}p\cdot d_0)$	.544 (.097)	0.000
Easy-information	$1-(b_0+b_1+s\bar{o}p\cdot (d_0+d_1))$	.822 (.099)	0.000
Hard-information	$1-(b_0+b_2+s\bar{o}p\cdot (d_0+d_2))$	.580 (.104)	0.000

Result 2: *Updating is stronger when information is less costly to process. This aligns with the theoretical prediction in Equation 1.10.*

We now move on to the effect of overprecision. If the weight on the prior increases with overprecision, i.e., the inequality in Equation (1.9), it must hold that

$$\frac{\partial \beta_{i,j*}}{\partial \omega_i} \cong \frac{\partial \hat{\beta}_{i,j}}{\partial sop_i} = -(\hat{d}_0 + \hat{d}_j) < 0 \quad \text{for each treatment } j.$$

Note that the effect is expected to shrink toward zero with increasing informativeness of the signal.[19] The resulting coefficient for the *active control* treatment, shown in Table 1.2 is in line with the predictions ($-\hat{d}_0 = -.283$). An increase in overprecision by one standard deviation is associated with a decrease in the weight on the signal by 28.3 percentage points. Along with the predictions from the model, this coefficient shrinks toward zero with an increase in the informativeness of the signal ($-(\hat{d}_0 + \hat{d}_2) = -.068$ for the *hard* treatment and $-(\hat{d}_0 + \hat{d}_1) = .047$ for the *easy* treatment). In either case, these estimates fail to attain statistical significance (one-sided p-values: 0.208, 0.407) and, thus, should be interpreted with caution. This leads to our second set of results:

Result 3: *In general, i.e., in the absence of a change in the informativeness of the signal or the cognitive costs, more overprecise respondents update less. This aligns with the theoretical prediction in Equation 1.9.*

Result 4: *The effect of overprecision on the updating rate is weaker and shrinks toward zero when the signal is more informative.*

We now focus on our last prediction, which is the interaction effect between overprecision and rational inattention. Our model postulates that the effect of rational inattention due to a reduction in costs on the updating rate should be amplified by the degree of overprecision in the sample (i.e., Equation (1.10)). Intuitively, since an

[19] See the mapping between the theoretical model and the empirical model in Equation (A.3.10) in the appendix.

overprecise prior requires more cognitive effort to be updated and since overprecise individuals underestimate the benefit of updating, a change in the marginal cost of information processing has a stronger effect on belief updating. For this, it must hold that

$$\frac{\partial^2 \beta^*_{i,j}}{\partial \omega_i \partial \lambda} \cong \frac{\partial \hat{\beta}_2}{\partial sop_i} - \frac{\partial \hat{\beta}_1}{\partial sop_i} = -(\hat{d}_2 - \hat{d}_1) < 0.$$

Referring to Table 1.2, the difference between the triple interaction terms is negative ($-(\hat{d}_2 - \hat{d}_1) = -.115$) in accordance with our hypothesis. Note that this difference is not significant at conventional levels (p-value= 0.297). This leads to our last result:

<u>Result 5:</u> *The effect of overprecision on the updating rate is stronger when the signal is more costly to process. This aligns with the theoretical prediction in Equation 1.11.*

Given the lack of statistical significance of the estimated effects of overprecision, these results should be interpreted with caution. One explanation for the imprecisely estimated coefficients could be a noisy measure of overprecision due to the particular experimental setting. On the one hand, our exclusion restrictions might not have detected all respondents who have used search engines to find the correct answers. Moreover, the overprecision questionnaire was placed last in the survey and fatigue might have decreased the attention of the respondents. Given that there were no attention checks, this might have had a negative consequence on the quality of the answers. This is supported by the relatively large dropout rate for this part of the survey. Comparing the distributions of the answers in Figure A.2.1 in the appendix to the distributions of the same questions in Bosch-Rosa et al. (2021) indeed shows a different answering behavior suggesting a lower answer quality.

1.5 Conclusion

In this chapter, we analyze the effects of rational inattention and overprecision on the formation and updating of beliefs. To do so, we develop a tractable model of belief formation where agents can be overprecise and subject to information processing costs due to limited attention. Both rational inattention and overprecision lead agents to update less after receiving new (public) information. Moreover, the model shows an interaction between rational inattention and overprecision. That is, a change in the marginal cost of information processing has a stronger effect on belief updating when agents are overprecise. An overprecise prior requires more cognitive effort to be updated. Moreover, overprecise agents underestimate the benefit of updating. Therefore, they react more to changes in information processing costs.

To test the predictions, we design and conduct a randomized information provision experiment in the context of inflation expectations. In line with the literature, our results show that respondents update their beliefs even upon seeing a piece of publicly available information. We also find indicative evidence for rational inattention as respondents do not update their beliefs at the same degree even when the information provided is identical, but update less when the text in which the information is delivered is cognitively more costly to process. However, while the results regarding overprecision go in the direction of our predictions, they do not attain significance at conventional levels.

Overall, our project contributes to the literature on rational inattention and belief updating by introducing overprecision, a type of overconfidence that is considered to be at the center of most behavioral biases Moore and Schatz (2017). Our results indicate that overprecision plays a role in the way people form their beliefs and interacts with rational inattention. This opens an interesting research avenue on belief updating and cognitive biases.

Chapter 2

Overconfidence and Financial and Political Behavior

This chapter is based on co-authored work with Steffen Ahrens and Ciril Bosch-Rosa. See Bosch-Rosa et al. (2021) for the full reference.

2.1 Introduction

Overconfidence is a pervasive and potent bias in human judgment (Kahneman, 2011; Mannes and Moore, 2013). It leads to wars (Johnson, 2004), to excessive entry into markets (Camerer and Lovallo, 1999), or to 80% of the population thinking that they are above-average drivers (Svenson, 1981). However, overconfidence is a general term that encompasses three different phenomena: overestimation, overplacement, and overprecision (Moore and Healy, 2008; Moore and Schatz, 2017). Overestimation has to do with absolute values—you think that you are better than you really are. Overplacement has to do with relative values—you think that your performance is better than that of others, when it is not. In this project, we focus on overprecision. Overprecision has to do with the degree of certainty with which a person judges her own knowledge—you think that your knowledge is more accurate than it really is. In other words, overprecision relates to the second moment of the distribution, such that a person may hold accurate beliefs on average but underestimate the variance of the possible outcomes (Malmendier and Taylor, 2015).

Overprecision has important consequences. From an economic point of view, overprecision may lead consumers to buy less insurance than they should (Grubb, 2015) or to large distortions in corporate investment decisions (Ben-David et al., 2013; Moore et al., 2015). In finance, overprecision is linked to systematic forecasting errors (Deaves et al., 2019), to excessive trading (Barber and Odean, 2001), and to an under-diversification of portfolios (Goetzmann and Kumar, 2008). In a political context, overprecision leads to ideological extremism, strong partisan identification (Ortoleva and Snowberg, 2015a,b; Stone, 2019), and increased susceptibility to "fake news" (Thaler, 2023). However, the existing evidence either uses indirect measures of overprecision, such as gender or the tendency to make extreme predictions, estimates derived from econometric models, or confidence intervals, a method that has been shown to be problematic (Teigen and Jørgensen, 2005; Bazerman and Moore, 2013; Moore et al., 2015).

In this project, we study the relationship between overprecision and the political and financial behavior of a nationally representative sample of the German population. To do so, we introduce a new method to elicit overprecision, which we call the "Subjective Error Method." This method consists of a two-step process. In the first step, participants answer a numerical question (e.g., In what year was Saddam Hussein captured by the US army? or how many meters tall is the Eiffel Tower?). In the second step, they are asked to estimate the "distance" (in the units of the question) between their response to the first question and the correct answer. In other words, in the second step, respondents are asked to report their expected *absolute error* to the first question (henceforth, subjective error). By comparing the realized true error to their subjective error, we can determine respondents' overprecision in a simple and direct way.

The richness of our data allows us to study the correlation of overprecision with respondents' socio-demographic characteristics and with their financial and political behavior. As a result, we observe that overprecision (as measured using the Subjective Error Method) is positively correlated with narcissism, negatively correlated with age, years of education, gross income, and financial literacy, but does not differ across genders. We also find that overprecision aligns well with several theoretical conjectures. Specifically, our measure is positively correlated with larger forecasting errors in respondents' stock price predictions and with lower portfolio diversification, as suggested by Odean (1998) and Barber and Odean (2000). Regarding subjects' political views and behavior, our measure of overprecision predicts a tendency to hold extreme political ideologies, as suggested by Ortoleva and Snowberg (2015b). Yet, in contrast to Ortoleva and Snowberg (2015b), our measure of overprecision is associated with voting absenteeism rather than an increased likelihood to vote. We surmise that the difference could be attributed to the different electoral systems in Germany and the United States. The alignment of the results with the theoretical predictions suggests the Subjective Error Method is a valid measure of overprecision and that overprecision impacts different aspects of respondents' lives.

Additionally, we test whether overprecision is a robust personality trait across different domains. In a companion online survey, administered to a representative sample of the German population, we implement the Subjective Error Method across five different domains (contemporary history, general knowledge, economics, four-week ahead stock price predictions, and a neutral counting task).[1] The results show that overprecision is robust within individuals across domains. This suggests that overprecision, as measured by the Subjective Error Method, is a persistent personality trait across different domains.

Our project contributes to the existing literature on overprecision in four dimensions: first, we directly elicit overprecision by introducing the Subjective Error Method, a novel technique that is easy to understand, quick to implement, and captures respondents' excess confidence in their own judgment. Second, applying our new measure of overprecision, we can confirm distinct theoretical predictions regarding the financial and political behavior of respondents. Specifically, we show that a higher degree

[1]The five domains differ with respect to the possibility of knowing the true answer. For the contemporary history, general knowledge, and economics domain, a correct answer exists on the day of the survey. For the neutral counting task, a correct answer exists but can only be estimated. For the stock price predictions, there exists no correct answer on the day of the survey.

of overprecision results in lower portfolio diversification, larger stock price forecasting errors, and ideological extremism. Third, while most of the existing literature on overprecision uses university students (e.g., Alpert and Raiffa, 1982), or special pools of subjects (e.g, Glaser and Weber (2007) use finance professionals and McKenzie et al. (2008) IT professionals), we test theoretical predictions across different domains on a representative sample of the German population. Finally, using an online survey, we are the first to show that overprecision is a personality trait that is robust within individuals across different domains.

The remainder of the chapter proceeds as follows: Section 2.2 discusses the notion of overprecision and introduces our measure of overprecision, the subjective error method. In Section 2.3, we present the SOEP-IS data set, correlate overprecision with various socio-demographic measures, and use our measure of overprecision to predict the behavior of respondents on various domains such as predicting asset market returns, portfolio diversification, or voting behavior. In Section 2.4, we present the companion online survey and test the robustness of overprecision across domains. The last section concludes.

2.2 Overprecision and the Subjective Error Method

2.2.1 Measuring Overprecision

Overprecision (also known as miscalibration) is a type of overconfidence that results from an excess of confidence in one's own information (Moore et al., 2015). It relates to the second moment of the belief distribution and thereby directly affects how information is processed. For this reason, it is widely used in finance and political science to model overconfident agents. For example, Odean (1998) find that overconfident traders trade excessively and hold underdiversified portfolios because they believe that their private signals are more precise than they really are. Scheinkman and Xiong (2003) combine overprecise traders with a constraint on short sale to explain the formation of asset market bubbles.[2] Turning to the political science literature, Ortoleva and Snowberg (2015b) find that more overprecise people hold more extreme political views, show stronger partisan identification, and tend to vote more. Consistent with this, Stone (2019) suggests that overprecision increases partisanship through excessively strong inferences from (biased) information sources. More recently, the literature has begun to study the role that overprecision plays in disseminating fake news (Pennycook et al., 2021; Thaler, 2023).

[2]For a longer discussion on the different models of overprecision used in the finance literature see Daniel and Hirshleifer (2015).

Yet, precisely because overprecision deals with the second moment of the belief distribution, it is difficult to measure (Moore et al., 2015). The most common way to measure overprecision, introduced by Alpert and Raiffa (1982), is to elicit the respondents' 90% confidence intervals (CI) for a series of numerical questions (e.g., How long is the Nile River?). Using this paradigm, a perfectly calibrated respondent would not capture the correct answer within the CI in one out of every ten questions. However, the literature has shown that this method creates implausibly high measures of overprecision, with the purported 90% CIs only containing the correct answer between 30% to 60% of the time (e.g., Russo and Schoemaker, 1992; Bazerman and Moore, 2013; Moore et al., 2015). The best explanation for such results is that respondents are not familiar with CIs and do not fully grasp what they are being asked (Moore et al., 2015). This was demonstrated by Teigen and Jørgensen (2005), who show that the elicited intervals resulting from asking 90% CIs are practically identical to those resulting from asking for 50% CIs.

While there are some alternatives to CIs when measuring overprecision, these tend to be either time-consuming or limited in the information they provide. For example, the two-alternative forced-choice (2AFC) method developed by Griffin and Brenner (2004) asks respondents to choose between two possible answers to a question and then indicate how confident they are that their answer is correct. By comparing the number of correct answers to the stated confidence, one can measure whether, on average, respondents are overconfident. However, this method has several drawbacks as it cannot distinguish between overprecision and overestimation of one's own knowledge (Moore et al., 2015) and cannot capture continuous distributions (see Moore et al. (2015) and Griffin and Brenner (2004) for a further discussion of the 2AFC method and its statistical limitations). Another approach to measuring overprecision is the Subjective Probability Interval Estimates (SPIES) method by Haran et al. (2010). The SPIES method elicits complete probability distributions from respondents. Although the SPIES method appears to measure overprecision more accurately than CIs (Moore et al., 2015), it is time-consuming, and it requires respondents to understand the concept of probability distributions. Additionally, because distributions can only be elicited by partitioning the support into discrete bins, researchers need to make a series of *ad hoc* decisions to implement and define the desired 90% boundaries of the distribution. Finally, Ortoleva and Snowberg (2015b) use an *estimation method* where they regress a self-reported measure of confidence in the accuracy of their answers on a six-point scale on a polynomial of the realized error. The drawback of this approach is that the individual measure of overprecision is dependent on the relationship between confidence and accuracy for the entire population of respondents, which might incorrectly classify subjects as over- or underprecise.[3]

To address these caveats, we introduce the Subjective Error Method, a novel method, which is easy to understand, quick and simple to implement, and does not depend on subjects' knowledge of statistical concepts or the properties of the entire sample.

2.2.2 The Subjective Error Method

The Subjective Error Method consists of asking two consecutive questions to respondents. The first question (a) can be on any topic but needs to have a numerical answer.[4] The second question (b) asks respondents how far away they expect their answer to question (a) to be from the true answer. In other words, the second question asks respondents to report their absolute subjective error. An example would be:

(a) *How long (in kilometers) is the Nile River?*

(b) *How far away (in kilometers) do you think your answer to (a) is from the true answer?*

By comparing the *subjective error* of respondents stated in (b) to the absolute *true error* from question (a), we get a measure of how over- or underprecise a respondent is about her knowledge.

To fix ideas, assume that a respondent's realized true error is normally distributed, with mean 0 and variance σ^2 as shown by the solid curve in Figure 2.1. A perfectly calibrated individual would, on average, correctly assess the distribution of the true error when answering questions using the Subjective Error Method. However, the perceived distribution for most respondents might not necessarily coincide with the true distribution. If the respondent is overprecise, then her perceived variance of the error $\hat{\sigma}^2$ is smaller than the true variance, i.e., the precision $\rho = 1/\hat{\sigma}^2$ is larger (dashed curve in Figure 2.1). In this case, the subjective error would, on average, consistently deviate from the realized true error, resulting in a systematic deviation across all questions.[5]

Denote the answer of respondent i to question j as $a_{i,j}$, her subjective error for question j as $se_{i,j}$, and the true answer to the question as ta_j, then our measure of overprecision for respondent i for question j is:

[3]See Appendix B.3 for a more detailed discussion with examples.

[4]Some examples of numerical questions are the result of multiplying 385 by 67, the length of the Nile River, or the year of Lady Diana's death. Some examples of questions that do not work are the name of the oldest son of Lady Diana, the color of the Batmobile, or the gender of the current prime minister of the United Kingdom.

[5]Note that the difference between the realized true error and the subjective error that would realize with the same cumulative probability is directly proportional to the difference in the precision of the underlying distributions.

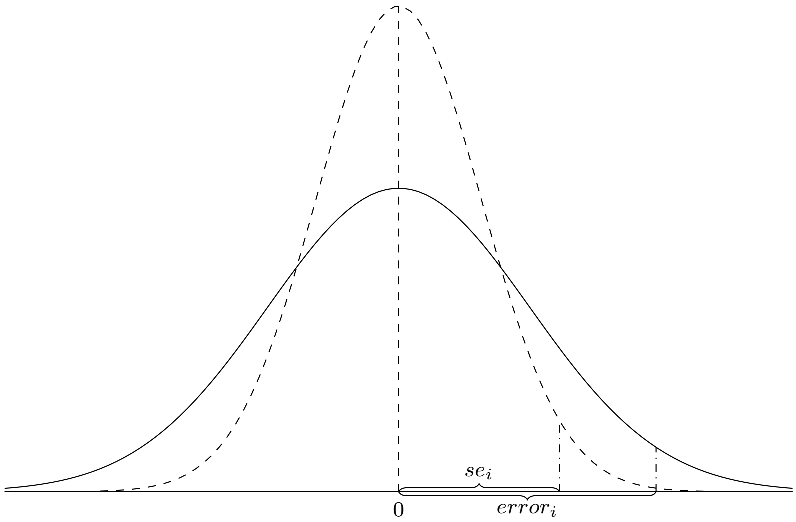


Figure 2.1: Two hypothetical distributions of the (subjective) error

The figure shows two hypothetical normal distributions of the (subjective) error. The solid curve shows the true distribution of the error with a standard deviation of 2 (precision of .25). The dashed curve shows the perceived distribution by an overprecise respondent with a standard deviation of 1.25 (precision of .64). The dash-dotted vertical lines indicate the subjective error se_i and the absolute true error $error_i$ resulting with the same cumulative probability.

$$error_{i,j} = |a_{i,j} - ta_j|, \tag{2.1}$$

$$op_{i,j} = error_{i,j} - se_{i,j}, \tag{2.2}$$

where equation (2.1) measures the absolute true error ($error_{i,j}$) of respondent i to question j. Note that this equation calculates the *absolute error*; that means that we do not care about the direction of the error but rather about its size. In equation (2.2), we calculate the difference between the subjective error ($se_{i,j}$) and the realized true error ($error_{i,j}$) of respondents i to question j. In this case, we do care about the direction of the error, as a respondent who underestimates her subjective error (i.e., $error_{i,j} > se_{i,j}$) is considered *overprecise*, while a respondent who overestimates her subjective error (i.e., $error_{i,j} < se_{i,j}$) is considered *underprecise*. Finally, those respondents who correctly guess their subjective error (i.e., $error_{i,j} = se_{i,j}$) are considered perfectly calibrated for that question.[6]

Eliciting overprecision using the Subjective Error Method rather than using CIs has several advantages. First and foremost, respondents do not need to have any statistical knowledge to answer the questions and the setup is easy to explain. Additionally,

[6] In principle, knowledge should not affect the measure of overprecision. This is because any reduction of errors in the first question is likely offset by a symmetric reduction of the subjective error, resulting in a "neutral" effect of knowledge. Such neutral effect is corroborated by the literature (e.g., Önkal et al., 2003; McKenzie et al., 2008) and by the results of our companion survey reported in Appendix B.6.1.

questions can be answered quickly, and it can be implemented easily in either computerized or pen-and-paper surveys. Another important advantage of the Subjective Error Method is that it is easy to make it incentive-compatible. For instance, one can put a quadratic scoring rule (Brier, 1950) or the binarized scoring rule (Hossain and Okui, 2013) on top of each question, and randomly pay only one of the two outcomes to avoid hedging across questions. This is in contrast with the more complicated scoring rules necessary to make CIs incentive-compatible (e.g., Jose and Winkler, 2009).

In a related paper, Enke and Graeber (2021) study the "subjective uncertainty about the optimal action" that experimental subjects have when confronted with choices across different economic domains. To measure such uncertainty, they take an approach very similar to the Subjective Error Method—they allow subjects to provide a symmetric interval of "uncertainty" around the answers provided to each question. Their results show that such symmetric bounds are robust within and across subjects and have strong predictive power across the different domains they study. Overall, while the setup proposed by Enke and Graeber (2021) is not designed to measure overprecision, it lends support to the Subjective Error Method as a robust tool to elicit the degree of uncertainty of respondents for a given answer.

2.3 The Subjective Error Method and the Behavior of Individuals

In this section, we apply the Subjective Error Method to study how overprecision correlates with socio-demographic characteristics (Section 2.3.3) and the political and financial behavior (Section 2.3.4) of a nationally representative sample of the German population.

2.3.1 Data

We use data from the Innovation Sample of the German Socio-Economic Panel (SOEP-IS). The Innovation Sample is a companion panel of the larger SOEP-Core, which has approximately 30,000 individual respondents. SOEP-IS is designed to host and test novel survey items (see, Richter and Schupp, 2015). We use the 2018 wave of the SOEP-IS, which had 4,860 individual respondents distributed across 3,232 different households. As in the SOEP-Core, all interviews are conducted face-to-face by a professional interviewer.

To construct our measure of overprecision, we use data from seven different questions. In each question, we ask respondents to answer two things, (a) the year of a specific historical event that occurred not more than 100 years ago, and (b) the distance (in years) between their answer to (a) and the correct answer to (a).[7] In other words, we ask respondents to answer a contemporary history question and then we ask them to report the absolute error they expect to make, i.e., their subjective error (see Section 2.2.2).

We ask seven different questions about events taking place between 1938 and 2003. The questions are designed to vary in difficulty and to cover different decades. The content of the questions ranges from the year in which the Volkswagen Beetle was introduced (1938) to the year in which Saddam Hussein was captured by the US Army (2003) (see Table B.2.1 and Table B.2.2 in the appendix for all questions and their correct answers in English and German, respectively).[8] These questions were asked to those respondents (902) who joined the panel in 2016. We supplement the data with additional data on personal characteristics from the survey years 2016–2018. We drop 55 respondents who did not answer any of the overprecision questions, since this is our main variable of interest, and 42 respondents with incomplete information. In total, we end up with a sample of 805 respondents across 584 different households.[9]

2.3.2 Measuring Overprecision

In Figure 2.2, we plot the density of answer $a_{i,j}$ for each question j. The red vertical line marks the correct answer. It is clear from the dispersion of the densities that some questions were easier for respondents than others. In Figure 2.3, we plot the realized true error ($error_{i,j}$) in the vertical axis and subjective error ($se_{i,j}$) in the horizontal axis for each of the seven questions. Additionally, we plot a 45-degree red line, so that any dot above is a respondent who is overprecise ($error_{i,j} > se_{i,j}$) in her answer to the question, and any point below corresponds to a respondent who is underprecise ($error_{i,j} < se_{i,j}$). It is clear from the figure that respondents are, on average, overprecise in their answers across all questions independent of their difficulty.

We construct overprecision for each question ($op_{i,j}$) following the outline in Sec-

[7]The questions are formulated in German. For the example in which we ask about the year of the death of Lady Diana we ask: (a) *In welchem Jahr starb Lady Diana, die erste Frau von Prinz Charles?* and then (b) *Was schätzen Sie, wie viele Jahre Ihre Antwort von der richtigen Antwort entfernt ist?*.

[8]Subjects could answer using any integer between 1900 and 2019 for question (a) and between 0 and 119 for question (b).

[9]To test whether our estimation sample is still representative of the German population, we compare the unweighted means of personal characteristics in our sample with the weighted means according to the sampling weights in the larger SOEP-Core, which is representative of the German population. The results in Table B.2.4 in the appendix show that our subsample is still broadly representative of the larger SOEP-Core, with only some significant but small and nonmeaningful differences. When applying the sampling weights to our estimation sample, the differences disappear.

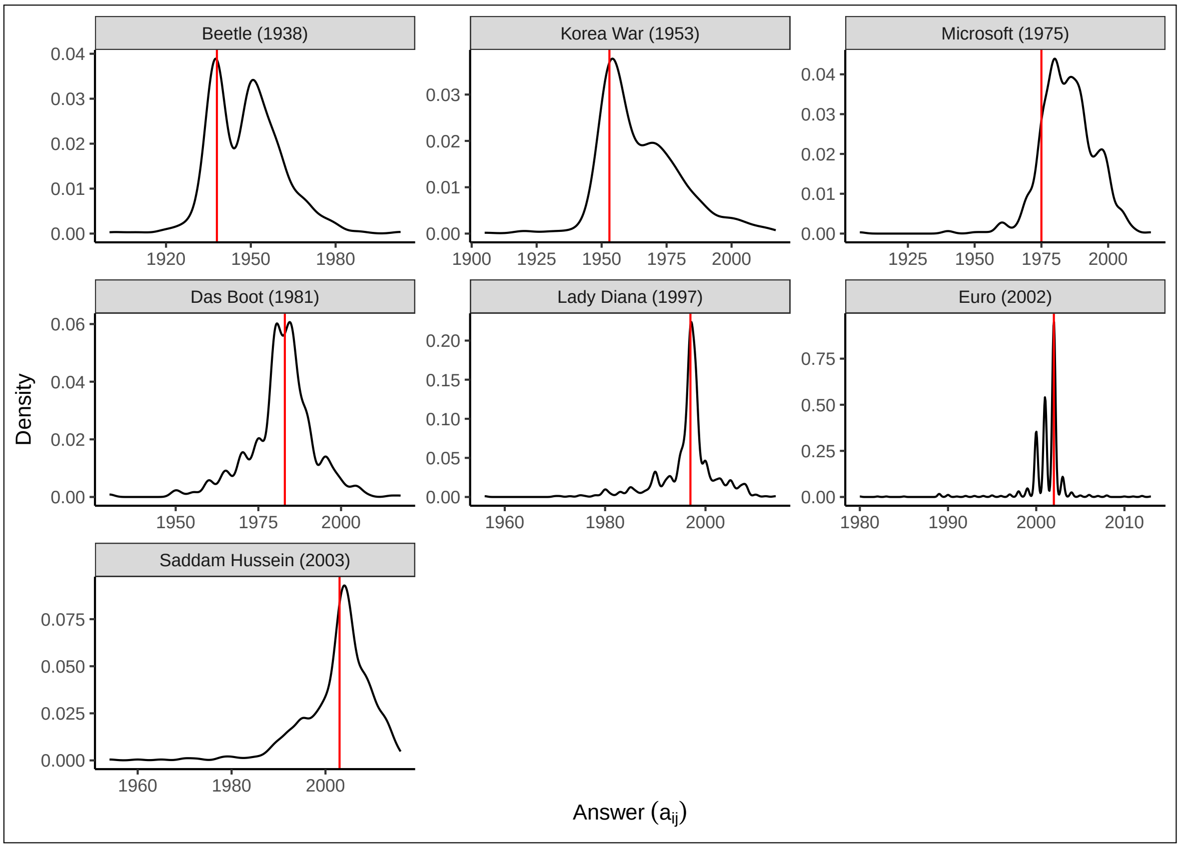


Figure 2.2: Distributions of the answers to each history question (SOEP-IS)

This figure shows the density of the answers ($a_{i,j}$) for each history question. The red vertical line marks the correct answer. Note that the vertical axis is different for each question.

tion 2.2.2. To measure consistency in the overprecision measure across the seven questions for each subject, we use congeneric reliability, which is commonly referred to as coefficient omega (e.g., Cho, 2016). Congeneric reliability indicates the share of variation (variance and covariance) among a set of variables that can be explained by an unobserved factor.[10] The results show that 49% of the variation among the seven items can be explained by a common factor, which we interpret as overprecision.

To create a unique measure of overprecision for each respondent i (op_i), we take

[10]Consider a model in which each observed outcome i of item j can be expressed as $T_{i,j} = \mu_j + \lambda_j F_i + e_{i,j}$, where $T_{i,j}$ is the i^{th} outcome of item j, μ_j is a constant term, $e_{i,j}$ is the individual score error, and λ_j is the factor loading on the latent common factor F. To construct congeneric reliability, we estimate the factor loadings, $\hat{\lambda_j}$, for the overprecision measure of each question with respect to one common factor. We interpret this common factor as overprecision. Congeneric reliability is calculated according to the formula $\frac{(\sum \hat{\lambda}_j)^2}{(\sum \hat{\lambda}_j)^2 + \sum \hat{\sigma}^2_{e_j}}$, where $\hat{\sigma}^2_{e_j}$ is the estimated variance of the error. This is a generalized version of Cronbach's alpha (Cronbach, 1951) and measures the share of variation among the set of items j that can be explained by the latent factor. While congeneric reliability allows for different factor loadings of the latent common factor, Cronbach's alpha assumes that the latent factor equally loads on all items and is, thus, a lower bound for reliability. For the case of τ-equivalence, i.e., $\lambda_j = \lambda_k \; \forall k$, all factor loadings are equal and both measures coincide.

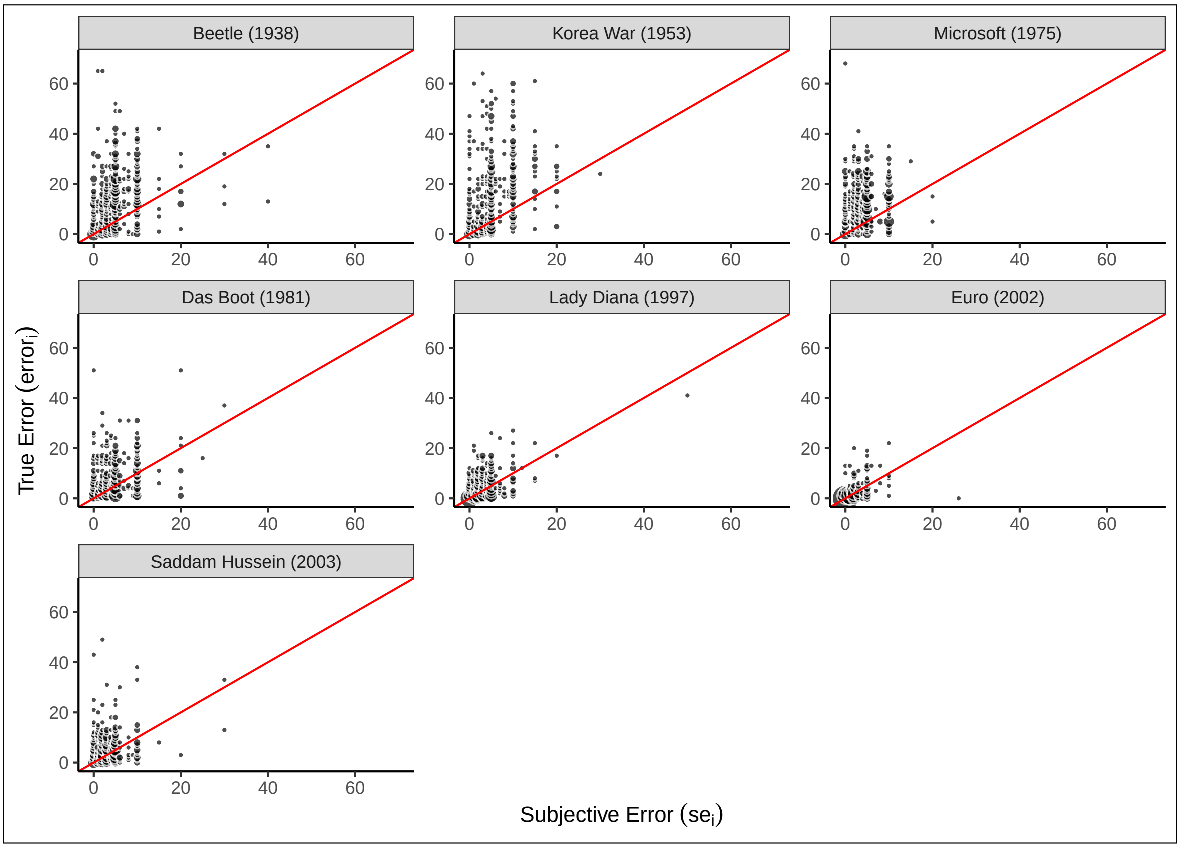


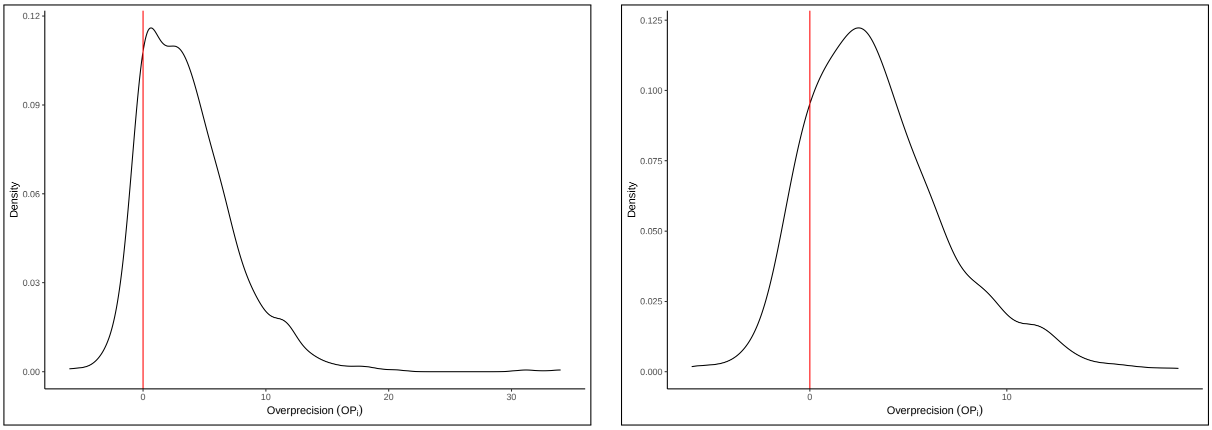
Figure 2.3: Relation between the true error and the subjective error (SOEP-IS)

This figure shows the relation between the realized true error ($error_{i,j}$) in the vertical axis and the subjective error ($se_{i,j}$) in the horizontal axis for each historical question. Any dot above (below) the 45-degree red line is an overprecise (underprecise) answer by the respondent.

the average overprecision across all seven questions j.[11] We plot the density of op_i in Figure 2.4a. Consistent with Figure 2.3, Figure 2.4a shows that the great majority of respondents (82%) are overprecise. On the other hand, and in contrast with most of the literature using CIs to measure overprecision, we find a relatively large number of respondents that are underprecise (approximately 11%).

Moreover, 7% of the respondents seem to be perfectly calibrated (vertical red line in Figure 2.4a) in the aggregate measure. Of these 52 respondents, 83% are perfectly calibrated across all the questions they answer. However, note that respondents could decide not to answer a question; 51% of the respondents answered all questions, with 5% answering only one (see Figure B.1.1 in the appendix for a detailed breakdown). Of those perfectly calibrated respondents, 40% answered only one question, and only 12%

[11]Given that a principal component analysis of the seven items yields a strong first factor, an alternative would be to construct the composite measure op_i using the principal component as in Ortoleva and Snowberg (2015b). The composite overprecision measure resulting from using the first component is very similar to using the simple average ($\rho^{Pearson} = .88; \rho^{Spearman} = .84; N = 805$). Additionally, to alleviate concerns about different scales, we also construct a standardized measure of overprecision by standardizing each measure of overprecision ($op_{i,j}$) before aggregating in Appendix B.3.



(a) This figure shows the density of op_i, which is the average overprecision for each respondent i across all questions j, for all respondents (N=805).

(b) This figure shows the density of op_i for a subset of respondents who answered all questions in the survey (N=410).

Figure 2.4: Distribution of overprecision (SOEP-IS)

answered all seven. This means that what we see in Figure 2.4a is an "upper bound" of perfectly calibrated respondents. As can be seen in Figure 2.4b, once we plot the density function for the subset of respondents that answered *all questions*, we find that respondents are substantially less calibrated, with the mode of op_i shifting to the right and leaving only 1% of the respondents perfectly calibrated; at the same time, there is an increase in the proportion of underprecise respondents (15%).

For ease of interpretation, we standardize the aggregate score (op_i) to be mean zero and standard deviation one (sop_i).

2.3.3 Socio-Demographic Determinants of Overprecision

In Table 2.1, we regress sop_i on a series of socio-demographic variables using five different OLS models. In all models, we control for age, gender, and years of education. In Column (2) we add the number of overprecision questions answered. In Column (3), we add the monthly gross individual income (*gross income*) measured in thousands of euros as well as dummies for labor force status (e.g., employed, unemployed, maternity leave, etc.) and a dummy for those respondents who were living in East Germany in 1989.[12] In Column (4), we add further personal characteristics, which are financial literacy, risk aversion, impulsivity, patience, and narcissism. Finally, in Column (5), we add federal state (*Bundesland*) and month-of-interview fixed effects.[13]

The results show that age, education, and income are negatively correlated with overprecision. For example, an increase in the gross income of 2,000 euros is associated

[12]Since *gross income* is only available for employed individuals, we code missing variables as 0 and include a dummy that is 1 for missing observations.

[13]Note that we only report coefficients that are statistically significant in Table 2.1.

Table 2.1: Socio-economic determinants of overprecision

This table presents the socio-economic determinants of overprecision. In Columns (1)-(5) we run an OLS with standardized overprecision measure *sop* as the dependent variable. In all Columns, we include age, gender, and education. In Column (2) we add the number of answered history questions. In Column (3) we include gross income and dummies for labor force status (employed, unemployed, retired, maternity leave, nonworking), and whether the respondent was a citizen of the GDR before 1989. In Column (4) we include further personal characteristics, which are financial literacy, risk aversion, impulsivity, patience, and narcissism. In Column (5) we also include fixed effects for the federal state (*Bundesland*) where the respondents live and the time at which they responded to the questionnaire. Variable definitions are in Table B.2.3 in the appendix. Standard errors in parentheses. Stars indicate significance: $^{*}p < 0.10$,$^{**}p < 0.05$,$^{***}p < 0.01$.

Dependent Variable: *sop*	(1)	(2)	(3)	(4)	(5)
age	-0.008***	-0.008***	-0.007**	-0.005	-0.005*
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
gender (female=1)	0.074	0.121*	0.094	0.134*	0.111
	(0.069)	(0.070)	(0.072)	(0.075)	(0.075)
years education	-0.053***	-0.062***	-0.050***	-0.043***	-0.037***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
answered		0.064***	0.067***	0.086***	0.085***
		(0.020)	(0.020)	(0.021)	(0.021)
gross income			-0.049**	-0.037	-0.039*
			(0.023)	(0.023)	(0.023)
fin. literacy				-0.481***	-0.398**
				(0.151)	(0.155)
narcissism				0.107***	0.100***
				(0.036)	(0.037)
N	805	805	805	805	805
adj. R^2	0.036	0.046	0.061	0.081	0.098
Constant Term	Yes	Yes	Yes	Yes	Yes
Employment & GDR 1989	No	No	Yes	Yes	Yes
Personal characteristics	No	No	No	Yes	Yes
Fixed Effects	No	No	No	No	Yes

with a reduction in overprecision by almost one-tenth of a standard deviation, and every 2 years of education are associated with a reduction in overprecision by about one-tenth of a standard deviation. Furthermore, overprecision is negatively correlated with our measure of financial literacy and positively correlated with our measure of narcissism. It is also important to note that the number of questions answered by respondents (*answered*), which we include in Column (2), is not random, with overprecision increasing as subjects answer more questions (see Figures B.1.2 and B.1.1 in the appendix for a graphical overview of these results). In all subsequent analyses, we use the above-mentioned variables as controls.

The results from Table 2.1 differ from those of Ortoleva and Snowberg (2015b), who do not find any correlation between income or education with their measure of overprecision. Ortoleva and Snowberg (2015b) also find that females are significantly less overprecise than males. Yet, the effect of gender on overprecision is far from universal in the literature, as, for example, López-Pérez et al. (2021), Deaves et al. (2009), and Wohleber and Matthews (2016) find no effect of gender on overprecision. This is supported by Bandiera et al. (2022) who find that both men and women are overconfident with no significant difference between gender by aggregating experimental findings over the last twenty years. The positive correlation with narcissism aligns with the results from the literature (e.g., Campbell et al., 2004; Hamurcu and Hamurcu, 2021). Finally, the literature on overprecision and financial literacy is scarce. Kramer (2016) reports that confidence is negatively correlated with financial advice seeking while objective measures of financial literacy are not. This suggests a negative relationship between overprecision and financial literacy, as we find.[14]

2.3.4 Overprecision and the Financial and Political Behavior of Respondents

In this section, we examine how our direct measure of overprecision correlates with respondent behavior in the political and financial domains. In Section 2.3.4.1, we describe the empirical methodology, and in Section **??**, we present the results.

2.3.4.1 Methodology

To test the predictions from the theoretical literature on overprecision, we use three different procedures. First, we run a regression of each outcome (y_i) on our measure of overprecision and a vector of control variables of the form:

$$y_i = \alpha + \beta sop_i + \boldsymbol{\gamma' X_i} + \epsilon_i, \tag{2.3}$$

where sop_i denotes the standardized overprecision measure, $\boldsymbol{X_i}$ is a vector of control variables, and ϵ_i is the random error term. We include all possible control variables available in the SOEP-IS that we assume to be correlated either with the dependent variable or with overprecision. These are age, gender, years of education (which serves

[14]In Appendix B.3, we show the robustness of our measure of overprecision by comparing it to five alternative approaches. These are i) a *standardized* measure, which standardizes each question before aggregating, ii) a *centered* measure, which centers the errors and subjective errors around their mean, allowing us to disentangle the second moment of the distribution (overprecision) from its first moment, iii) a *relative* approach, which takes into account the relative distance between the subjective error and the realized true error, iv) an *age-robust* measure, which is constructed using only those questions concerning events that occurred after the respondent was born, and v) a *residual* approach following the regression methodology of Ortoleva and Snowberg (2015b).

as a proxy for cognitive ability), monthly gross labor income, dummy variables for the labor force status (employed, unemployed, maternity-leave, non-working, and retired), measures of impulsivity, patience, narcissism, financial literacy, and risk aversion, a dummy variable for having lived in the German Democratic Republic in 1989, the number of overprecision questions answered by each respondent, state fixed effects, and interview date (month and year) fixed effects. The latter absorbs any variation in the outcome that is driven by the different timing of the survey, e.g., the development of the asset prices. Additionally, we include a measure of political interest in the political analyses.[15] A test for multicollinearity shows no strong linear dependencies across the explanatory variables. We estimate (2.3) using OLS and present the point estimate of the standardized overprecision measure sop_i from the full regression and its unadjusted p-value respectively in Columns (1) and (2) of Table 2.2.[16] Since we test the behavior of respondents across several dimensions, we also report the Sidak-Holm adjusted p-value for multiple hypothesis testing in Column (3).

Second, we follow Cobb-Clark et al. (2019) and estimate the "R^2 rank" of our standardized measure of overprecision sop_i. This is obtained by running a step-wise regression in which we sequentially keep adding variables to the model. To do so, in step 1, we regress the behavior of interest on each of the K control variables in the specification separately. Of these K regressions, we pick the control variable with the highest R^2. In step 2, we regress $K - 1$ times the behavior of interest on the control variable selected in the first step plus each of the $K - 1$ remaining controls. This is continued until all K variables have been added to the model. The resulting R^2 rank is determined by the step at which each control variable was added to the model. Therefore, the higher the "R^2 rank" of sop_i, the more the variable can explain the variation in the outcome, i.e., rank 1 delivers the highest R^2. We report the results in Column (4) of Table 2.2 along with the maximum number of variables to be included in the model as specified above.

Finally, we employ a least absolute shrinkage and selection operator (LASSO) to test whether our overprecision measure has predictive power for the outcome variable in an out-of-sample prediction. LASSO is a machine learning application that is frequently applied to improve the predictive power of statistical models. The objective of the LASSO approach is to choose those variables with the highest predictive power from the set *of all possible control variables.* It does so by estimating a penalized regression

[15] In Table B.2.5 in the appendix, we also include the Big Five personality traits (Rammstedt and John, 2007). These are only available from the 2017 SOEP-IS, and because not all respondents in our sample responded to them, we lose 55 observations. Yet, the results remain robust to the inclusion of the Big Five personality traits.

[16] Adjusting the degrees of freedom by the number of questions used to construct the measure of overprecision does not significantly affect the results.

by minimizing the sum of squared residuals and a penalty term for the sum of the coefficients.[17] This is implemented 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.[18] If sop_i is included in the model, then it has predictive power for the outcome. We report the results in Column (5) of Table 2.2 along with the number of control variables chosen by LASSO and the resulting R^2 of the model in Column (6). In Column (7), we report the number of observations, which may vary due to missing observations in the outcome variables.[19]

2.3.4.2 Prediction Results

The results of our three analytical approaches are summarized in Table 2.2.[20] We first discuss financial behavior outcomes and then outcomes regarding political behavior.

Financial Behavior Outcomes

The first hypothesis concerns the forecast errors of asset price predictions in the stock market. Benos (1998) and Odean (1998) argue that overprecise investors hold incorrect beliefs about the future valuation of assets because they overweight their private signals when forming expectations. Direct empirical support for the association of overprecision and forecast errors in financial markets is provided by Deaves et al. (2019), who correlate the predictions of German stock market forecasters with a measure of overprecision. Additionally, Hilary and Menzly (2006) provide evidence consistent with this association for North American analysts.[21] Therefore, we expect overprecise respondents to be less accurate in their predictions. To test this prediction we use the absolute distance of the one- and two-year-ahead predictions of the German Stock Index (DAX), Germany's blue-chip stock market index, from the realized value.[22] Since

[17]Formally $\min_\beta \frac{1}{2N}\sum_{i=1}^{N}(y_i - \alpha - \sum_j \beta_j x_{ij})^2 + \lambda\sum_j |\beta_j|$ for the linear case, where j are the coefficients which are included in the model and λ is a given tuning parameter. See Tibshirani (1996) for more details.

[18]The algorithm proceeds step-wise and estimates the model for each λ starting at the smallest λ that delivers zero non-zero coefficients and ending at a λ of 0.00005 in a grid of 100. In each step, a different number of variables could be added or removed from the model.

[19]A test of the means of personal characteristics for the estimation samples and the entire sample (N=805) shows no significant differences. The only exception is a slightly higher share of male respondents in the stock market regressions. We therefore consider the estimation samples to be representative of the entire sample (N=805).

[20]In Appendix B.3, we test the robustness of our results using the five alternative approaches mentioned in Section 2.3.3. The results principally replicate.

[21]However, note that, unlike our method, Hilary and Menzly (2006) and Deaves et al. (2019) rely on indirect proxies to construct their measure of overprecision.

[22]We use the closing price based on the day of the interview to calculate exact forecast errors for each respondent. Note that the one-year-ahead observations from the 2018 waves are almost all from

Table 2.2: Results of the baseline analysis

This table presents the estimation results as described in Section 2.3.4. Each row is a separate analysis with the respective dependent variable listed in the left column. The number of observations (Column (7)) varies due to missing observations in the outcome variable. The maximum number of observations is 805. Column (1) lists the point estimate of the standardized overprecision measure *sop* from the full regression as specified in Section 2.3.4.1 along with the unadjusted p-value (Column (2)) and the Sidak-Holm adjusted p-value for multiple hypothesis testing (Column (3)). Column (4) displays the result from the R^2 procedure specified in Section 2.3.4.1 along with the maximum possible variables to be included in the model. The regressions with political outcomes as dependent variable additionally include a self-reported measure of political interest. Column (5) specifies the result of the LASSO procedure as specified in Section 2.3.4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)). Variable definitions are in Table B.2.3 in the appendix. Stars indicate significance: $^{*}p < 0.10, ^{**} p < 0.05, ^{***} p < 0.01$.

Dependent variable	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) LASSO R^2	(7) N
Financial Behavior:							
DAX forecast error	0.083*	0.056	0.108	4/41	yes/14	0.10	548
1-year ahead	*0.529*	*0.308*		*7/41*	*yes/21*	*0.16*	*578*
2-year ahead	*3.078***	*0.016*		*4/41*	*yes/8*	*0.04*	*557*
portfolio diversification	-0.131***	0.000	0.002	3/41	yes/19	0.14	774
Political Behavior:							
extremeness	0.087**	0.041	0.117	6/42	yes/14	0.05	716
left-right	-0.008	0.854	0.854	18/42	no/14	0.08	716
non-voter	0.032**	0.011	0.041	3/42	yes/18	0.14	706

single forecast errors might be prone to random noise, we aggregate both errors using the principal component, which we standardize to be mean zero and standard deviation one (*DAX forecast error*).[23] Additionally, we report the results for both forecast errors separately (*1-year ahead* and *2-year ahead*).[24]

The results in Table 2.2 show that our measure of overprecision is positively correlated with forecast errors in asset prices. An increase in overprecision of 1 standard deviation is associated with an increase in the principal component in the forecast errors by 0.083 standard deviations. The LASSO estimation results reveal that overprecision is also a good predictor of these forecast errors since it is selected as an explanatory variable for the models of stock market forecasts; it also ranks fourth in the R^2 rank approach.

Next, we test the theoretical prediction by Odean (1998) that overprecision is associated with underdiversified portfolios. Intuitively, overprecise investors overweigh

the period before March 2019 and are thus unaffected by the stock market decline caused by the coronavirus crisis in March 2020.

[23]The principal component analysis shows a strong first factor with an eigenvalue of 1.65. All other factors are below the common cutoff of 1.0.

[24]We include a dummy variable that indicates asset ownership as possible control variables in the predictions to account for different information sets in a robustness test in Table B.2.6 in the appendix. The qualitative results remain unaffected by this change, although the sample size decreases.

their private information, thereby trading too frequently while concentrating on an overly limited number of favorable assets. Goetzmann and Kumar (2008) provide empirical evidence supporting this prediction for traders in the US and Merkle (2017) does so for traders in the UK. While the former relies on the asset turnover proxy, the latter elicits overprecision directly through survey questions. We test this hypothesis using a standardized measure with mean 0 and standard deviation of 1 that captures the degree to which a respondent diversifies her hypothetical portfolio among stocks, real estate, government bonds, savings, and gold (*std_divers*).[25]

It is important to note that by this approach, we do not make any claim on the optimal degree of portfolio diversification. We rather test whether, conditional on the individual degree of risk aversion, overprecision is associated with a tendency towards a certain asset category. We argue that this approach is in line with the theoretical arguments of Odean (1998) who shows that overconfident traders overreact to their personal information and underdiversify by investing more in a certain asset.

Our results confirm the theoretical prediction that overprecision is associated with underdiversification. The point estimate in Column (1) in Table 2.2 shows that a 1 standard error increase in overprecision leads to a 0.131 standard deviation decrease in our diversification measure. That means that the optimal portfolio of overprecise respondents is skewed towards a certain asset category. Moreover, overprecision is among the LASSO estimation variables and ranked third in the R^2 rank approach.

Political Views and Voting Behavior

According to Ortoleva and Snowberg (2015b), overprecision leads people to believe that their own experiences are more informative about politics than they really are. For instance, overprecise people may consult biased media outlets without fully accounting for this bias or exchange information on social media without realizing that much of the information comes from politically like-minded peers. Against this background, the authors show theoretically and empirically that overprecision leads to ideological extremeness and strengthens the identification with political parties, increasing the likelihood to vote. Yet, the literature remains inconclusive on whether these associations hold for liberals and conservatives alike. While Moore and Swift (2011) and Ortoleva and Snowberg (2015b) find that conservatives seem more susceptible to overprecision than liberals, Ortoleva and Snowberg (2015a) show that this association only

[25]For a detailed description of the measure, see Table B.2.3 in the appendix. The measure of diversification displays an inverse-U relation with risk aversion. More risk-averse respondents skew their portfolio toward safer assets such as savings and gold whereas more risk-loving respondents skew their portfolio toward riskier assets such as stocks and real estate. This lends credibility to the diversification measure.

holds in election years.

To test whether overprecision correlates with the political preferences of respondents, we use their self-reported ideology on a scale from 0 (extreme left) to 10 (extreme right) to construct the variable *left-right*. Using the answer to the same question, we also construct *extremeness*, which measures from 0 to 5 how far away from the political center respondents see themselves. We standardize both variables to be mean zero and standard deviation one. Finally, to study whether overprecise respondents are more likely to vote, we use a dummy that equals 1 if a respondent indicated being a non-voter in the (ex-post) opinion poll (*Sonntagsfrage*) for the 2017 federal elections to the German *Bundestag* (*non-voter*).

In line with Ortoleva and Snowberg (2015b), the results of Table 2.2 suggest that overprecision is correlated with ideological extremeness. Overprecision is among the variables chosen by the LASSO estimation and ranks high (sixth) in the R^2 rank approach. Confirming Ortoleva and Snowberg (2015a), we do not find evidence that overprecision is associated more strongly with any side of the political spectrum, as it is not correlated with political ideology and is not among the variables chosen by the LASSO estimation. Furthermore, overprecision is ranked quite low (18/39) in the R^2 rank approach. Finally, we find that overprecision is a strong predictor of voting absenteeism, with overprecision being chosen by the LASSO estimation and ranked third in the R^2 rank approach. Hence, it seems that overprecision increases the likelihood of voting absenteeism rather than increasing the likelihood of voting: An increase in the standard deviation for overprecision of 1 results in a 3 percentage point increase in the likelihood of not voting.

The last result seems to be in contradiction with the result of Ortoleva and Snowberg (2015b). However, the voting behavior of overprecise respondents in the United States and Europe is difficult to compare. In Ortoleva and Snowberg (2015b) partisanship is measured *within* the Republican and Democratic parties. Because both of these parties have high chances of winning the elections, those more identified with such parties have stronger incentives to vote for them Miller and Conover (e.g., 2015). By contrast, in Germany, more extreme respondents gravitate to fringe parties (e.g., Die Linke, AfD, NPD)[26] with smaller chances of winning elections, so the incentives to vote are very different than for those in the dataset used by Ortoleva and Snowberg (2015b).[27] Hence, the theoretical assumptions underlying the predictions made by

[26]If we pool all respondents voting for radical parties (AfD, NPD, and Die Linke) and compare them to the voters of the rest of parties, a nonparametric test confirms the tendency of radical party voters to ideological extremeness (Mann-Whitney U p-value<0.001).

[27]Take as an example the explicit (self-imposed) *cordon sanitaire* that all major democratic parties have imposed around the AfD. Angela Merkel's intervention and the series of resignations that followed the 2019 Thuringian election shows how strongly this *cordon* is enforced.

Ortoleva and Snowberg (2015b) regarding voter turnout and overprecision are a good description of voting behavior in the two-party system of the United States but are not appropriate for the more disperse German system.

The results in this section show that the majority of respondents in the sample are overprecise. Our measure of overprecision is correlated with a range of personal characteristics mostly consistent with previous results in the literature. Moreover, in line with the theoretical literature, we find that overprecision is positively correlated with stock market forecast errors, negatively correlated with portfolio diversification, and positively correlated with political extremism. Taken together, these results suggest that our measure of overprecision captures a type of behavior that is consistent with overprecision.

2.4 The Subjective Error Method Across Domains

The results from Section 2.3 show that our measure of overprecision is associated with different aspects of respondents' behavior and aligns with theoretical predictions. The fact that overprecision is measured in a completely unrelated domain suggests that overprecision is an underlying personality trait. To test whether the Subjective Error Method described above consistently captures overprecision across different domains and, ultimately, whether overprecision is a persistent personality trait, we run a *pre-registered* online survey in a representative sample of the German population.[28]

2.4.1 Survey Design

The survey consists of five independent domains of five questions each, with all respondents going through all questions (see the full set of questions in Table B.2.7 in the appendix). The five domains are:

1. ***Neutral***: In this domain, respondents are flashed for 8 seconds with five different 20x20 matrices of black triangles and gray squares. After each matrix, they are then asked to estimate the number of black triangles in each of the five shown matrices and to report their subjective error. This task is similar to that of Bosch-Rosa et al. (2020) and has the advantage that it is independent of any socio-economic traits, such as wealth or education, and avoids any heterogeneity in experience and prior knowledge across respondents.

[28] The online survey and its analysis were pre-registered at AsPredicted.org (#118284) and the survey was administered by Bilendi/Respondi.

2. ***Contemporary history***: In this domain, we ask the five most answered historical questions in the SOEP survey as described in Section 2.3. The contemporary history domain allows us to correlate the results of the online survey and those of the SOEP survey in Appendix B.4.

3. ***General knowledge***: In this domain, respondents answer five numerical general knowledge questions and report their subjective error for each one. Some examples of questions in this domain include the number of teeth of a polar bear, the number of keys on a concert piano, or the number of African countries that are part of the UN. This domain captures a wide range of knowledge types and allows us to test the robustness of overprecision and the Subjective Error Method across various topics.

4. ***Future stock prices***: In this domain, respondents are asked to predict the 28-day forecast for the price of five different assets (Benz, Puma, BMW, Deutsche Post, BASF) and report their subjective error for each one. This domain enables us to test overprecision in the financial domain and, importantly, measures overprecision of future events. Unlike the other domains, subjects are guessing about something that will happen, not something with a correct answer at the time they are asked.

5. ***Economics***: In this domain, respondents answer five questions related to the German economy and report their subjective error for each one. To maintain consistency in the range of answers across questions, this domain is limited to percentage changes. Some examples include the percentage change in the German CPI from 2011 to 2021, the percentage change in the German nominal GDP from 2006 to 2021, or the percentage change in the German DAX from 2014 to 2021. We include this domain given the importance of overprecision in economic decision-making and close to the financial behavior we analyze in the SOEP survey.

We randomize the order of the domains except for the first domain, which was always the neutral domain. This was done because, in the neutral domain, we include three practice rounds before the five rounds we use to measure overprecision to familiarize respondents with the matrices. The difference between practice rounds and the main rounds is that in the practice rounds the correct answer is shown to the respondents after answering the questions, which is not the case in the main rounds. To account for the use of *Google* or other search engines in the other domains, we ask subjects at the end of the survey whether they used such methods to answer our survey. Additionally, in the contemporary history, general knowledge, and economic domains we included an extra question that acts as "*Google* control." These questions are presented in the same format as all other questions but are difficult and unlikely to be known by respondents.[29] Importantly, the answers to the *Google* controls are not used to measure the overprecision of respondents.

In addition to the key dependent variable specified above, we collect demographic variables such as age, gender, years of education, income, nationality, and mathematical literacy determined by solving three mathematical problems. For each domain, before the start of the questions, we ask respondents to self-report their knowledge of the topic on a scale of 0 (not knowledgeable at all) to 100 (very knowledgeable). Finally, to ensure high-quality data, at the end of the survey, we ask respondents to self-report the amount of effort they put into answering the survey and include attention checks in all domains. Respondents that fail the attention checks are automatically excluded from the survey.

2.4.2 Data

We collected 1.000 complete responses. To ensure that we only keep informative responses, we exclude all respondents who admit to using a third party to answer our questions from the analysis. We also exclude respondents who we identify as '*Googlers*' by using our control questions. Additionally, we exclude the lowest five percentiles on the self-reported effort measure. This leaves us with 839 respondents for the baseline analysis.[30] The summary statistics of both the full sample and the sample after the data cleaning process can be found in Table B.2.10 in the appendix. A full list of variables can be found in Table B.2.9 in the appendix. The data-cleaning process does not substantially alter the sample composition with respect to the collected variables.

[29]Following our pre-registration, we consider a respondent to have used a search engine if two conditions are met: answering the *Google* controls correctly and stating a subjective error of zero, and answering correctly and stating zero subjective error for at least three other questions in this domain. The respondent is then excluded from the entire analysis if this behavior is detected in any domain. The *Google* control questions are the year in which Joachim Sauer, husband of Angela Merkel, was born (1949), the upper bound in kilograms of the Bantamweight class in female Olympic boxing (54kg), and the percent change of M1 in the Euro area from 2015 to 2021 (86%).

[30]We show the robustness of the results in this section in Appendix B.5 using different other exclusion restrictions on the sample as specified in the pre-registration.

2.4.3 Measuring Overprecision

To have an overview of the data, in Figure 2.5 we plot the distributions of the answers in all five domains.[31] As can be seen, for most of the questions across the five domains, the answers are distributed around the true answer. This indicates that respondents were paying attention and could answer the questions presented. Nonetheless, it is also clear from the dispersion of the answers and the distance of the mode to the true answer that some questions were easier to guess than others. In Figure 2.6, we plot the realized true error ($error_{i,j}$) on the vertical axis against the subjective error ($se_{i,j}$) on the horizontal axis for each of the five questions in each domain.[32] We add a 45-degree line, so that any dot above is an overprecise observation ($error_{i,j} > se_{i,j}$) and any point below is underprecise ($error_{i,j} < se_{i,j}$). The results show that respondents are, on average, overprecise in their answers across all questions independent of the domain.

2.4.4 Overprecision Across Domains

To test whether respondents are overprecise across domains, we construct an aggregate overprecision measure for each domain using the simple mean.[33] For better comparability, we standardize the aggregate measure for each domain to have a zero mean and a standard deviation of one as we did with the SOEP data.[34] Following our pre-registration, for each domain, we only construct the aggregate overprecision measure if the respondent answered at least four out of the five questions to have meaningful estimates and decrease the noise. We then analyze the relationship in three ways: i) via a principal component analysis, ii) via a partial correlation analysis, and iii) via a leave-one-out analysis.[35]

Principal Component Analysis (PCA): the principal component analysis (PCA) is a dimensionality-reduction method for large datasets that identifies common patterns among the variables and creates new latent variables (the principal components) that capture as much variation (variance and covariance) of the dataset as possible. All

[31]We plot the distribution of the answers to the three questions which we use to detect respondents who we assume to have used search engines in Figure B.1.3 in the appendix.

[32]We plot the realized true error ($error_{i,j}$) against the subjective error ($se_{i,j}$) for the three questions we use to detect respondents who we assume to have used search engines in Figure B.1.4 in the appendix.

[33]Before aggregating, we divide the answers in the neutral domain by 4 since the scale differs. In our pre-registration, we specified that we would use both the simple average and the principal component across all domains. However, since the results only marginally change, we do not report the results using the principal component as aggregation method, which are available upon request.

[34]Standardizing the aggregate measure does not change the qualitative results.

[35]We show the robustness of the following results in Appendix B.5 using different exclusion restrictions on the sample as specified in the pre-registration.

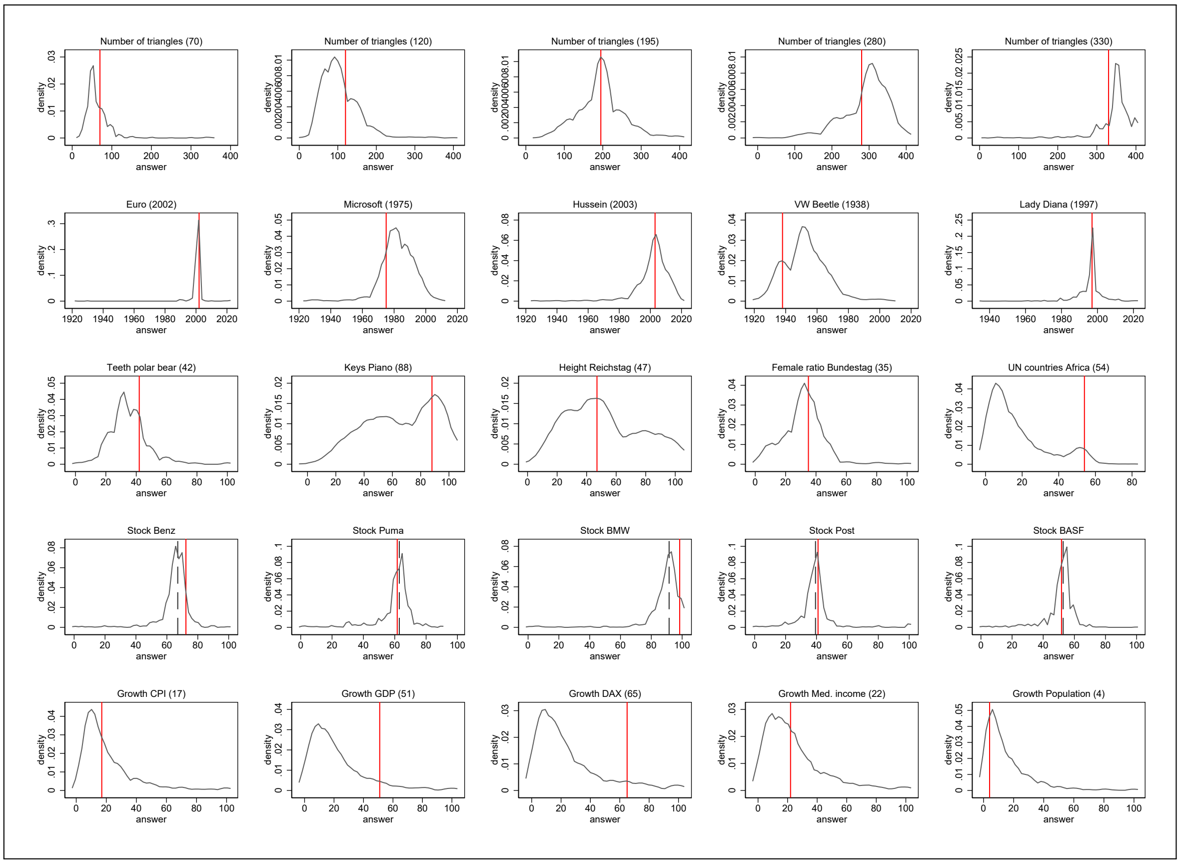


Figure 2.5: Distributions of the answers to each question (survey)

This figure shows the density of the answers ($a_{i,j}$) to each question in all five domains. The vertical red line marks the correct answer. For the stocks, the vertical red line marks the weighted average of the 28-day-ahead stock price and the vertical black dashed line the weighted average of the stock price on the day of the interview. Note that the vertical axis is different for each question. The corresponding graphs for the additional questions to detect the use of search engines can be found in Figure B.1.3 in the appendix.

principal components can be ranked by their eigenvalues, with the first principal component capturing the most variation in the data. This first component identifies the most important underlying pattern in the data and is the most important latent variable in the dataset. In our case, if our measures of overprecision across domains can be reduced to one single principal component, we interpret this as capturing the individual overprecision of respondents and showing that respondents are overprecise across domains. The analysis is based on the 552 respondents for which we could calculate an aggregate score for every domain. The results yield only one factor with an eigenvalue above the Kaiser criterion of 1.0, which implies that there is only *one* latent variable that explains the observed variance and covariances of the five items. Moreover, the factor loadings across all five domains are positive, which shows that this trait is persistent across the five domains. [36] In other words, the principal component analysis shows

[36] The eigenvalue of this factor is 2.29, with the respective factor loadings are 0.52, 0.76, 0.74, 0.69, and 0.65.

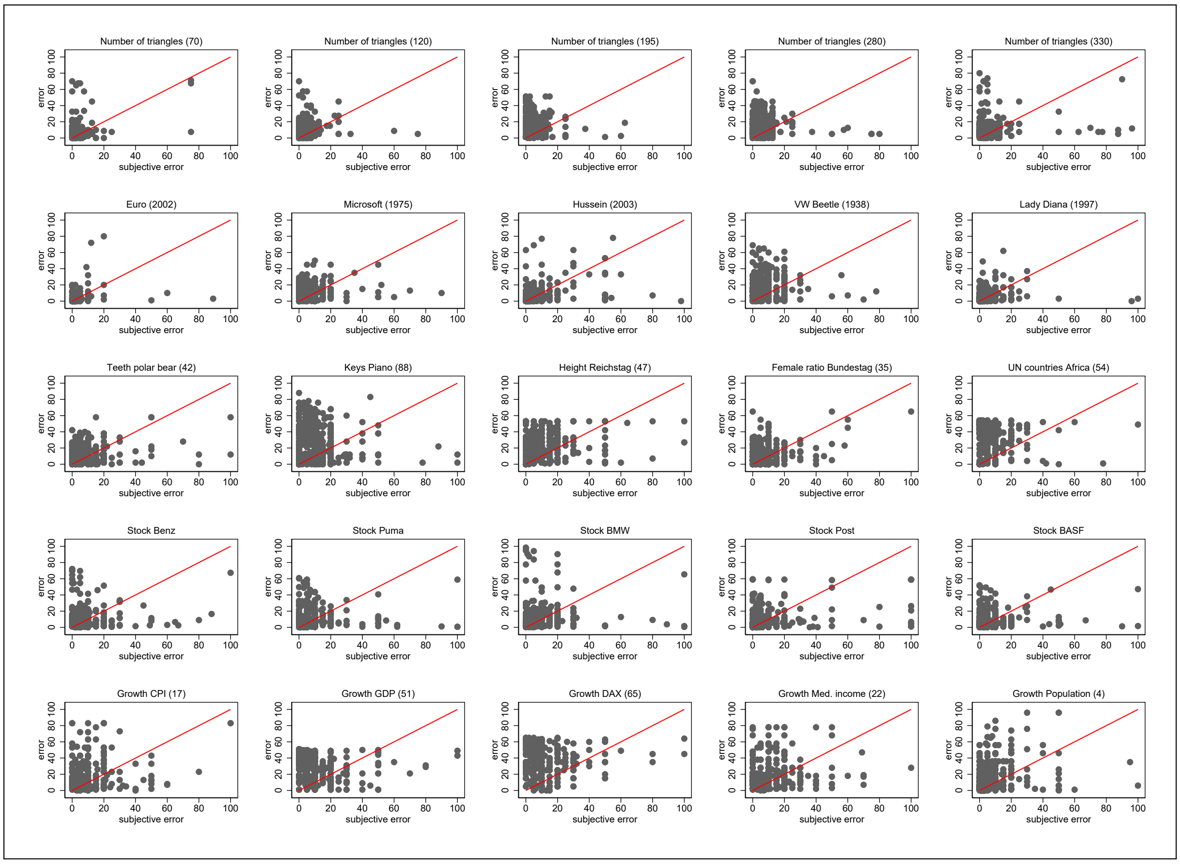


Figure 2.6: Relation between the true error and the subjective error (survey)

This figure shows the relation between the realized true error ($error_{i,j}$) in the vertical axis and the subjective error ($se_{i,j}$) in the horizontal axis for each question in all five domains. Any dot above (below) the 45-degree red line is an overprecise (underprecise) answer by the respondent. Note that the results for the neutral domain are divided by four to make the results comparable to the other domains. The corresponding graphs for the additional questions to detect the use of search engines can be found in Figure B.1.4 in the appendix.

that there is only one underlying factor that can explain the observed variation in the overprecision measures and that all domains contribute positively to it. Therefore, we interpret this factor to be the individual overprecision of respondents.

Partial correlation analysis: the partial correlation analysis allows us to measure the correlation across domains by controlling for the socio-demographic characteristics of respondents. To do so, we estimate the correlation across the domain-specific measures of overprecision that would be observed between the two variables under consideration if all other control variables were fixed. Table 2.3 shows the partial correlation coefficients after controlling for age, gender, education, income, nationality, state, mathematical literacy, and a measure of self-reported knowledge on the topic of the domain. The results show that the Subjective Error Method measures of overprecision are positively correlated across domains, with the strongest correlation being between contemporary history and general knowledge. These results are confirmed

Table 2.3: Partial correlation coefficients between domains

This table presents the estimated partial correlation coefficients ρ between the aggregate overprecision measures across the five domains. The control variables are age, gender, education, income, nationality, state, mathematical literacy, and a measure of self-reported knowledge on the topic of the domain. Variable definitions are in Table B.2.9 in the appendix.

Domain 1	Domain 2	ρ	standard error	N
Neutral	History	0.17	0.03	688
Neutral	Knowledge	0.21	0.04	626
Neutral	Stocks	0.30	0.04	676
Neutral	Economics	0.18	0.04	639
History	Knowledge	0.52	0.04	609
History	Stocks	0.35	0.04	638
History	Economics	0.37	0.05	620
Knowledge	Stocks	0.34	0.04	591
Knowledge	Economics	0.32	0.04	580
Stocks	Economics	0.28	0.04	618

graphically in Figure 2.7, where we show a binned scatter plot of the aggregate overprecision measure across each pair of domains.

Leave-one-out analysis: the leave-one-out analysis follows the methodology described in Morrison and Taubinsky (2019). We first calculate the distribution of the aggregate overprecision measure for each domain. For each pair of domains, we then partition the sample into the highest 25% (group 1) and the lowest 75% (group 2) based on the overprecision measure in one domain and then test whether the overprecision measure in the other domain is significantly larger for group 1 than for group 2 using a standard t-test. The intuition of this method is that if the Subjective Error Method is capturing the same trait across domains, then the highest 25% in one domain should also be more overprecise in the other domain. We report the results of these pairwise comparisons in Table 2.4. The results show that for all pairwise combinations, overprecision is significantly higher in the second domain for those individuals which are in the highest overprecision group in the first domain.

Taken together, the results from all three pre-registered analyses show that there is a strong relationship between the overprecision measures across all domains. This indicates that the Subjective Error Method consistently measures overprecision across domains and, importantly, that overprecision is a stable personal trait across different domains at a given point in time. The results from the leave-one-out analysis in particular suggest, that it is possible to measure overprecision in a different domain than outcome variables of interest. This further supports the analysis in Section 2.3, where we analyze the relationship between overprecision measured in the domain of

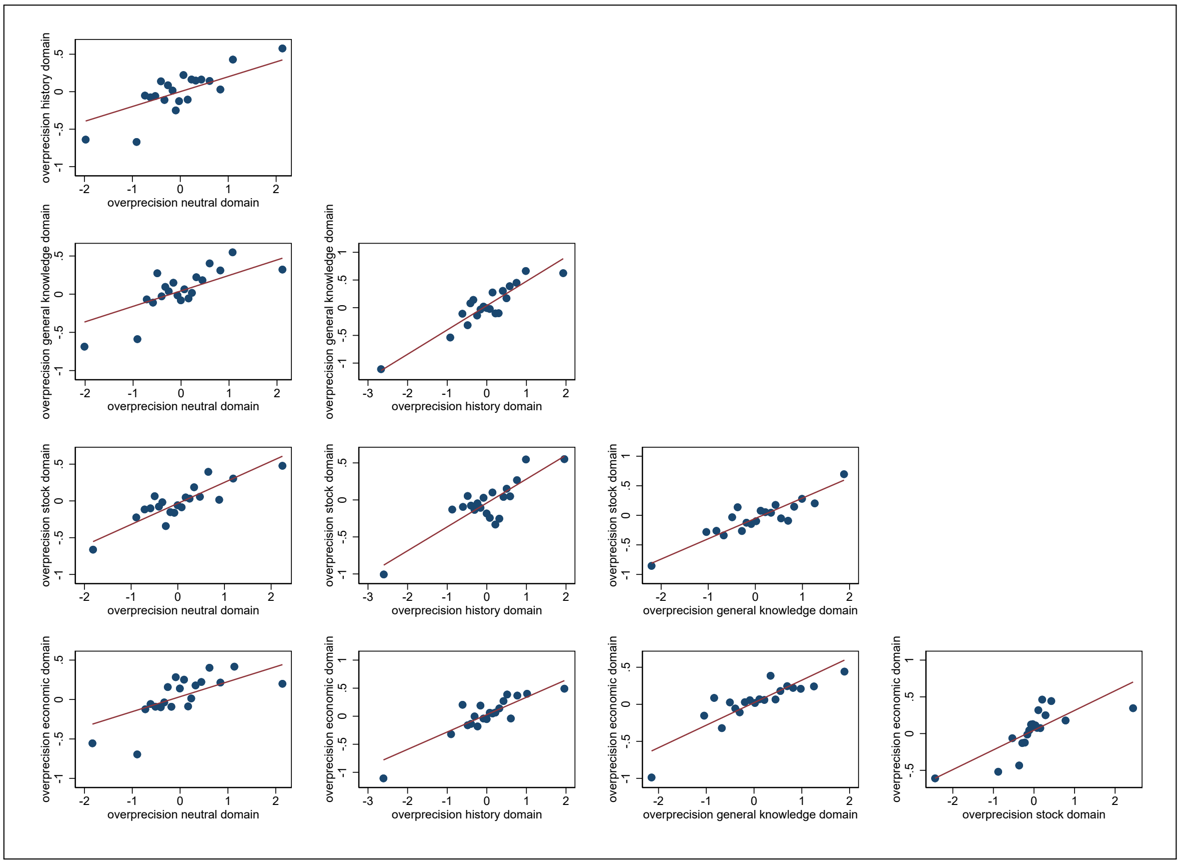


Figure 2.7: Binned scatter plots for each pair of overprecision measures

This figure shows binned scatter plots for each pair of overprecision measures. The number of bins is 20 in each plot. The red line is a linear fit between the two domains.

historical knowledge and the financial and political behavior of individuals.

2.5 Conclusion

We study how overconfidence correlates with the political and financial behavior of a nationally representative sample. To do so, we implement the Subjective Error Method in the 2018 wave of the Innovation Sample of the German Socio-Economic Panel (SOEP-IS). The Subjective Error Method is a new way to measure overprecision that, in contrast to previous methods, is intuitive to respondents and quick to implement.

We show that our measure of overprecision lends empirical support to several theoretical predictions from the financial and political science literature. Specifically, overprecision correlates with larger forecasting errors in predicting stock prices (Odean, 1998) and lower levels of portfolio diversification (Barber and Odean, 2000). Additionally, as predicted and shown in Ortoleva and Snowberg (2015a), more overprecise

Table 2.4: Results of the leave-one-out analysis between domains

This table presents the results of the leave-one-out analysis between the domains. *In sample* signifies the domain in which the quartiles based on overprecision were computed. The sample is then partitioned into the lower 75% and upper 25% groups. *Out sample* signifies the domain in which overprecision is then measured and tested between both groups. *Lower 75%* shows the means, standard deviation, and the number of observations in the *Out sample* for the lower three quartiles of overprecision based on the *In sample* and *Upper 25%* the means, standard deviation, and the number of observations in the *Out sample* for the upper quartile. The last column reports the p-values from two-sided t-tests of the difference against the value 0.

Sample		Lower 75%			Upper 25%			Difference	
In	Out	mean	sd	N	mean	sd	N	Δ	p-value
Neutral	History	-0.08	1.09	540	0.27	0.71	163	-0.35	< 0.01
Neutral	Knowledge	-0.06	0.88	484	0.35	0.96	149	-0.41	< 0.01
Neutral	Stocks	-0.10	0.92	522	0.24	0.99	168	-0.34	< 0.01
Neutral	Economics	-0.04	0.90	495	0.29	0.69	152	-0.32	< 0.01
History	Neutral	-0.05	0.86	621	0.16	1.23	165	-0.22	0.01
History	Knowledge	-0.09	0.90	489	0.48	0.84	144	-0.57	< 0.01
History	Stocks	-0.11	0.87	536	0.32	1.09	154	-0.43	< 0.01
History	Economics	-0.05	0.90	499	0.34	0.69	148	-0.38	< 0.01
Knowledge	Neutral	-0.05	0.92	629	0.18	1.05	157	-0.23	0.01
Knowledge	History	-0.10	1.06	552	0.35	0.79	151	-0.45	< 0.01
Knowledge	Stocks	-0.09	0.88	541	0.24	1.12	149	-0.32	< 0.01
Knowledge	Economics	-0.03	0.91	499	0.27	0.67	148	-0.30	< 0.01
Stocks	Neutral	-0.10	0.88	621	0.35	1.12	165	-0.45	< 0.01
Stocks	History	-0.09	1.05	551	0.33	0.81	152	-0.42	< 0.01
Stocks	Knowledge	-0.04	0.90	499	0.33	0.90	134	-0.37	< 0.01
Stocks	Economics	-0.05	0.87	495	0.32	0.78	152	-0.37	< 0.01
Economics	Neutral	-0.07	0.93	634	0.27	0.99	152	-0.34	< 0.01
Economics	History	-0.08	1.06	561	0.31	0.77	142	-0.38	< 0.01
Economics	Knowledge	-0.02	0.89	500	0.27	0.97	133	-0.29	< 0.01
Economics	Stocks	-0.10	0.91	542	0.28	1.01	148	-0.38	< 0.01

respondents hold more extreme political ideologies. As for the socio-demographic determinants of overprecision, we find that years of education, age, and gross income reduce respondents' overprecision but do not detect any effect of gender on overprecision. Further, we find a negative relationship between overprecision and financial literacy and, as one would expect, a positive relationship between overprecision and narcissism. Both the relationship with respondents' behavior and with the socio-demographic determinants are robust to a series of modifications, lending further credence to our approach.

To test whether the Subjective Error Method consistently measures respondents' overprecision across domains (and ultimately if overprecision is a personality trait), we administered a companion survey to a representative sample of the German population across five different domains. We elicited oveprecision in contemporary history, general knowledge, economics, four-week ahead stock price predictions, and a "neutral" task that respondents had not encountered before. The results confirm the robustness of our measurement procedure suggesting that the Subjective Error Method captures a personality trait that is persistent across different domains.

Overall, our work contributes to a literature that tries to understand overconfidence, "the most significant of the cognitive biases" (Kahneman, 2011), and how it affects our lives. Because we show that overconfidence is a trait that is robust across domains which can result in reckless behavior and lead to extreme political views, our results and methodology should be of interest not only to economists and political scientists but also to psychologists, financial researchers, policymakers, and educators.

Chapter 3

Managerial Overconfidence and Bank Bailouts

This chapter is based on a co-authored publication with Daniel Gietl. See Gietl and Kassner (2020) for the full reference of the published version.

3.1 Introduction

Excessive risk-taking in the banking sector played an important role in the financial crisis of 2007-2009 (see e.g., Thakor, 2015). Banks worldwide invested in large stocks of subprime mortgage-backed securities, which resulted in the bursting of the US housing bubble in the fall of 2007 (see e.g., Diamond and Rajan, 2009). Two of the main reasons for excessive risk-taking in the banking sector - which have so far only been considered independently - are government guarantees and managerial overconfidence.

In the part of the finance literature assuming perfectly rational agents, government guarantees are seen as a major cause for excessive risk-taking, as they weaken the incentive for bank creditors to price in banks' risk-taking. This lack of market discipline makes it attractive for shareholders to shift losses to the government. The empirical relevance of this risk-shifting incentive has been shown repeatedly. In the United States, for example, financial institutions that had previously received government assistance under the Troubled Asset Relief Program subsequently shifted to riskier assets (Duchin and Sosyura, 2014). In Germany, savings banks that had their government guarantees removed cut their credit risk substantially afterwards (Gropp et al., 2014).

In the behavioral finance literature, overconfident managers are seen as a core reason for excessive risk-taking.[1] Overconfident managers overestimate the expected return on risky investments, which causes them to take on higher risks (see e.g., Hirshleifer and Luo, 2001; Malmendier and Tate, 2008; Gervais et al., 2011). Overconfidence is particularly pronounced in complex, high-risk environments with noisy feedback, and thus under conditions that are vividly present in the banking sector.[2] Indeed, there is comprehensive evidence that banks with overconfident CEOs take on more risk. Banks governed by overconfident CEOs were more aggressive in lending before the financial crisis of 2007-2009. During the crisis years, these banks suffered from greater increases in loan defaults, larger declines of stock return performances, and a higher likelihood of failure than banks managed by non-overconfident CEOs (Ho et al., 2016).[3]

It is well established that managerial overconfidence and moral hazard arising from government guarantees cause excessive risk-taking in the banking industry. Up to this

[1] Moore and Healy (2008) distinguish three notions of overconfidence: overestimation, overplacement, and overprecision. We focus on overconfidence as the manager's *overestimation* of the success probability of his investment. Hence, we relate to the empirical literature that investigates the effects of overconfidence in the sense of overestimation on firm outcomes by using personal portfolios of top managers as a proxy for overconfidence (see e.g., Malmendier and Tate, 2005a; Deshmukh et al., 2013).

[2] While there is substantial evidence that individuals generally overestimate their own abilities and talents (e.g., Taylor and Brown, 1988), there are several reasons why bank managers are supposed to be even more overconfident than the lay population (see Section 3.2.4 for details). Glaser et al. (2005) find that professional traders and investment bankers are indeed more overconfident than students.

[3] In addition, banks with overconfident CEOs generally experience higher stock return volatility (Niu, 2010) and have shown higher real estate loan growth prior to the financial crisis (Ma, 2015).

point, however, overconfidence and government guarantees have not been analyzed in a common framework. It is thus neither clear how to regulate and tax financial markets that are simultaneously characterized by these two features, nor how banks set up contracts in such an environment. We aim to fill these gaps by incorporating managerial overconfidence and limited bank liability into a principal-agent model of the banking sector. In this setting, we allow the government to optimally set a bonus tax in order to correct for the inefficiencies resulting from overconfidence and government guarantees.

Our model consists of three stages and three players. In the first stage, the government sets the welfare-maximizing bonus tax. We define welfare as the weighted sum of the bank's profit, the manager's utility, the government's bonus tax revenue and bailout costs. Stage 2 turns to the bank's maximization problem. The bank chooses the performance-related bonus and the fixed wage that maximize the bank's expected after tax profit. In the third stage, the manager decides whether to accept the bank's contract. If the manager accepts the contract, he chooses the level of effort and risk-taking.

Based on the work of Besley and Ghatak (2013) and Hakenes and Schnabel (2014), we incorporate two principal-agent problems in our model. The first principal-agent problem arises between the government and the bank because of government guarantees. Government guarantees imply that the government will step in to partly bail out external investors if the bank defaults. External investors, knowing that they are paid even in case of a bank default, do not fully price in the bank's risk. Hence, the bank has an incentive to induce excessive risk by means of high bonuses in order to draw on the government guarantees.[4] The second principal-agent problem arises between the bank and the manager. The banker has costs from effort- and risk-taking and thus does not provide as much effort and risk as desired by the bank. Since the bonus increases effort- and risk-taking, the bank can use it to influence both principal-agent problems to its own advantage.

The other key feature of our model - besides the moral hazard resulting from government guarantees - is managerial overconfidence. Seminal findings in the psychology literature show that individuals overestimate the probabilities of advantageous events, especially if the individuals believe to have control over the probabilities of those events (e.g., Langer, 1975) and if they are highly committed to the outcome (e.g., Weinstein, 1980). We incorporate these findings by modeling overconfidence as an overestimation of the returns to risk-taking. This implies that an overconfident manager takes greater

[4] Caprio and Levine (2002) highlight two features that differentiate banks from nonfinancial firms. First, the greater safety net that accompanies banks. And second, the opaqueness of banks, which amplifies agency problems.

risk, increases risk more strongly for a marginal increase in the bonus, and overvalues the expected utility that he obtains from the bonus.

Our analysis delivers three results. First, we derive the optimal bonus tax and find that it always increases in overconfidence, if returns to risk-taking are positive. Government guarantees lead to inefficiently high risk-taking, which is especially attractive for the bank to exploit when the manager is overconfident. In systemically important financial institutions, it is thus optimal to curb the social implications of overconfidence with a larger bonus tax.

Second, our main result is that managerial overconfidence always necessitates an intervention into banker pay, even if shareholders fully internalize the bailout costs. Overconfidence creates an incentive for the bank to increase its bonus in order to save compensation costs, because an overconfident manager overvalues the utility derived from bonuses. This incentive drives up bonuses and thus causes socially excessive risk-taking, even if shareholders have no incentive to draw on government guarantees. Unlike instruments regulating shareholders risk-taking incentives (e.g., capital requirements), a direct intervention into banker pay (via bonus taxes or bonus caps) can implement the socially desirable bonus, because these instruments additionally tackle the inefficiencies arising from the manager's overvaluation of the bonus.

Third, we find that overconfident bankers and banks with large government guarantees match in equilibrium. As banks with larger government guarantees benefit more from inducing excessive risk-taking by the manager, these banks also benefit more from hiring an overconfident manager. The selection of overconfident managers into banks that receive large bailout subsidies has substantial implications for taxpayers. It leads to a high default risk of these banks and causes large expected bailout costs for taxpayers. We argue that direct interventions into banker pay (e.g., a bonus tax or cap) are particularly suited to avoid the matching between overconfident managers and banks with large government guarantees.

Taken as a whole, the three main results of our project suggest that the presence of managerial overconfidence calls for bonus taxes in systemically important financial institutions. Bonus taxation can curb the bank's risk-shifting incentives, deter the exploitation of managerial overvaluation, and avoid the selection of overconfident managers into systemically important financial institutions.

Our project relates to three strands of the literature. First, it relates to the literature on the optimal taxation and regulation of banker compensation. Besley and Ghatak (2013) examine the optimal tax scheme for banker compensation in financial markets that are characterized by government guarantees. They find that this optimal tax-scheme is progressive in the size of the government guarantee and can increase both equity and efficiency. Radulescu (2012) shows, using a principal-agent model, that without relocation of managers, a country that does not introduce a exogenous bonus tax will be worse off in terms of welfare whereas the result changes if managers can relocate. Investigating the international competition for bank managers, Gietl and Haufler (2018) find that there can be either a ‘race to the bottom’ or a ‘race to the top’ in bonus taxation when managers are mobile across countries and banks are protected by government guarantees. Hakenes and Schnabel (2014) and Thanassoulis and Tanaka (2018) investigate non-tax regulatory measures. Hakenes and Schnabel (2014) find that bonus caps are welfare-increasing for sufficiently large bailout expectations, because they curb the ability for banks to induce excessive risk. Thanassoulis and Tanaka (2018) show that a combination of clawback rules and restrictions on the curvature of pay can induce an executive to implement socially optimal risk choices. While these papers look at the optimal taxation and regulation, respectively, of compensation in the presence of government guarantees, they do assume fully rational bankers. Our project contributes to this strand of literature by investigating how taxation and regulation have to adapt when bankers are not fully rational but overconfident.

A second important strand of literature concerns the effects of managerial overconfidence. Following the seminal paper of Malmendier and Tate (2005a), an influential literature investigating the effects of managerial overconfidence on firm outcomes has emerged.[5] Empirical evidence shows that firms can benefit from CEO overconfidence, for example because overconfident CEOs capitalize on innovative growth opportunities better (Hirshleifer et al., 2012) and because firms can exploit the managerial overvaluation of incentive pay to lower compensation costs (Humphery-Jenner et al., 2016).[6] Overconfident CEOs, however, can also reduce shareholder value by engaging in value destroying investments and mergers (Malmendier and Tate, 2008). While this literature focuses on the impact of overconfidence on firm outcomes, we show how managerial overconfidence affects optimal government policies. More precisely, the project demonstrates that managerial overconfidence creates an incentive for the government to directly intervene into banker pay to tackle excessive risk-taking instead of using capital requirements to do so.

We also contribute to the literature on the matching between overconfident managers and firm characteristics. Gervais et al. (2011) analyze how compensation contracts optimally adapt to managerial overconfidence.[7] The authors find that, in equi-

[5] See Malmendier and Tate (2015) for an overview.

[6] The latter is a standard feature in behavioral contract theory (see e.g., Koszegi, 2014). De la Rosa (2011) and Gervais et al. (2011) show theoretically that firms have an incentive to exploit the managerial overvaluation of incentive pay.

[7] There is indeed evidence that firms adjust their contracts to managerial overconfidence. For instance, Humphery-Jenner et al. (2016) find that overconfident executives and non-executives receive

librium, overconfident managers are selected into risky, undiversified growth firms. Graham et al. (2013) show empirically that there is indeed a positive relationship between CEO overconfidence and growth firms. Beyond that, Hirshleifer et al. (2012) find that firms in innovative industries are more likely to be run by overconfident CEOs. Our project shows that overconfident managers may also match according to the regulatory environment faced by banks, and are more likely to be found in banks with large government guarantees, low bonus taxes, and lax capital requirements. Especially the first gives rise to an intervention by the government since here overconfident managers are especially harmful for the taxpayer.

This chapter is structured as follows. Section 3.2 introduces the basic setup of our three-stage model. Section 3.3 analyzes the risk-taking decisions of rational and overconfident managers. Section 3.4 investigates the maximization problem of the bank as well as the bank's optimal contract for the manager. Section 3.5 sets up the welfare function and derives the optimal bonus tax. Section 3.6 shows why overconfidence necessitates an intervention into banker pay. Section 3.7 investigates the competition for overconfident managers. Section 3.8 discusses several policy implications before Section 3.9 concludes.

3.2 Setup

In the following Section, we introduce the setup of our model. In Stage 1, the government sets its welfare-maximizing bonus tax t. In Stage 2, the bank, a financial intermediary which is financed through equity and deposits,[8] chooses the profit-maximizing bonus z, which depends on the investment return, and the fixed wage F. The bank is run by a manager who is hired by the shareholders. In Stage 3 we analyze the decision of the manager whether to accept the bank's contract based on his *perceived* expected utility. If the manager accepts the contract, he decides on the levels of effort, e_i with $i \in \{L, H\}$, which affects the bank's portfolio return, and of risk, $q \in [0, 1]$, of the bank's portfolio.

3.2.1 The Technology

We follow Bolton et al. (2015) in modelling the technology. By turning its liabilities V into a portfolio of assets, the bank can get a stochastic portfolio return $\tilde{y} - 1$ per unit

incentive-heavier compensation contracts.

[8]For brevity, we call these units banks. However, our model generally also applies to non-bank financial intermediaries which are characterized by government guarantees and strong agency problems.

of asset, where the portfolio value $\tilde{y}$ per unit of assets can take the following values:

$$\tilde{y} = \begin{cases} y + x(\alpha, e_i) & \text{with probability } \beta q \\ y & \text{with probability } 1 - q \\ 0 & \text{with probability } (1-\beta) q \end{cases}, \text{ with } y \geq 1. \tag{3.1}$$

Thus, after realization, bank value is given as $\tilde{y}V$. The corresponding probabilities of the returns are determined by the endogenous unobservable decision of the manager on risk-taking $q \in [0, 1]$ and the exogenous *return to risk* $\beta \in (0, 1)$. The parameter values are such that the probabilities are bounded between zero and one. If the manager does not take any risk, $q = 0$, the *safe return* of the portfolio is y.[9] Risk-taking q shifts probability mass away from the safe return to the tails. The high return $y+x(\alpha, e_i)$ with probability βq consists of the safe return and a risk premium $x(\alpha, e_i)$, where $x(\alpha, e_i)$ depends on the *return to effort*, $\alpha \in (0, 1)$, and the observable but unverifiable effort choice, e_i. We assume that the risk premium is positive, i.e., $x(\alpha, e_i) > 0$, and that effort positively influences the risk premium, i.e., $x(\alpha, e_H) > x(\alpha, e_L)$. Thus, higher effort e_H increases the mean return of the portfolio. Moreover, we assume that the difference $x(\alpha, e_H) - x(\alpha, e_L)$ is sufficiently large. We further assume that the marginal benefit for an increase in risk-taking is positive, i.e., $\frac{\partial E[\tilde{y}]}{\partial q} \equiv r_i = \beta(y + x(\alpha, e_i)) - y > 0$. This assumption simply states that β is sufficiently large such that risk-taking increases bank value in the absence of any bailouts.[10]

3.2.2 The Government

The government provides an incomplete deposit insurance, which we assume to be exogenously given, by paying a share $v_i \in [0, 1]$ of outstanding deposits to the depositors of bank i in the case of default ($\tilde{y} = 0$). We will formally introduce the deposit insurance in Section 3.2.3. A more complex model would motivate the existence of deposit insurance as a means to avoid bank runs when banks engage in maturity transformation (c.f. Diamond and Dybvig, 1983).[11] We, however, focus on the principal agent problems that characterize the banking industry and thus follow the dominant approach in the literature (e.g., Besley and Ghatak, 2013; Hakenes and Schnabel, 2014) and take government guarantees as exogenously given. In addition to the deposit

[9] We abstract from the probability of a crisis event, i.e., that even in the absence of risk-taking there is a positive probability for default. This could easily be incorporated, however, would make the model less tractable without altering the results.

[10] Relaxing this assumption would yield certain regions where risk-taking is not desired by the bank, if government guarantees are low, and, hence, a bonus would be zero. However, the core results of the project are unaffected by this assumption.

[11] See Barth et al. (2021) for an overview of deposit insurance schemes and a discussion of their welfare effects.

insurance, the government exogenously sets a minimum capital requirement $(1-s)$. As the bank prefers deposits over equity due to the deposit insurance, the capital requirement is always binding.

The government sets an optimal bonus tax to maximize welfare. Welfare is the weighted sum of profits Π, the managers utility u, and the government's net revenue, which is the revenue of the bonus tax T minus the bailout cost B, and is given by

$$W = \Pi + u + (T - B). \tag{3.2}$$

To isolate the role of taxation in the interaction of overconfidence and government guarantees, we assume that government revenue and private income have the same welfare weight. Hence, pure transfers from taxpayers to the bank have no effect on the welfare measure.[12] Our baseline model focuses on the bonus tax as policy instrument, as the bonus tax not only acts as a Pigouvian tax, but also redistributes from the financial sector to the government. This redistributive aspect reflects the goal of many governments to get the financial sector to "make a fair and substantial contribution toward paying for any burden associated with government interventions to repair the banking system" (International Monetary Fund, 2010).

3.2.3 The Bank

The bank transforms its liabilities according to the technology specified above. The bank's liabilities V, which we normalize to 1, are composed of a share $1-s$ of equity and a share s of deposits ($s \in [0,1]$) and covered by an incomplete deposit insurance as described above. The risk-neutral depositors demand an expected return of d per unit of deposits. As we normalize the bank's liability volume V to 1, depositors thus demand a total return of sd. We assume that, if positive returns are realized, the bank is able to repay the depositors an agreed return $s(d+X)$, where X is the additional unit return the depositors require in order to be compensated for their potential loss in the case of default. If the bank defaults ($\tilde{y} = 0$), the government steps in and pays the exogenous share $v_i \in [0,1]$ of sd to the depositors of bank i. This share v_i can be interpreted as the level of government guarantees that bank i receives. The *financing constraint* is then given by

$$[1-(1-\beta)q]s(d+X) + (1-\beta)qv_i sd = sd. \tag{3.3}$$

[12] We thank an anonymous referee for pointing this out. Refer to the working paper version (Gietl, 2018) for a solution with a higher welfare weight for government revenue.

Solving for X, we obtain

$$X = \frac{d(1-\beta)q(1-v_i)}{1-(1-\beta)q}. \tag{3.4}$$

Eq. (3.4) shows that the higher is the government guarantee v_i, the smaller is the extent as to which the default probability of the bank, $(1-\beta)q$, is priced in by depositors. If depositors are completely insured by the government (i.e., $v_i = 1$), they do not price in the default risk at all ($X = 0$), because the depositors receive their full repayment even in the case of bank default.

We assume that the manager is needed to run the bank and, thus, that it is always in the shareholders' best interest to hire the manager. The bank pays a non-negative bonus z_i depending on the output. The bonus takes the form

$$z_i = \begin{cases} z_H \geq 0 & \text{if } \tilde{y} = y + x(\alpha, e_H) \\ z_L \geq 0 & \text{if } \tilde{y} = y + x(\alpha, e_L) \end{cases}. \tag{3.5}$$

In addition to the bonus, the bank pays a non-negative fixed wage $F \geq 0$ to the manager regardless which return realizes.[13] This form of contract is consistent with limited liability since neither bonus payments nor the fixed wage can be negative.

We choose this form of contract since the shareholders, who are the residual claimants, want to induce effort and risk-taking. Since effort only affects the return under risk-taking, they pay a bonus to move mass away from the lower riskless return y. Moreover, a bonus under no risk-taking would lower the bank's profits derived from the government guarantee. From here it follows, that the bank does not pay a positive bonus in the case of default since this would incentivize the manager to take more risk than the shareholders prefer and thereby destroy firm value.

As deposits are partly insured by the deposit insurance, a first principal agent problem arises between the government and the bank. In the case of bank default, $\tilde{y} = 0$, the government partly bails out depositors. The partially insured investors do not fully price in the default probability of the bank, which enables the bank to shift losses to the government. Hence, the bank has an incentive to use the bonus z_i to incentivize the manager to take on excessive risk at the expense of the government.

The expected bank profit is, thus, given by

$$\Pi = \beta q[(y + x(\alpha, e_i)) - (1+t)z_i - s(d+X)] + (1-q)[y - s(d+X)] - F. \tag{3.6}$$

Eq. (3.6) shows that the expected bank profit consists of the state-specific profit of the bank weighted by the respective equilibrium probabilities minus the fixed wage. If the

[13]We thus assume that the bank's equity can cover the fixed wage.

bank realizes a return above y, it pays $s(d+X)$ to its depositors, the net bonus z_i to its manager, and bonus taxes tz_i to the government. If the bank realizes a portfolio return of y it pays back $s(d+X)$ to depositors. If the bank defaults, $\tilde{y}=0$, it does not pay back depositors. In this case the payments to depositors are partially covered by the deposit insurance, which does not enter the bank's profit expression. As the fixed wage F is paid by the bank in all states, bank's shareholders realize a loss in the case of default.

3.2.4 The Manager

The risk-neutral manager, who faces the outside option $\bar{u} > 0$ and convex costs of risk-taking, is offered the state-contigent contract as described above. We assume risk neutrality in combination with convex costs since i) there is evidence that bankers are risk neutral or very mildly risk averse (see e.g., Thanassoulis, 2012) and ii) it yields an interior solution to the maximization problem and makes the model more tractable as under assuming risk aversion without altering the core results of the project.[14] By assuming risk neutrality, we follow earlier literature such as John et al. (2000) or Chaigneau (2013).

Exerting effort and taking risk involves private, non-monetary costs for the manager. No active risk-taking, $q=0$, can be interpreted as the natural risk-level of the portfolio. Raising risk beyond this natural risk-level (i.e., choosing $q>0$) causes private costs as the manager has to actively search for riskier investments or to move into new asset classes. Moreover, costs from developing strategies for hiding risk from the regulatory supervisors have to be borne by the manager. Hence, the parameter q can be seen as the effort to increase the risk level beyond its natural level, whereas the parameter e can be interpreted as the productive effort that increases the mean-return of the portfolio. To achieve a higher risk-higher return portfolio, the manager has to look for more opportunities, asset classes, or borrowers with certain characteristics. This is time consuming and thus imposes costs on the manager.

The manager can either exert high effort, e_H, or low effort, e_L, whereby effort has utility costs φ_i which are defined as $\varphi_H = \varphi > 0$ in the case of high effort and normalized to zero, i.e., $\varphi_L = 0$, in the case of low effort. The offered contract has, therefore, to be incentive compatible. For simplicity, we assume that the cost function

[14] If we assumed risk aversion, it would be more costly for the bank to incentivize the manager since the manager discounts the bonus in the case of success. This would decrease the bonus and increase the fixed wage, however, the results would not be affected qualitatively.

for risk-taking is quadratic and given by

$$c(q) = \frac{\mu q^2}{2}, \tag{3.7}$$

with $\mu > 1$. Furthermore, μ is assumed to be sufficiently large to ensure that the endogenous risk-choice of the manager is bounded at 1 from above. These private costs, along with non-observable risk-taking and observable but unverifiable effort choices by the manager, cause a second moral hazard problem in the model between the manager and the bank. Specifically, the manager exerts less effort and risk-taking than desired by the bank. The bank can mitigate this principal-agent problem by paying a bonus z_i which incentivizes the manager to increase effort and risk. In addition to the bonus payment z_i, the manager receives a fixed wage F that is independent of the realized return.

We furthermore assume that the manager is overconfident and overestimates the returns to risk-taking.[15] We model this by assuming that the perceived return to risk, which we denote as $\hat{\beta}(\theta)$, is a function of overconfidence, where $\frac{\partial\hat{\beta}(\theta)}{\partial\theta} > 0$, $\frac{\partial\hat{\beta}(\theta)^2}{\partial\theta^2} < 0$, and $\hat{\beta}(\theta) \in [\beta, 1)$. The exogenous parameter θ measures the level of overconfidence. For $\theta = 0$ the manager is rational and evaluates the probabilities correctly, i.e., $\hat{\beta}(\theta = 0) = \beta$. For $\theta > 0$, however, the manager overestimates the actual return to risk β. Due to the manager overestimating the returns to risk-taking, the probabilities as perceived by an overconfident manager differ from the actual probabilities in eq. (3.1). The returns as considered by the manager are given by

$$\tilde{y} = \begin{cases} y + x(\alpha, e_i) & \text{with probability } \hat{\beta}(\theta)q \\ y & \text{with probability } 1-q \\ 0 & \text{with probability } (1-\hat{\beta}(\theta))q \end{cases}. \tag{3.8}$$

Our analysis will show that overconfidence affects the bank's optimal bonus and fixed wage, and thus critically influences the principal agent problems both between the bank and the manager, and between the government and the bank.

We assume overconfidence of the manager since the psychology literature shows that individuals generally overestimate their own abilities and talents (see Taylor and Brown (1988) for a review) and the probabilities of advantageous events (e.g., Langer, 1975). As Taylor and Brown (1988) conclude: "A great deal of research in social, personality, clinical, and developmental psychology documents that normal individuals possess unrealistically positive views of themselves [and] an exaggerated belief in their

[15] Our assumption that overconfident managers overestimate the return to risk-taking is backed up by several finance studies that suggest overconfident CEOs have a higher tendency to undertake risky projects (e.g., Niu, 2010; Hirshleifer et al., 2012; Ho et al., 2016).

ability to control the environment". There are several reasons why top bank managers are likely to be even more overconfident than the lay population. First, successful bankers are likely to become overconfident due to the self-attribution bias. Top bankers have experienced success in their careers. As individuals generally overestimate the extent to which they have contributed to their own success (Langer, 1975), successful bankers and traders are especially prone to becoming overconfident (see e.g., Daniel et al., 1998; Gervais and Odean, 2001).[16] Second, selection effects may imply that overconfident individuals are more likely to become top bankers than non-overconfident people. For example, overconfident individuals overestimate the expected value of performance pay and thus self select into jobs with high performance pay such as banking. Finally, Goel and Thakor (2008) show that if firms promote based on the best performances, then overconfident managers are more likely to be promoted as they take on larger risks.[17]

Hence, the manager chooses whether to accept the offered contract based on his *perceived* utility given by

$$\hat{u}_i = \hat{\beta}(\theta) q_i z_i + F - \varphi_i - \frac{\mu q_i^2}{2}, \tag{3.9}$$

where we define q_i as the risk choice when effort e_i is implemented, and then decides on the level of risk-taking. The *participation constraint* is, thus, given by

$$\hat{u}_i = \hat{\beta}(\theta) q_i z_i + F - \varphi_i - \frac{\mu q_i^2}{2} \geq \bar{u}. \tag{3.10}$$

The level of effort is defined by the *incentive constraint*

$$F + \hat{\beta}(\theta) q_H z_H - \varphi - \frac{\mu q_H^2}{2} \geq F + \hat{\beta}(\theta) q_L z_L - \frac{\mu q_L^2}{2}. \tag{3.11}$$

In the following, we proceed to solve our model by backward induction.

3.3 Manager's Choices and Perceived Utility

In Stage 3, the government has set its bonus tax t and the bank has chosen the manager's contract (z_i and F) given the effort level $i \in \{L, H\}$ the bank wants to implement.

[16] If agents receive *negative* (but unbiased) noisy feedback on their own performance, however, then they attribute the negative feedback to being unlucky (i.e., they think their feedback underrepresents their individual performance), as shown by Grossman and Owens (2012).

[17] First evidence confirms that top bankers are indeed more overconfident than the general population. Using questionnaires and experiments, Glaser et al. (2005) find that professional traders and investment bankers are more overconfident than students. Graham et al. (2013) examine psychometric tests and conclude that CEOs are more optimistic than the general population.

Given his contract, the manager maximizes his *perceived* expected utility. For an overconfident manager the perceived expected utility deviates from his actual expected utility as he misjudges the probabilities of the exogenous returns.

The perceived expected utility is given by eq. (3.9) and depends positively on the manager's estimate of the success probability $\hat{\beta}(\theta)$, the bonus z_i, and the fixed wage F. The perceived expected utility decreases in the risk-taking costs, given by eq. (3.7), and the effort-taking costs, φ_i.

For a given level of effort e_i, determined by the incentive constraint in eq. (3.11), maximizing eq. (3.9) with respect to q yields

$$q_i^* = \frac{\hat{\beta}(\theta) z_i}{\mu}. \tag{3.12}$$

Hence, the manager's optimal risk level q_i^* increases in the level of overconfidence θ and the bonus payment z_i. Since the cost parameter, μ, is assumed to be sufficiently high, q_i^* is bounded at 1 from above.

Using eq. (3.12) in eq. (3.8), we can derive the realized equilibrium probabilities of the different returns:

$$\tilde{y} = \begin{cases} y + x(\alpha, e_i) & \text{with probability } \beta \frac{\hat{\beta}(\theta)}{\mu} z_i \\ y & \text{with probability } 1 - \frac{\hat{\beta}(\theta)}{\mu} z_i \\ 0 & \text{with probability } (1-\beta) \frac{\hat{\beta}(\theta)}{\mu} z_i \end{cases}. \tag{3.13}$$

A higher bonus leads to more risk-taking, which unambiguously increases the tail probabilities. The effect of the bonus on the medium return is unambiguously negative, as the bonus shifts probability mass to the tails to incentivize effort and risk-taking. Note that an increase in overconfidence amplifies the marginal effects of the bonus on the equilibrium probabilities as overconfidence increases the marginal effect of the bonus on risk-taking. Since neither the manager's optimal effort nor the risk level depend on the fixed wage F, the equilibrium probabilities are independent of the fixed wage.

Finally, substituting eq. (3.12) in eq. (3.9) gives us the maximized perceived expected utility, given the effort e_i the manager exerts, as

$$\hat{u}_i^* = \frac{\hat{\beta}(\theta)^2}{2\mu} z_i^2 + F - \varphi_i. \tag{3.14}$$

This shows that both a higher bonus and a higher fixed wage increase the perceived utility. An overconfident manager ($\theta > 0$) overvalues the influence of the bonus on his utility as he overestimates the likelihood of receiving the bonus.

3.4 Bank's Bonus and Fixed Wage Decisions

In Stage 2, we turn to the bank and its behavior. Substituting the optimal risk choice by the manager in eq. (3.12) into eq. (3.6) yields the expected profit of the bank

$$\Pi = \beta q_i^*[(y + x(\alpha, e_i)) - (1+t)z_i - s(d+X)] + (1-q_i^*)[y - s(d+X)] - F. \quad (3.15)$$

We assume that it is optimal for the bank to induce high effort, i.e., $\Pi(e_H) > \Pi(e_L)$. We derive the condition for the assumption to hold in Appendix A. The condition in eq. (C.1.14) shows that this is always the case if the difference $x(\alpha, e_H) - x(\alpha, e_L)$ is sufficiently large to outweigh the costs of effort φ which are compensated by the bank. The bank sets the bonuses, z_H and z_L, and the fixed wage F to maximize its expected after-tax profits.

Substituting the financing constraint in eq. (3.4) into eq. (3.15), the bank's maximization problem is given by

$$\begin{aligned}
&\max_{z_H, z_L, F} \Pi = \beta q_H^*[(y + x(\alpha, e_H)) - (1+t)z_H] + (1-q_H^*)y - F + (1-\beta)q_H^* v_i sd - sd \\
&\quad \text{s.t. (i) participation constraint: } \hat{u}_H^* = F + \hat{\beta}(\theta)q_H^* z_H - \varphi - \frac{\mu q_H^{*2}}{2} \geq \bar{u} \\
&\qquad \text{(ii) incentive constraint: } \hat{\beta}(\theta)q_H^* z_H - \varphi - \frac{\mu q_H^{*2}}{2} \geq \hat{\beta}(\theta)q_L^* z_L - \frac{\mu q_L^{*2}}{2} \qquad (3.16) \\
&\qquad \text{(iii) } q_H^* = \arg\max_{q_H} \hat{u}_H = \hat{\beta}(\theta)q_H z_H + F - \varphi - \frac{\mu q_H^2}{2} \\
&\qquad \text{(iv) } F \geq 0,\ z_H > 0,\ z_L > 0.
\end{aligned}$$

The bank's maximization problem in eq. (3.16) has three main constraints: the *financing constraint* in eq. (3.4), the *incentive constraint*, and the *participation constraint.* First, the *financing constraint* implies that the bank has to ensure that depositors invest in the bank. As the depositors are partly insured by the government and do not accurately price in the bank's default risk, the bank derives a subsidy $(1-\beta)q_H^* v_i sd$ from the government guarantee. Second, the *incentive constraint* implies that the bank has to design the contract in such a way that the manager exerts high effort. And third, the *participation constraint* implies that the manager's perceived expected utility of the bank's contract must be at least as large as the manager's fixed outside utility ($\bar{u}$). Otherwise the manager will not accept the contract. Moreover, the bonus and the fixed wage have to be positive.

We restrict our analysis to the case where both the bonus z_i and the fixed wage F are used in equilibrium, which is the case generally observed for senior managers,[18] and

[18] For bankers earning more than 1 million euros in EU banks, for example, the average ratio

where the bonus is determined by an interior solution, i.e., the incentive constraint is not binding. This condition for all possible levels of bonus taxes (i.e., $t \geq 0$) is given by

Lemma 1 *Interior solution*
The fixed wage is used and the bonus is determined by an interior solution for all possible levels of bonus taxes (i.e., $t \geq 0$) if

$$\frac{\sqrt{2\mu\varphi}}{\Omega_H + \sqrt{2\mu\varphi}}2\beta < \hat{\beta}(\theta) < \frac{\sqrt{2\mu(\bar{u}+\varphi)}}{\Omega_H + \sqrt{2\mu(\bar{u}+\varphi)}}2\beta, \tag{3.17}$$

where $\Omega_H = r_H + (1-\beta)v_i sd$ and $r_H = \beta(y + x(\alpha, e_H)) - y$.
Proof: See Appendix A.

First, Lemma 1 rules out the case where the manager is so overconfident that the perceived utility exceeds the outside option even without paying the fixed wage. Second, it ensures that the incentive constraint is not binding and therefore yields an interior solution for the bonus. Since $\hat{u} > 0$, i.e., the outside option is positive, there exists a solution space for $\hat{\beta}(\theta)$.[19]

Given that an interior solution for the optimal bonus exists, i.e., Lemma 1 holds, the first order condition of the bonus z_H is given by[20]

$$\frac{\partial \Pi}{\partial z_H} = r_H\frac{\hat{\beta}(\theta)}{\mu} - 2\beta(1+t)z_H\frac{\hat{\beta}(\theta)}{\mu} + (1-\beta)v_i sd\frac{\hat{\beta}(\theta)}{\mu} + \frac{\hat{\beta}(\theta)^2}{\mu}z_H = 0. \tag{3.18}$$

An increase in the bonus has four effects on the bank's profit. First, the bonus increases effort and risk-taking of the manager, which increases the expected return of the bank's portfolio. Second, the monetary bonus costs of the bank rise. Third, the bonus increases risk-taking of the manager, which shifts the costs of repaying depositors to the government. Fourth, the bonus reduces the fixed wage that is necessary for the bank to fulfill the participation constraint of the manager. Importantly, this effect is especially strong for an overconfident manager.

Solving eq. (3.18) for z_H yields the optimal bonus

$$z_H^* = \frac{r_H + (1-\beta)v_i sd}{2\beta(1+t) - \hat{\beta}(\theta)} \equiv \frac{\Omega_H}{\Psi}, \text{ where } \Omega_H > 0 \text{ and } \Psi > 0. \tag{3.19}$$

The bonus z_H^* increases in the marginal benefit of the bonus, Ω_H, since the incentive effect of the bonus increases the banker's effort and risk-taking, which raises the

between variable and fixed pay was 104% in 2016 (European Banking Authority, 2018).

[19]See Appendix A for a more detailed discussion.

[20]See Appendix A for the detailed solution of the bank's maximization problem in eq. (3.16).

probability of realizing the high return and the probability to draw on the government guarantee. The bonus decreases in the marginal net costs of the bonus, Ψ. The marginal net costs of the bonus, Ψ, are the marginal bonus costs of the bank (which rise in the bonus tax t) minus the bank's marginal savings on the fixed wage.[21] These marginal savings stem from the fact that a higher bonus reduces the fixed wage that is necessary to fulfill the manager's participation constraint. Note that the savings are larger for an overconfident manager, as he overvalues the utility that he derives from the bonus and is therefore willing to accept a lower fixed wage. This result relates to the literature of behavioral contract theory (see e.g., Koszegi, 2014). By paying a little more for high output and much less for low output, a principal can always exploit an overconfident agent.[22] The assumption in eq. (3.17) ensures that $2\beta - \hat{\beta}(\theta) > 0$ and thus that the net costs are always positive ($\Psi > 0$).

The bonus for low effort, z_L, is always set to zero since the bank wants to induce e_H and uses z_L only to make the incentive constraint bind.[23]

The fixed wage F is determined by the participation constraint in eq. (3.10) and given by

$$F^* = \bar{u} - \frac{\hat{\beta}(\theta)^2}{2\mu} z_H^{*2} + \varphi = \bar{u} - \frac{\hat{\beta}(\theta)^2 \Omega_H^2}{2\mu\Psi^2} + \varphi. \tag{3.20}$$

The fixed wage F^* rises in the utility of the manager's outside option and falls in the manager's level of overconfidence. The latter is due to overconfidence making the bonus relatively more attractive (substitution effect) and lowering the overall compensation needed for satisfying the manager's participation constraint (income effect). A bonus tax increases the fixed wage as it reduces the bonus z_H^*.

To sum up, the more overconfident the manager, the higher is the bonus that he receives and the lower is his fixed wage. First, this is due to the overconfident manager increasing risk-taking more for a given increase in the bonus than a rational manager. And second, an overconfident manager overvalues the bonus. Hence, bonuses become more attractive for the bank as they can be used to exploit the manager and lower compensation costs. We also find that the bonus increases in the level of the government guarantee. This is because the government guarantee makes risk-taking

[21] The bonus tax, thus, always reduces the bonus in our model. Dietl et al. (2013) show that it can be optimal for a principal to increase bonuses as a response to a bonus tax, if an agent is highly risk averse. The literature on banker's risk preferences, however, shows that banker's are very mildly risk averse or even risk neutral (see Thanassoulis, 2012).

[22] Humphery-Jenner et al. (2016) provide empirical evidence that firms exploit overconfident CEO's overvaluation of incentive pay in order to lower compensation costs. The incentive to exploit managerial overvaluation has also been derived theoretically by De la Rosa (2011) and Gervais et al. (2011).

[23] In principal, the bank could also set a negative bonus z_L. However, since the bank wants to induce high effort, z_H must at least outweigh the costs of effort. The bank would, thus, not save on compensation costs if z_L was below zero.

more attractive, which can be induced with bonuses.

3.5 The Government

In this section we look at the role of the government. In Section 3.5.1 we define and discuss the welfare function. Section 3.5.2 derives the optimal bonus tax and discusses its properties.

3.5.1 The Welfare Function

The government maximizes welfare with respect to the bonus tax t. Since the government puts equal weights on private income and government revenue, the welfare function is given as

$$W = \Pi^* + u^* + (T - B). \tag{3.21}$$

Our social welfare function takes into account the bank's profit Π^* in eq. (3.16) and the manager's *actual* expected utility $u^* = \beta q_H^* z_H^* + F^* - \frac{\mu q_H^{*2}}{2} - \varphi$.[24] Additionally, the social welfare function entails the government's bailout costs, B, and its bonus tax income T. The social welfare function includes the welfare of all agents since risk-neutral depositors always receive an expected return of sd independent of the bonus tax. The depositors' payoffs are thus not included explicitly in our welfare function.

The bailout costs are given by

$$B = (1-\beta)q_H^* v_i sd = (1-\beta)\frac{\hat{\beta}(\theta)}{\mu} z_H^* v_i sd. \tag{3.22}$$

Note that eq. (3.22) implies that overconfidence increases the likelihood of bailouts for two reasons. First, for a given contract, overconfident managers take on more risk as they overestimate the success probability of risky investments. And second, the bank creates higher powered compensation contracts for overconfident managers, which amplifies the behavioral effects of overconfidence and increases risk-taking further. As overconfidence raises the likelihood of bailouts, it increases the subsidy to the bank.

The tax revenue T is given by

$$T = t\beta q_H^* z_H^* = t\beta \frac{\hat{\beta}(\theta)}{\mu} z_H^{*2}. \tag{3.23}$$

[24]For the *actual* expected utility, the utility derived from the bonus is weighted by the actual probability of the bonus βq_H^* in eq. (3.13) and not by the perceived probability $\hat{\beta}(\theta) q_H^*$ as in the perceived utility in eq. (3.9). This is because the actual outcome of the manager is determined by βq_H^* and not by his biased beliefs.

Hence, overconfident managers create larger tax revenues, as they generate higher expected bonus payments, $\beta q_H^* z_H^*$. First, overconfident managers receive a higher bonus. And second, they take on more risk, which leads to a higher probability of the bonus being paid. Hence, with respect to the tax revenue, the government can benefit from overconfident managers as they generate more bonus tax income.

The government's net revenue, $T - B$ is positive, if the tax revenue dominates the bailout costs. It is also possible, however, that the expected bailout costs B dominate the tax revenue T, which implies a negative net revenue for the government. This is the case when the default probability of the bank is large and when the level of government guarantees v_i is high.[25]

Substituting the bank profit from eq. (3.16) and the actual utility, our welfare function is thus given by

$$W = \beta q_H^* (y + x(\alpha, e_H)) + (1 - q_H^*)y - sd - \frac{\mu q_H^{*2}}{2} - \varphi. \tag{3.24}$$

The welfare function can be subdivided into two parts. First, the first three terms in the third line of eq. (3.24) capture the bank's profit net of the bank's payments to the banker. Second, the behavioral costs of the manager (i.e., the effort- and risk-taking costs φ and $\frac{\mu q_H^{*2}}{2}$) lower welfare, because they reduce the manager's utility. Note that the expected bonus payments $\beta q_H^* z_H^*$ and the fixed wage F are simply transfers from the bank to the banker and, since we assume equal welfare weights, the tax $t\beta q_H^* z_H^*$ and the bailout $(1 - \beta) q_H^* v_i sd$ are simply transfers between the bank and the government and, therefore, do not directly affect welfare in eq. (3.24).

3.5.2 The Optimal Bonus Tax

We now proceed to derive the optimal bonus tax t^*. Substituting eq. (3.12) into eq. (3.24) and differentiating the welfare function with respect to t gives

$$\frac{\partial W}{\partial t} = \frac{\hat{\beta}(\theta)}{\mu} \left\{ r_H \frac{\partial z_H^*}{\partial t} - \hat{\beta}(\theta) z_H^* \frac{\partial z_H^*}{\partial t} \right\}. \tag{3.25}$$

On the one hand, a bonus tax lowers the expected return of the bank's investment due to the lower effort-taking incentives ($r_H \frac{\partial z_H^*}{\partial t} < 0$). On the other hand, the bonus tax has a positive welfare implication since it reduces the manager's risk-taking costs ($-\hat{\beta}(\theta) z_H^* \frac{\partial z_H^*}{\partial t} > 0$).

[25] We take capital requirements and government guarantees as exogenously given. In fact, it can be shown that, absent bonus taxation, welfare is always decreasing in the v_i due to the risk-shifting incentive of the firm. There are, however, other reasons outside the model that require government guarantees such as to avoid bank runs (c.f. Section 3.2).

Whether the bonus tax is used in equilibrium is determined by the first order condition at $t = 0$, which is derived in Appendix B and given by

$$\frac{\partial W}{\partial t}_{|t=0} = \left[\frac{\beta\hat{\beta}(\theta)\Omega_H}{\mu\Psi^3}\right]\{2(2\beta - \hat{\beta}(\theta))(1-\beta)v_i sd + 4\Omega_H(\hat{\beta}(\theta) - \beta)\} > 0. \tag{3.26}$$

Eq. (3.26) shows that the first marginal unit of bonus tax always increases welfare.[26] The bonus tax lowers the bank's profit. At $t = 0$ this negative welfare effect is always dominated by the positive effect, namely the reduction of the manager's risk costs. In Appendix B we show that under the assumption that the net return to risk is positive, i.e., if $r_H = \beta(y + x(\alpha, e_H)) - y > 0$, there is always an interior solution for the bonus tax.

Setting the first order condition in eq. (3.25) equal to zero, we get the optimal bonus tax

$$t^* = \frac{(2\beta - \hat{\beta}(\theta))(1-\beta)v_i sd + 2\Omega_H(\hat{\beta}(\theta) - \beta)}{2\beta r_H}. \tag{3.27}$$

Note that the assumption $r_H = \beta(y + x(\alpha, e_H)) - y > 0$ implies that the denominator of the optimal bonus tax in eq. (3.27) is always positive. The bonus tax affects the manager's risk-taking choice in equilibrium. As the government guarantee leads to diverging interests between the bank and the government, the risk-reducing effect of the bonus tax is a valuable Pigouvian tool to decrease the exploitation of the overconfident manager. In the following we will show that the tax increases with the risk-shifting incentives and with the exploitation of overconfidence and decreases with capital requirements.[27]

We use comparative statics for eq. (3.27) to analyze the properties of the optimal bonus tax. Differentiating t^* with respect to v_i gives

$$\frac{\partial t^*}{\partial v_i} = \frac{(1-\beta)sd\left[(2\beta - \hat{\beta}(\theta)) + 2(\hat{\beta}(\theta) - \beta)\right]}{2\beta r_H} > 0. \tag{3.28}$$

Eq. (3.28) shows that the bonus tax increases in the level of bailout guarantees v_i. The larger the bailout guarantees, the higher the optimal risk-taking for the bank, because depositors price in the bank's risk-taking to a smaller extent. Hence, bailout guarantees make the bonus tax more attractive as the tax curbs the bank's inefficiently high risk-taking. The effect is stronger if overconfidence is high.

[26]Note that for $t = 0$ eq. (3.17) implies that $2\beta > \hat{\beta}(\theta)$ and that $\Omega_H > 0$.

[27]Moreover, the tax decreases with the net return to risk-taking of the bank which positively enters the welfare function.

The effect of a tightening of capital requirements on the optimal bonus tax is given by

$$\frac{\partial t^*}{\partial(1-s)} = -\frac{(1-\beta)v_i d\left[(2\beta - \hat{\beta}(\theta)) + 2(\hat{\beta}(\theta) - \beta)\right]}{2\beta r_H} < 0. \tag{3.29}$$

Tighter capital requirements (i.e., larger $1-s$) reduce the leverage of the bank, which implies that the bank can shift fewer costs onto the government. Hence, capital requirements and bonus taxes are strategic substitutes.

Finally, we investigate how the optimal bonus tax depends on overconfidence. Differentiating t^* with respect to θ, we get

$$\frac{\partial t^*}{\partial \theta} = \frac{2\Omega_H - (1-\beta)v_i sd}{2\beta r_H}\frac{\partial\hat{\beta}(\theta)}{\partial\theta} = \frac{2r_H + (1-\beta)v_i sd}{2\beta r_H}\frac{\partial\hat{\beta}(\theta)}{\partial\theta} > 0. \tag{3.30}$$

An overconfident manager overestimates the returns to risk. Hence, managerial overconfidence makes it cheaper for the bank to induce risk-shifting and to draw on the bailout subsidy. This leads to inefficiently high risk-taking and can be mitigated with a larger bonus tax. This effect is stronger the higher the risk-shifting incentive.

In other words, overconfidence mitigates the principal-agent problem between the bank and the manager as it becomes cheaper for shareholders to align the manager's behavior with the bank's objective. This is detrimental for welfare since it imposes higher costs on the manager and leads to socially inefficient risk-taking which is exacerbated by government guarantees. The principal-agent problem between government and bank becomes more severe in the presence of overconfidence, and the government optimally sets a higher bonus tax in order to align the bank's with the government's interests.

We summarize our main results of Section 3.5 in

Proposition 1 *Optimal bonus tax*

If the net return to risk-taking is positive, i.e., $r_H = \beta(y + x(\alpha, e_H)) - y > 0$, *then*
(*i*) *the welfare-maximizing bonus tax* t^* *is given in eq.* (3.27) *and*
(*ii*) t^* *always increases in the level of overconfidence* θ.

Proofs: See Appendices B and C.

The key finding in Proposition 1 is that the optimal bonus tax always increases in overconfidence, and more so if risk-shifting incentives are stronger. This is particularly the case for systemically important financial institutions as they receive bailout subsidies through both explicit and implicit government guarantees. These guarantees create an externality which leads to inefficiently high risk-taking, which is especially attractive to exploit if the manager is overconfident. In systemically important financial institutions, it is thus optimal to curb the implications of overconfidence with a higher bonus tax.

Recent evidence shows that managerial overconfidence indeed not only affects firm outcomes, but also causes substantial externalities. Banks with overconfident CEOs generally experience higher stock return volatility (Niu, 2010) and have shown higher real estate loan growth prior to the financial crisis (Ma, 2015). During the recent financial crises, banks managed by CEOs suffered from greater increases in loan defaults and a higher likelihood of failure than banks governed by non-overconfident CEOs (Ho et al., 2016). Due to the inefficiency caused by banks' risk-taking and failures, it is necessary for the government to counteract the adverse effects arising from overconfidence in the banking industry. In the following section we discuss why the bonus tax is better suited to do so than other instruments (e.g., capital requirements) by comparing it to the first-best solution.

3.6 Do We Need to Intervene in Banker Pay?

Following the financial crisis of 2007-2009, a lively discussion has emerged about whether or not the government should intervene in banker pay. We shed light on the role of managerial overconfidence in this debate in the following. To do so, Section 3.6.1 derives the socially optimal bonus and compares it to the bonus set by the bank. Section 3.6.2 then uses the example of capital requirements to illustrate why the socially optimal bonus cannot be obtained without interventions in banker pay, if bankers are overconfident.

3.6.1 The Socially Optimal Contract

In this section we derive the socially optimal bonus when the government does not directly intervene in the banker's compensation (i.e., $t = 0$). We then compare this bonus, $z_{H,S}$, to the one chosen by the bank in eq. (3.19), which we reformulate as $z_{H,B}$.

In Appendix C we maximize the welfare function in eq. (3.24) with respect to the bonus, which gives us the socially optimal bonus:

$$z_{H,S_{|t=0}} = \frac{r_H}{\hat{\beta}(\theta)}. \tag{3.31}$$

This bonus increases with the net return to risk-taking since this increases welfare. However, the socially optimal bonus decreases in overconfidence since the overvaluation of the bonus increases risk-taking by the manager and, thus, increases the costs of risk-taking. We can now investigate how the bank's bonus in eq. (3.19) deviates from the socially optimal bonus, if the government does not intervene into banker pay:

$$z_{H,B_{|t=0}} - z_{H,S_{|t=0}} = \frac{2r_H(\hat{\beta}(\theta) - \beta) + \hat{\beta}(\theta)(1-\beta)v_i sd}{(2\beta - \hat{\beta}(\theta))\hat{\beta}(\theta)} > 0. \tag{3.32}$$

The bonus chosen by the bank is unambiguously larger than the socially optimal bonus.[28] The bank does not internalize the bailout costs of the government. Hence, it prefers more risk, which can be induced with a higher bonus. Moreover, the bank exploits the managerial overvaluation, which leads to the manager providing too much effort and risk relative to the actual probability of getting the bonus. Thus, both overconfidence and bailouts lead to higher levels of risk-taking. The last term in the numerator shows that overconfidence amplifies the effect of the bailout on the bonus.

Note that an upper bound for bonuses, a bonus cap, set at $z_{H,S_{|t=0}}$ can implement the socially optimal bonus. The cap has the same qualitative behavioral effects as the bonus tax discussed in Section 3.5.2, since it also lowers the bonus and raises the fixed wage.[29]

3.6.2 Capital Requirements

This section investigates, whether capital requirements can implement the socially optimal bonus. To see if an increase in the capital requirements, $1-s$, brings the bank bonus closer to the social optimum, we differentiate eq. (3.32) with respect to $(1-s)$:

$$\frac{\partial(z_{H,B_{|t=0}} - z_{H,S_{|t=0}})}{\partial(1-s)} = -\frac{\hat{\beta}(\theta)(1-\beta)v_i d}{(2\beta - \hat{\beta}(\theta))\hat{\beta}(\theta)} < 0. \tag{3.33}$$

Eq. (3.33) implies that tighter capital requirements indeed reduce the gap between the bank's bonus and the socially optimal bonus. With tighter capital requirements, the bank internalizes the downside risk of its investment to a larger extent and thus has a smaller incentive to induce risk-taking via bonuses.[30] Whether capital requirements

[28]Correspondingly. the fixed wage chosen by the bank, F_B, is smaller than the socially optimal fixed wage, which is given by $F_S = \bar{u} - \frac{\hat{\beta}(\theta)^2}{2\mu} z_{H,S}^2 + \varphi$.

[29]A bonus cap, however, does not raise tax revenue. Hence, in a setting where the government has an incentive to redistribute from the financial sector to the government the optimal bonus tax dominates the optimal bonus cap with respect to welfare. This could be caused by marginal costs of public funds which are the loss of society that the government causes when it raises additional revenues to finance its spending (see e.g., Browning, 1976).

[30]Note that this result is different from the literature on the effects of corporate governance failures within firms. Fahn et al. (2019), for example, show that for non-financial firms an increase in equity

can actually establish the socially optimal bonus is determined by

$$\lim_{(1-s)\to 1} (z_{H,B_{|t=0}} - z_{H,S_{|t=0}}) = \frac{2r_H(\hat{\beta}(\theta) - \beta)}{(2\beta - \hat{\beta}(\theta))\hat{\beta}(\theta)} > 0. \tag{3.34}$$

Eq. (3.34) shows that capital requirements alone cannot implement the socially desirable bonus level, if the manager is overconfident ($\theta > 0$). Even in the extreme case with capital requirements approaching 100%, the bank's bonus is higher than socially optimal.[31]

Recall from Section 3.6.1 that there are two reasons why the bank's bonus is higher than the socially optimal bonus. First, the bank uses the bonus to maximize its value of the government subsidy. Capital requirements can tackle this problem, as they force the bank to internalize the externalities of its risk-taking. And second, the bank sets an inefficiently high bonus in order to exploit the manager, if he is overconfident. This higher bonus has the side effect that risk-taking is greater (see eq. (3.12)) than under the socially optimal bonus. Capital requirements cannot tackle the inefficiencies arising from the exploitation of managerial overvaluation.

For a rational manager ($\theta = 0$), capital requirements can establish the socially optimal bonus (cf. eq. (3.34)), as there is no possibility for the bank to exploit the manager. Unlike an overconfident manager, a rational manager derives the same perceived utility from one dollar of expected bonus payments as from one dollar of fixed wage.

Moving away from capital requirements and generalizing our argument, Appendix D derives the bank's bonus $z_{H,R_{|t=0}}$ under the assumption that regulation achieves that the bank fully internalizes the bailout costs of the government ($(1-\beta)q_H^* v_i sd$). Analogously to the capital requirements, the bank's bonus is higher than socially optimal, if the manager is overconfident. In the presence of overconfidence, curbing shareholders' risk-shifting incentives alone is not enough, as the bank has an incentive to use bonuses in order to exploit the manager's overvaluation.

We summarize Section 3.6.2 in

financing increases incentives to provide effort. This is driven by the fact, that debt increases the temptation of the principal to renege relational contracts needed to incentivize the agent. The financial sector, however, is characterized by risk-shifting incentives caused by guarantees. Eufinger and Gill (2017) argue that in the financial sector moral hazard originating from government guarantees, rather than corporate governance failures within a bank, is the primary driver of excessive risk-taking. Therefore, we abstract from these corporate governance failures and focus on the risk-shifting incentives of the principal which drives the results.

[31] An increase in capital requirements has other potential downsides (e.g., a decrease in lending to firms) that are not dealt with in our model. See, for example, Van den Heuvel (2008) for an analysis of the welfare costs of capital requirements.

Proposition 2 *Shareholders' risk-shifting incentives and the socially optimal bonus*

If the manager is overconfident (i.e., $\theta > 0$), capital requirements alone cannot implement the socially desirable bonus. The bank's bonus, $z_{H,B_{|t=0}}$, is then always larger than the socially desirable bonus, $z_{H,S_{|t=0}}$, even if the bank fully internalizes the government's bailout costs.

Proofs: See eq. (3.34) *and Appendix D.*

A direct intervention into banker pay (e.g., bonus taxes or bonus caps) can however implement the socially desirable bonus, as it addresses both motives for the excessive use of the bonus at the same time. Direct interventions into banker pay not only tackle the inefficiencies caused by incentives for excessive risk-taking, but also the adverse effects arising from the manager's overvaluation of the bonus. A bonus tax, for example, increases the bank's costs of the bonus relative to its costs of the fixed wage. Hence, the higher is the bonus tax, the lower is the incentive of the bank to save fixed wage costs by offering an excessive bonus.[32] Our result is similar to intervening into the structure of bank CEO compensation, as proposed by Chaigneau (2013). He finds that the regulator can restore efficient risk-taking by regulating the structure of compensation, where the managers receives equity and a fixed wage, if managers are not overconfident. However, a compensation structure which is beneficial in the case of an unbiased manager might not necessarily be optimal if agents are overconfident. Thus, the optimal structure of CEO compensation is likely to also depend on the level of overconfidence.

Our results suggest that the EU bonus cap, similar to bonus taxation, mitigates the socially adverse effects of managerial overconfidence. This regulation became effective across the European Union in 2014 as part of the Capital Requirements Directive IV. The EU bonus cap limits bonuses paid to senior managers and other "material risk takers" in the financial sector to 100% of their fixed salary (200 % with shareholder approval). Our analysis implies that the bonus cap curbs the exploitation of managerial overvaluation, because it limits the banks' ability to lower compensation costs via higher bonuses and lower fixed wages and thus lowers excessive risk-taking in equilibrium.

[32] Taxing the bonus is equivalent to a nonlinear tax schedule taxing the gross revenue (before wage payments) if the high return realizes. Intuitively, this reduces the net revenue and thus decreases the incentives for the shareholders to exploit the manager. This would mean that the government imposes a tax on risky investment projects that yield a higher return. It can also be interpreted as a linear tax with deductibility of certain costs such that they offset the income in the riskless state. We thank a referee for pointing this out to us. However, in reality this might be difficult to implement since the regulator would have to decide which revenues to tax, i.e., which are the investment projects that induce riskier behavior. Taxing the bonus is, on the contrary, relatively easy to implement since these payments are observable.

More generally, Proposition 2 suggests that interventions into banker pay are part of the optimal regulatory package for the banking industry. The existing literature has identified competition for mobile bankers as the major reason to intervene directly into banker compensation instead of only curbing shareholders' risk-shifting incentives. For example, Bannier et al. (2013) find that the competition for bankers with heterogeneous and unobservable skill leads to excessive bonuses. This causes a level of risk-taking that is not only excessive for society but also for the banks themselves. Thanassoulis (2012) shows that the competition for bankers increases bankers' pay, which gives rise to a negative externality as rival banks have to increase banker remuneration as well. This increase in banker pay drives up the remuneration costs of banks and thus their default risk. Our finding in Proposition 2 adds to these findings by showing that bonuses in the banking industry are excessive from a social point of view, even when competition for managerial talent in the banking sector is weak. This is because overconfidence creates an incentive for banks to exploit managerial overvaluation.

3.7 Competition for Overconfident Bankers

To shed light on the competition for overconfident managers, this section introduces hetereogeneities in bank characteristics and managerial overconfidence. Specifically, we are interested in how government guarantees, bonus taxes, and capital requirements affect the matching between banks and overconfident managers. Section 3.7.1 derives the equilibrium contracts and allocation when banks compete for an overconfident manager. In Section 3.7.2 we analyze how this competitive equilibrium is affected by heterogeneities in government guarantees, capital requirements, and bonus taxes.

3.7.1 Equilibrium Contracts Under Competition

In this section, we introduce heterogeneities in bank characteristics and managerial overconfidence. Specifically, there are two banks $i \in \{1, 2\}$ that potentially differ in the level of government guarantees v_i, the bonus taxes t_i, and the capital requirements $1 - s_i$. There are two types of managers $j \in \{OC, N\}$ that only differ in managerial overconfidence θ_j. We assume that type OC, who we refer to as overconfident manager, is more overconfident than type N ($\theta_{OC} > \theta_N \geq 0$), who we refer to as rational manager.

The two banks compete for the services of the overconfident manager via their compensation packages. We assume that the overconfident manager is scarce (i.e., there is only one overconfident manager) and that rational managers are abundant.[33]

[33] Our approach is thus similar to Gervais et al. (2011), who model the competition for a scarce overconfident manager in the absence of government guarantees and government policies.

Hence, the bank that does not hire the overconfident manager in equilibrium will hire a rational manager instead. The manager j's outside option to working for bank i is determined by the contract that the other bank I ($\forall\, i, I \in \{1,2\},\ i \neq I$) offers to him.

As rational managers are abundant, the two banks do not compete for their services. Hence, the bonus and fixed wage of a rational manager in bank i, $z_{H,i,N}$ and $F_{i,N}$, are the same as in the previous sections. Substituting the bank bonus from eq. (3.19) and the fixed wage from eq. (3.20), we get bank i's optimal profit when hiring the rational manager N:

$$\Pi^*_{i,N} = y - \bar{u}_N - s_i d + \frac{\hat{\beta}(\theta_N)}{2\mu}\frac{\Omega_i^2}{\Psi_{i,N}} - \varphi,$$
$$\text{where } \Omega_i = \Omega_{H,i} = r_H + (1-\beta)v_i s_i d \text{ and } \Psi_{i,N} = 2\beta(1+t_i) - \hat{\beta}(\theta_N). \tag{3.35}$$

It is easy to see from eq. (3.35) that bank i's profit rises in the level of overconfidence. This is because overconfidence increases effort- and risk-taking and reduces the compensation costs needed to convince the manager to work for the bank. Hence, banks benefit more from hiring an overconfident manager than from hiring a rational manager, and compete for the services of the overconfident manager.

In equilibrium, the overconfident manager OC works for the bank i that is willing to offer him his highest perceived utility. The maximum willingness to pay of bank i for manager OC in terms of his perceived utility, $\hat{u}_{i,max}$, is determined by

$$\Pi^*_{i,OC} = y - \hat{u}_{i,max} - s_i d + \frac{\hat{\beta}(\theta_{OC})}{2\mu}\frac{\Omega_i^2}{\Psi_{i,OC}} - \varphi = \Pi^*_{i,N}. \tag{3.36}$$

Hence, $\hat{u}_{i,max}$ is the level of OC's perceived utility for which bank i is indifferent between hiring him and hiring the rational manager N. Substituting $\Pi^*_{i,N}$ from eq. (3.35) and solving for $\hat{u}_{i,max}$, we get

$$\hat{u}_{i,max} = \bar{u}_N + \frac{\beta\Omega_i^2(1+t_i)\left[\hat{\beta}(\theta_{OC}) - \hat{\beta}(\theta_N)\right]}{\mu\Psi_{i,OC}\Psi_{i,N}}. \tag{3.37}$$

Eq. (3.37) determines in which bank the overconfident manager works. The bank with the higher willingness to pay for the overconfident manager, $\hat{u}_{i,max}$, hires the overconfident manager in equilibrium. This willingness to pay rises in the exogenous outside option of the rational manager $\bar{u}_N$, and in the level of overconfidence of the overconfident manager.

For the bank i that hires the overconfident manager in equilibrium, it is optimal to offer this manager a contract for which he is indifferent between working for bank i

and the other bank I.[34] This is given by

$$\hat{u}_{i,OC} = \hat{u}_{I,max}. \tag{3.38}$$

Recall from eq. (3.14) that the perceived utility $\hat{u}_{i,OC}$ that manager OC derives from bank i, depends on the bonus, $z_{H,i,OC}$, and the fixed wage, $F_{i,OC}$. As in previous sections, bank i chooses the profit-maximizing bonus $z_{H,i,OC}$ given in eq. (3.19). The fixed wage is used to attract the overconfident manager to work for bank i and thus adjusts to fulfill eq. (3.38). Hence, by substituting $\hat{u}_{I,max}$ from eq. (3.37) and the bonus from eq. (3.19), we get the equilibrium wage of the overconfident manager

$$F_{i,OC} = \bar{u}_N + \frac{\beta\Omega_i^2(1+t_i)\left[\hat{\beta}(\theta_{OC}) - \hat{\beta}(\theta_N)\right]}{\mu\Psi_{i,OC}\Psi_{i,N}} - \frac{\hat{\beta}(\theta_{OC})^2}{2\mu}\frac{\Omega_i^2}{\Psi_{i,OC}^2} + \varphi. \tag{3.39}$$

The first two terms capture the willingness to pay for the overconfident manager of the bank I that loses the bidding war for the overconfident manager. The first term in eq. (3.39), $\bar{u}_N$, implies that the better the rational manager's outside option, the more expensive he will be for the bank and the more attractive is the overconfident manager in comparison. The second term shows that the higher is OC's level of overconfidence, the more valuable he is for the losing bank, which drives up his fixed wage in the bank that hires him. Hence, due to the competition for his services, the overconfident manager can now capture (some of) the rent that his overconfidence creates.[35] Effectively, the manager's overconfidence commits him to exert more effort and risk, which generates bank profits that he can (partly) capture under competition.[36] The third term is the perceived utility that the overconfident manager derives from the bonus in the bank he works for. The higher this perceived utility from the bonus, the smaller the fixed wage has to be in order to attract the overconfident manager.

To summarize, Section 3.7.1 shows that, in equilibrium, the banks' contracts and the managers' allocation are given by

[34] For simplicity, we assume here that if both banks offer the overconfident manager the same perceived utility, he will decide to work for the bank with a higher maximum willingness to pay.

[35] If the two banks are identical, then the overconfident manager captures the whole rent, $\Pi^*_{i,OC} - \Pi^*_{i,N}$, of his excess overconfidence, $\theta_{OC} - \theta_N$. As under Bertrand Competition, the two banks will in this case overbid each other until the banks' profits for OC are just as low as the banks' profits for the rational manager. If the two banks differ (e.g in the level of the government guarantee v_i), then the overconfident manager will typically not be able to obtain the whole rent, because the losing bank I is not willing to bid up his fixed wage until $\Pi^*_{i,OC} = \Pi^*_{i,N}$ holds.

[36] Gervais et al. (2011) show, in a theoretical model, that a manager can actually benefit from his overconfidence when firms compete for his services.

Lemma 2 *Competitive equilibrium*

In equilibrium, the bank i with the higher maximum willingness to pay,

$$\hat{u}_{i,max} = \bar{u}_N + \frac{\beta\Omega_i^2(1+t_i)\left[\hat{\beta}(\theta_{OC}) - \hat{\beta}(\theta_N)\right]}{\mu\Psi_{i,OC}\Psi_{i,N}}$$

employs the overconfident manager with the bonus $z_{H,i,OC}$ *in eq.* (3.19) *and the fixed wage* $F_{i,OC}$ *in eq.* (3.39). *The other bank I employs the rational manager with the bonus* $z_{H,I,N}$ *in eq.* (3.19) *and the fixed wage* $F_{I,N}$ *in eq.* (3.20).

In Section 3.7.2, we use Lemma 1 to see how the matching between overconfident managers and banks depends on government guarantees, bonus taxes, and capital requirements. We can use comparative statics on the maximum willingness to pay, $\hat{u}_{i,max}$, to determine how changes in the exogeneous parameters affect the sorting of managers.

3.7.2 Matching

This section analyzes the sorting of managers with respect to government guarantees, capital requirements, and bonus taxes.[37] The effect of the government guarantee on the willingness to pay for the overconfident manager is given by

$$\frac{\partial \hat{u}_{i,max}}{\partial v_i} = \frac{2\beta\Omega_i(1+t_i)\left[\hat{\beta}(\theta_{OC}) - \hat{\beta}(\theta_N)\right](1-\beta)s_i d}{\mu\Psi_{i,OC}\Psi_{i,N}} > 0. \tag{3.40}$$

Eq. (3.40) shows that the maximum willingness to pay for the overconfident manager, $\hat{u}_{i,max}$, unambiguously increases in the level of government guarantees, v_i. A bank with higher government guarantees benefits more from excessive risk-taking as it can shift more of the repayment costs to depositors, $s_i d$, onto the government. An overconfident manager takes on more risk than a rational manager as he overestimates the success probability of risky investments, and is thus especially attractive for banks that receive large government guarantees. Hence, the higher is the government guarantee of a bank, the larger is the positive effect of overconfidence on the bank's profit, which drives up the willingness to pay for the overconfident manager, $\hat{u}_{i,max}$.

From eq. (3.40) and Lemma (2), it follows that the overconfident manager ceteris paribus works for the bank with a higher level of government guarantees in equilibrium. Lemma (2) also implies that the overconfident manager earns a higher bonus than the rational manager. First, overconfidence makes the bonus more attractive for the bank.

[37]Throughout this section we assume that the bonus tax is exogenously given.

And second, the overconfident manager works for the bank with a higher government guarantee, which has a higher risk appetite and accordingly sets a higher bonus.

The effect of the capital requirement on the sorting of the overconfident manager is determined by

$$\frac{\partial \hat{u}_{i,max}}{\partial(1-s_i)} = -\frac{2\beta\Omega_i(1+t_i)\left[\beta(\hat{\theta}_{OC}) - \hat{\beta}(\theta_N)\right](1-\beta)v_i d}{\mu\Psi_{i,OC}\Psi_{i,N}} < 0. \tag{3.41}$$

Eq. (3.41) implies that bank i's willingness to pay for the overconfident manager is the lower, the tighter are the capital requirements (i.e., the higher $(1-s_i)$). From the bank's perspective, overconfident managers have the advantage that they take on more risk and that their risk-taking is cheaper to incentivize. Tighter capital requirements, however, lower the shareholders' risk appetite, as they imply that shareholders internalize a larger share of the bank's risk-taking. The shareholders' lower risk appetite, induced by tighter capital requirements, entails that the bank benefits less from employing an overconfident manager. Hence, ceteris paribus, overconfident managers work for banks with lax capital requirements.

Considering an exogeneous bonus tax, the effect of the bonus tax on the willingness to pay for the overconfident manager is given by

$$\frac{\partial \hat{u}_{i,max}}{\partial t_i} = \frac{\beta\Omega_i^2\left[\hat{\beta}(\theta_{OC}) - \hat{\beta}(\theta_N)\right]\left[-4\beta^2(1+t_i)^2 + \hat{\beta}(\theta_{OC})\hat{\beta}(\theta_N)\right]}{\mu\Psi_{i,OC}^2\Psi_{i,N}^2} < 0. \tag{3.42}$$

Eq. (3.42) implies that, in equilibrium, overconfident managers work for banks where bonus taxes are relatively low. Note that the bonus tax is especially suitable to affect the selection of overconfident managers. Like capital requirements, the bonus tax curbs the bank's incentive to shift risks, which decreases the benefit from employing an overconfident manager. In addition, and unlike capital requirements, the bonus tax makes it more costly for the bank to exploit the fact that an overconfident banker overvalues the bonus. Hence, if the government wants to avoid the selection of overconfident managers into certain institutions, the bonus tax is a particularly effective tool.

We summarize our findings in

Proposition 3 *Matching*

The willingness to pay for an overconfident manager increases with larger government guarantees v_i, lower bonus taxes t_i, and laxer capital requirements $1-s_i$. The matching of overconfident managers follows from Lemma (2).

Proof: Follows directly from equations (3.40), (3.41), (3.42), *and Lemma* (2).

The finding that overconfident managers select into banks with large government guarantees causes significant efficiency losses. The selection of overconfident managers into institutions with large bailout guarantees increases the likelihood of bailouts for two reasons. First, for a given contract, overconfident managers take on more risk as they overestimate the success probability of risky investments. And second, the bank creates higher powered compensation contracts for overconfident managers, which amplifies the behavioral effects of overconfidence and increases risk-taking further. The rise in the likelihood of bailouts increases the bailout subsidy, B, and thus the transfer of the government to the bank and the banker.

In reality, there will be further equity losses caused by redistributive effects between banks and the taxpayers from which we abstracted in the analysis by assuming equal welfare weights. Beyond the direct bailout costs, B, the financial crisis of 2007-2009 has shown that there are large externalities both within the financial market as well as from financial institutions to non-financial firms. A selection of overconfident managers, who increase the default risk, into banks that are systemically important enough to receive government guarantees is thus hazardous for the economy. Proposition 3 suggests that the government can influence the selection of managers. A bonus tax is particularly well suited to do so, because it can tackle the exploitation of managerial overvaluation.

3.8 Discussion

This section briefly investigates some policy implications of our analysis. Section 3.8.1 discusses the international policy competition for mobile bankers. In Section 3.8.2 we summarize why our model supports the implementation of bonus taxes in systemically important financial institutions and discuss deferrals and clawbacks of variable renumeration.

3.8.1 International Policy Competition

Proposition 3 suggests that governments can affect the matching of managers with banks by changing the bonus tax t and/or changing the capital requirements, $1-s$. This has implications for governments that compete for internationally mobile bankers.[38] In a non-cooperative setting of these two instruments, the governments can set high bonus taxes or strict capital requirements in order to have a selection of rational bankers in the domestic country. Conversely, if governments set low bonus taxes or lax capital

[38]There is ample evidence that bankers are mobile across countries (see e.g., Greve et al., 2009, 2015). For example, Staples (2008) shows that almost 70% of the 48 largest commercial banks have one or more non-national board members.

requirements, there will be a selection of overconfident bankers in the domestic country. These findings can be of interest to the literature on tax competition for mobile bank managers (see e.g., Gietl and Haufler, 2018) and to the literature on regulatory competition in capital requirements (see e.g., Dell'Ariccia and Marquez, 2006), which do not consider overconfidence.

Recall from Section 3.5.1 that overconfident managers create larger bailout costs, B, but also generate greater tax revenue, T. Hence, it is an interesting avenue for future research to investigate under which conditions there is a 'race to the bottom' or a 'race to the top' in bonus taxes when (some) bankers are overconfident. For example, it could be rational for governments to attract overconfident bankers, if there is a joint liability of bailout costs between the countries (i.e., a country partly comes up for the bailout costs of another country and vice versa). In this case, governments can benefit from the greater tax revenue that overconfident managers create, and only partly come up for the larger domestic bailout costs that overconfident managers cause.

3.8.2 Policy and Systemically Important Financial Institutions

Our model supports the implementation of bonus taxes in systemically important financial institutions (SIFIs). In SIFIs, risk-shifting incentives, $(1-\beta)v_i sd$, are strong due to explicit (e.g., due to deposit insurance) and implicit (e.g., because the SIFI is too big to fail) government guarantees. The bonus tax can counteract these socially adverse incentives. Hence, the optimal bonus tax rises in the bank's risk-shifting incentives (see eq. (3.28)). As managerial overconfidence exacerbates the risk-shifting problem, the optimal bonus tax further increases in overconfidence (see Proposition 1). In banks with weak risk-shifting incentives, however, the optimal bonus tax should be lower.

The main result, Proposition 2, shows that direct interventions into banker pay are well suited to establish the socially optimal bonus if bankers are overconfident. Overconfidence creates an incentive for the bank to exploit the managerial overvaluation of bonus payments. Unlike capital requirements, bonus taxes can counteract the bank's incentive to exploit managerial overvaluation and are thus able to deter excessive risk-taking. This is especially important in systemically important financial institutions where the social costs from defaults are potentially large.

Proposition 3 shows that overconfident managers select into banks with large government guarantees. This matching implies large bailout costs for taxpayers. Bonus taxes are particularly well suited to counteract this selection since they additionally tackle the exploitation of managerial overvaluation, which further reduces the benefit of hiring an overconfident manager. Hence, Proposition 3, like Proposition 1, suggests that bonus taxes should be larger in systemically important financial institutions than in institutions that carry less systemic risk, albeit for different reasons. Bonus taxes should be higher in SIFIs to mitigate excessive risk-taking (Proposition 1) and to deter the matching of overconfident bankers and SIFIs (Proposition 3).

Following the financial crisis of 2007-2009, several countries have considered and implemented deferals and clawbacks of variable renumeration and thereby removed the limited liability by the manager. In the United Kingdom, for example, the variable pay of bankers is partly subject to deferral and clawbacks for up to seven and ten years, respectively, from the date of a variable remuneration award.[39] This regulation aims to reduce excessive risk-taking in the banking industry by forcing bankers to internalize the costs of potential future losses. Thanassoulis and Tanaka (2018) find that, in the presence of government guarantees, clawback rules can establish socially optimal risk choices of a rational bank CEO.[40] In their model, clawbacks can discourage socially excessive risk-taking as they penalize the banker in case of the bank's default.[41]

Our analysis implies, however, that the effectiveness of deferred pay and clawbacks in SIFIs is limited if the banker is overconfident ($\theta > 0$). An overconfident banker underestimates the probability of bank default. He thus underestimates any expected penalty that he might incur in the case of default. Hence, overconfidence deters the intended effect of clawbacks and deferred pay to make the banker internalize downside risks.

3.9 Conclusion

In this chapter we have incorporated managerial overconfidence and limited bank liability into a principal-agent model of the banking industry. Overconfident managers overestimate the returns to risk-taking, which implies that they exert more effort and risk than rational managers. We find that the optimal bonus tax increases as a response to managerial overconfidence, if returns to risk-taking are positive. This is because government guarantees create an externality of the bank's behavior on the government, which is especially attractive to exploit, if the manager is overconfident. These socially adverse incentives can be counteracted with a bonus tax.

[39] See FCA PS 15/16 for details on the rules regarding bonus deferals and clawbacks for bankers in the United Kingdom.

[40] Thanassoulis and Tanaka (2018) emphasize that the clawback rules need to be assisted by rules on the convexity of CEO pay. Otherwise the bank can adjust the CEOs renumeration to circumvent the risk-reducing role of clawbacks.

[41] In a similar vein, Chaigneau (2013) suggests that a credible threat of sanctions for CEOs of failed banks can curb risk-shifting incentives.

Most importantly, our model shows that overconfidence necessitates an intervention into bankers' pay. Curbing the risk-shifting incentives of shareholders (e.g., via capital requirements) alone is not sufficient, as overconfidence leads to excessive bonuses even if shareholders fully internalize the externalities of their risk-taking. This is because shareholders exploit the fact that overconfident managers overestimate the probability of obtaining the bonus. Hence, shareholders have an incentive to increase their usage of bonuses to lower their total compensation costs at the expense of the overconfident banker. The bonus tax makes it more expensive for the bank to exploit managerial overvaluation and thus reduces excessive risk-taking in equilibrium.

Finally, our model suggests that overconfident managers work for banks with large government guarantees. These banks have a larger risk appetite and thus benefit more from employing overconfident managers than banks with smaller government guarantees. Hence, overconfident managers select into banks where they are particularly detrimental for taxpayers. Bonus taxes are particularly well suited to counteract this selection, as they not only curb the bank's risk-taking incentive, but also make it more costly for the bank to exploit an overconfident manager's overvaluation of the bonus. All in all, our model suggests that the presence of managerial overconfidence makes bonus taxes in systemically important financial institutions necessary.

Our project raises several questions for future research. For example, our prediction that overconfident managers sort into banks (and, more generally, firms) according to the regulatory environment could be empirically tested by using personal portfolios of CEOs to determine overconfidence (as in Malmendier and Tate, 2005a). Another promising research avenue is the international policy competition for mobile, overconfident bankers. Our model shows that policy parameters such as bonus taxes and capital requirements affect the selection of overconfident and rational managers in a country. Endogenizing such a policy parameter could shed light on whether it is optimal for all countries to set strict regulation/taxation and drive out overconfident managers, or if it's actually optimal for some countries to have a high-risk banking sector run by overconfident agents. We plan to cover this issue in future research.

Chapter 4

Managerial Overconfidence, Risk-Taking, and Financial Regulation

This chapter is based on single-authored work. See Kassner (2023) for the full reference.

4.1 Introduction

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

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

In this chapter, I study whether and how stricter financial regulation affects risk-taking of financial institutions with overconfident CEOs, using detailed financial data on listed firms in the U.S. financial sector for the years 1999 to 2019. CEO overconfidence is measured by their option exercising behavior, following Malmendier and Tate (2005a), and risk using different stock market-based risk measures. In a first step, I document a decrease in overconfidence-induced risk – which is the additional risk at financial institutions with overconfident CEOs – during the period of stricter financial regulation after the global financial crisis. In a second step, I show that this decrease in overconfidence-induced risk is only observable for financial institutions subject to enhanced regulation and, hence, attributable to stricter financial regulation.

To document the changes in the relationship between CEO overconfidence and risk

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

over time in the first step, I compare financial institutions with overconfident CEOs to financial institutions without overconfident CEOs in a fixed effects framework including a wide array of control variables. I find that risk-taking at financial institutions with overconfident CEOs is higher before the financial crisis. In terms of magnitude, having an overconfident CEO increases risk-taking by more than 15%, depending on the specification and the risk measure. However, during the period after the financial crisis, which is characterized by stricter regulation, risk-taking at financial institutions with overconfident CEOs converges to the levels of financial institutions with non-overconfident CEOs. In contrast, once large parts of the regulation are repealed – such as in the case of the Economic Growth, Regulatory Relief, and Consumer Protection ACT (EGRRCPA) of 2018 – overconfidence-induced risk-taking re-emerges, reaching almost the same extent as before. These results provide initial evidence that the nexus between managerial overconfidence and risk-taking is influenced by the regulatory environment.

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

The results are robust to several modifications of the analysis. To rule out alternative explanations concerning the option-based overconfidence measure, I examine the degree of optimism in a linguistic analysis of the Management Discussion and Analysis (MD&A) sections of the annual reports as well as hypothetical diversification strategies of the CEOs. The results show that the option-based overconfidence

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

measure is consistent with overconfident behavior across the entire observation period. As noted, the analysis already includes a wide range of control variables and firm and year fixed effects. Nonetheless, I address the potential concern of endogenous selection of overconfident CEOs in three ways: i) by closely examining the timing around the appointment of new CEOs, ii) by focusing on the subset of non-turnover CEOs, and iii) by instrumenting overconfidence using the age of the CEO. The main results are further robust to the inclusion of additional control variables, and to changes in the estimation methodology and the sample composition. Also they hold not only for the aggregate market-based risk measures, but also for approval decisions on individual loans and, thus, active risk-taking decisions.

This project 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., Landier and Thesmar, 2009; Graham et al., 2013; Huang et al., 2016), risk management (Adam et al., 2015), dividend policy (Deshmukh et al., 2013), merger decisions (Malmendier and Tate, 2008), and forecasting (Hribar and Yang, 2016). However, there are also positive aspects to CEO overconfidence. Hirshleifer et al. (2012) and Galasso and Simcoe (2011), for example, show that overconfident managers engage more in innovation and obtain more patents and thereby increase the value of the firm, while also increasing the volatility of the stock returns of the firm.

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

[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 et al., 2011). Furthermore, Goel and Thakor (2008) argue that, since promotion is usually based on performance, an overconfident manager is more likely to be promoted. In line with the theory, Graham et al. (2013) empirically show that CEOs are significantly more optimistic than the lay population.

global financial crisis.

I contribute to this literature by examining the relationship between CEO overconfidence and risk-taking in the financial sector in a dynamic setting. While this relationship has been treated as rather static in the existing literature, I document that the relationship between CEO overconfidence and risk-taking in the financial sector varies over time. The results indicate that overconfidence-induced risk is reduced in times that are characterized by stricter regulation. This helps to better understand whether risk in the financial sector caused by individual behavior reacts to changes in the economic environment and whether further scope for regulation remains to restrain overconfident behavior. Moreover, this project is the first to examine individual loan approval decisions of financial institutions in the context of managerial overconfidence.

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

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

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

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

tween firms with overconfident and non-overconfident CEOs was still prevalent in the financial sector in the period after the passage of the SOX.

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

This chapter proceeds as follows: Section 4.2 presents the main regulatory changes, the data, and discusses the overconfidence measure. Section 4.3 presents the estimation strategy, documents the changes in overconfidence-induced risk over time, and delivers robustness tests. Section 4.4 examines the role of the regulatory environment. Section 4.5 concludes.

4.2 Regulatory Background, Data, and Variables

4.2.1 Regulatory Background

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

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

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

4.2.2 Data

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

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

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

tions in all relevant variables contains 238 firms and 2448 firm-year observations.[7] I winsorize the accounting variables at the 1^{st} and 99^{th} percentiles.

4.2.3 Variables

4.2.3.1 Risk Measures

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

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

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

4.2.3.2 Control Variables

The baseline firm-level control variables are standard in the literature and constructed as follows: size ($size_t$) is calculated as the natural logarithm of total assets, the annual

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

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

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

return on assets (roa_t) is calculated as net income over total assets, book leverage ($leverage_t^b$) is calculated as book value of assets over book value of equity, deposits ($deposits_t$) are total deposits over total assets, and liquidity ($liquidity_t$) are cash and short-term investments over assets. Moreover, I control for the fiscal year-end stock price in all estimations.[10]

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

4.2.3.3 Overconfidence Measure

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

A CEO is overconfident when postponing the exercise of *exercisable* deep-in-the-money options. Since there is only aggregate data available for the option portfolios of the respective CEOs prior to 2006, I follow earlier studies in constructing the overconfidence measure based on the average degree of moneyness of the CEO's option portfolio in a given year (e.g., Campbell et al., 2011; Ho et al., 2016). Average moneyness for *exercisable* options in a given year is calculated as the realizable value per

[10]For a detailed presentation of the variables refer to Table D.1.1 in the appendix.

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

option divided by the estimated average exercise price, which is the price at which the CEO has the option to buy the underlying stock. A CEO is classified as overconfident when postponing the exercise of options which were at least 100% in the money, i.e., the stock price is at least twice as high as the strike price. Using 100% as cutoff ensures that only highly overconfident CEOs are classified as overconfident (see e.g., Campbell et al., 2011).

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

The late-exercising behavior might, however, be rational if the CEOs ex-post systematically profit from holding the options longer due to, for example, superior information. To rule this out, I test whether CEOs with option portfolios above 100% moneyness benefited *ex-post* from holding these options by constructing an alternative hypothetical investment strategy. More precisely, I compare the returns from selling the options in year $t+1$ at the highest possible price, to capture the highest degree of inside information, to the returns from selling these options at the highest price in year t, investing the proceeds into the S&P500, and selling again after the same period of time in $t+1$. In other words, I test whether the late-exercising CEOs earned excess returns compared to the diversification strategy. The results in Table 4.1 show that, on average, the CEOs did not significantly earn more by holding their options as compared to the diversification strategy, even when assuming the highest degree of inside information.

Malmendier and Tate (2005a) and Malmendier and Tate (2008) discuss further alternative explanations, which might play a role in the late-exercising behavior of options, but conclude that overconfidence is the most consistent explanation. Moreover, a high correlation between the option-based measure and a press-based measure of overconfidence, which classifies CEOs according to their portrayal in the press, supports the measure (see e.g., Malmendier and Tate, 2008; Hirshleifer et al., 2012). In a recent study, Kaplan et al. (2022) deliver evidence that the option-based measure indeed

[12]If a CEO switches between firms in the observed period, all tenures are taken into account. Observations with zero options or a value of exercisable unexercised options of zero are treated as non-overconfident whereas observations where the realizable value per option equals the fiscal year-end stock price, which implies a strike price of zero, are treated as overconfident. If information about the CEO in tenure is missing for certain years, I impute the level of overconfidence from the previous period. I omit these observations in a robustness test in section 4.3.3.3.

Table 4.1: Returns to late-exercising

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

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

reflects overconfident behavior using detailed personality assessments of CEOs.

Nonetheless, post-crisis regulation might have influenced the option-exercising behavior of the CEOs directly via, for example, changes in executive compensation. To ensure that the option-based overconfidence measure consistently captures overconfident behavior over time, I analyze the tone of the *Management Discussion and Analysis* (MD&A) section of the annual reports (10-K). In the MD&A section, the firm's management analyzes the firm's performance with qualitative and quantitative measures. It is argued that in this section, the management, and thus the CEO, most likely reveal information via the tone (see e.g., Loughran and McDonald, 2011). A more overconfident CEO should use more positive words, relative to negative words, all else equal. For this purpose, I parse this section from the respective 10-K reports from the *SEC EDGAR* database. To end up in the sample, I require these sections to contain at least 250 words since in many cases this section is only incorporated by reference. For approximately two-thirds of the firms, I am able to obtain the respective MD&A sections. I then analyze the degree of optimism in the tone of these sections by contrasting the number of positive words ($f_{positive}$) to the number of negative words ($f_{negative}$) as defined by the Loughran and McDonald (2011) dictionary.[13] More precisely, I use the proportion of positive words to negative words ($tone_r = \frac{\sum f_{positive}}{\sum f_{negative}}$) as a first raw measure. As a second measure ($tone_w$), I weigh each word by the commonality across documents before computing the proportion. The weight is calculated as $ln((e-1)+\frac{N}{df})$, where N is the total number of documents in the sample and df is the number of documents containing the respective word. Hence, less common words receive a higher weight whereas words that appear in every document receive a weight of 1.

To test whether the option-based measure consistently captures overoptimistic behavior over time, I regress the natural logarithm of the continuous tonal measures on the option-based overconfidence dummy interacted with a dummy variable distinguishing four different periods, based on the discussion in Section 4.2.2, using OLS. I

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

Table 4.2: Option-based overconfidence and the tone of the MD&A section

This table presents the regression results for the analysis of the relationship between the option-based overconfidence measure and the tone of the MD&A sections of the annual reports for the years 1999 to 2019. The natural logarithm of the tonal measure for firm i in year t, which is either the share of positive over negative words, as defined by the Loughran and McDonald (2011) dictionary, (column (1)) or the weighted share of positive over negative words (column (2)), is regressed on $OC_{i,t}$, a binary variable which is one if a firm has an overconfident CEO at time t, as defined by the option-based measure, interacted with an indicator variable distinguishing four different periods, and a vector of controls including size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, the fiscal year-end stock price, and the number of words contained in the MD&A section as well as firm and year fixed effects. Variable definitions are in Table D.1.1. Hubert-White heteroskedasticity consistent standard errors in parentheses. Stars indicate significance: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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

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 4.2. Column (1) shows the results for the raw measure and column (2) for the weighted measure. Both specifications show that the option-based overconfidence measure is significantly and positively correlated with the degree of optimism in the tone of the MD&A section. In terms of size, having an overconfident CEO, as classified by the option-based measure, is associated with a 10-12% higher proportion of positive words in the MD&A section, conditional on the firm's performance. Moreover, the results show that this relationship is similar across the different time periods since the coefficients on the interaction terms with the respective periods are close to zero and insignificant.

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

Table 4.3 shows summary statistics of the full unbalanced sample (panel (1)), the means of the overconfident (column (2)) and non-overconfident (column (3)) subsamples, and the difference between the two samples (column (4)) to provide some indication of the nature of the sample. Around 30% of the CEO-year observations are

Table 4.3: Summary statistics of selected variables

This table presents summary statistics for the main variables used in this study for the years 2000 to 2019. The sample is unbalanced. Balance sheet data is taken from *Compustat North America Fundamentals*, option data from *Execucomp Annual Compensation*, and stock market data from *CRSP*. Panel (1) shows the summary statistics for the full sample, column (2) for the overconfident sample, column (3) for the non-overconfident sample, and column (4) the difference. Variable definitions are in Table D.1.1. Stars indicate significance of a paired t-test: $^{*}p < 0.1$,** $p < 0.05$,*** $p < 0.01$.

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

classified as overconfident.[14] Further, the average daily stock return volatility is .02 ($e^{-3.938}$), the average beta 1.19, and the average mean squared error .00024 ($e^{-8.355}$). The difference between the two sub-samples is significantly different from zero for most of the control variables and confirms the need to control for these variables in the subsequent analysis.

4.3 Managerial Overconfidence and Risk-Taking

4.3.1 Descriptive Evidence

Figure 4.1, which plots the sample mean of the three risk measures over time, shows that stock return volatility and the idiosyncratic risk component were highest during the financial crisis but at relatively low levels before and after. In contrast to that, the co-movement with the stock market already shows a buildup in systemic risk before the onset of the financial crisis. Turning to the difference between financial institutions with overconfident CEOs and without, the figure shows across all measures that, on average, risk at financial firms with overconfident CEOs is higher before 2008, with no different trend observable. During the period of increased regulatory oversight after 2008, both types converge across all risk measures. After deregulation in 2018, risk is, on average, again higher at financial firms with overconfident CEOs, though not to the same degree as in the pre-crisis period.

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

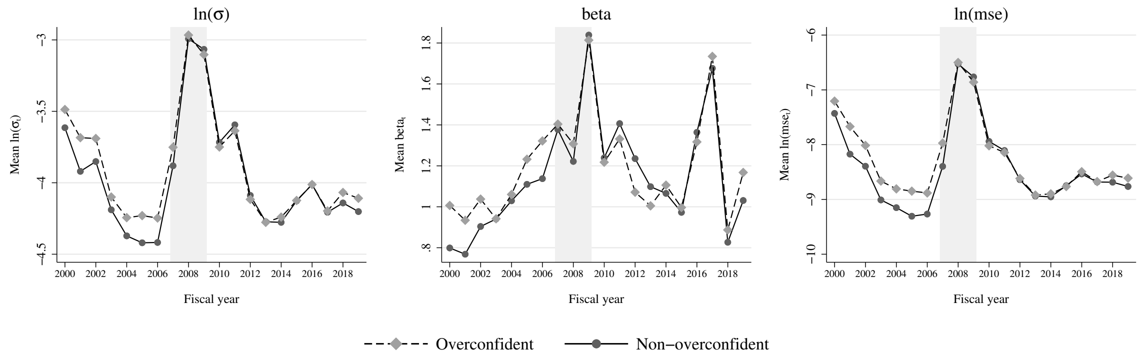


Figure 4.1: Development of risk over time

This figure shows the development of risk measured as the natural logarithm of the standard deviation of daily stock returns (left), the market beta (center), and the natural logarithm of the mean-squared-error of a single index model (right). Diamonds represent the average of the respective risk measure for firms with overconfident CEOs and dots the average risk for firms with non-overconfident CEOs. Variable definitions are in Table D.1.1. The shaded area indicates the financial crisis.

Table 4.4, which shows the difference between financial institutions with overconfident CEOs and financial institutions with non-overconfident CEOs for the three different time periods observed in Figure 4.1, confirms these results. Risk of financial institutions with overconfident CEOs was, on average, significantly higher in the period before 2008 (column (1)). During the period from 2008 to 2017, both types of financial institutions converged in their level of risk (column (2)) with no significant difference remaining. Starting from 2018, risk is again significantly higher at financial institutions with overconfident CEOs (column (3)) albeit at a smaller difference.

Thus, the descriptive analysis reveals heterogeneous changes in risk across time. This evidence is consistent with additional risk and uncertainty about future returns that are priced in by the market during times of higher discretionary power of overconfident CEOs, as discussed in Section 4.2. Table 4.4, however, also shows heterogeneous changes in other firm characteristics over time. Therefore, it is important to control for these firm characteristics in the regression analysis in the following section.

4.3.2 Regression Analysis

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

[15]Following Ho et al. (2016), I also estimate a weighted least squares version of the above-specified equation using weights related to size in a robustness test in section 4.3.3.5.

Table 4.4: Differences in selected variables across CEO type

This table presents the differences in the means of the main variables used in this study between financial institutions with overconfident CEOs and non-overconfident CEOs for different time periods. The sample is unbalanced. Variable definitions are in Table D.1.1. Stars indicate significance of a paired t-test: $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

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

econometric model is designed as follows:

$$\begin{aligned} risk_{i,t} =& \alpha + \sum_{j\neq 2006} \mu_j \mathbb{1}[t=j]_{i,t} \\ &+ \beta_0 OC_{i,t-1} + \sum_{j\neq 2006} \beta_j OC_{i,t-1} \times \mathbb{1}[t=j]_{i,t} \\ &+ \boldsymbol{\gamma' X_{i,t}} + \nu_i + u_{i,t}, \end{aligned} \tag{4.1}$$

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

The coefficient β_0 denotes the average difference in risk-taking between financial institutions with overconfident CEOs and financial institutions with non-overconfident

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

In addition to the dynamic event study model in Equation (4.1), I also estimate a pooled version by pooling the years in the three periods observed in Figure 4.1 and discussed in Section 4.2. For this, the measures of risk are regressed on the binary overconfidence variable interacted with an indicator variable for each of the three periods and firm-level controls in a fixed effects framework using OLS. The econometric model is designed as follows:

$$\begin{aligned} risk_{i,t} =& \alpha + \sum_{j \neq 2006} \mu_j \mathbb{1}[t=j]_{i,t} \\ &+ \beta_0 OC_{i,t-1} + \sum_{p \neq \{2000,2007\}} \beta_p OC_{i,t-1} \times \mathbb{1}[t \in p]_{i,t} \\ &+ \boldsymbol{\gamma' X_{i,t}} + \nu_i + u_{i,t}, \end{aligned} \tag{4.2}$$

where $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The three periods are the periods from 2000 to 2007, from 2008 to 2017, and from 2018 to 2019 as observed in Figure 4.1 and discussed in Section 4.2.

Figure 4.2 plots the gradient of overconfidence of the dynamic event study model, which is the above-mentioned linear combination of β_0 and β_j, for each year j of the OLS regression of Equation (4.1) along with the gradient of overconfidence of the OLS regression of the pooled model in Equation (4.2) for the three measures of risk. The results show that risk is significantly higher at financial institutions with overconfident CEOs in the period from 2000 to 2007, with no significant pre-trend observable. This result is consistent with the existing evidence from the literature (see e.g., Ho et al., 2016) and consistent with a laxer regulatory environment giving the overconfident CEOs more discretionary power. Consistent with the argumentation of Cheffins (2015), the passage of the SOX in 2002, which was effective in mitigating the negative consequences of CEO overconfidence in the general economy (Banerjee et al., 2015), did not affect overconfident CEOs in the financial sector. The gradient of overconfidence, however, is not significantly different from zero during the period

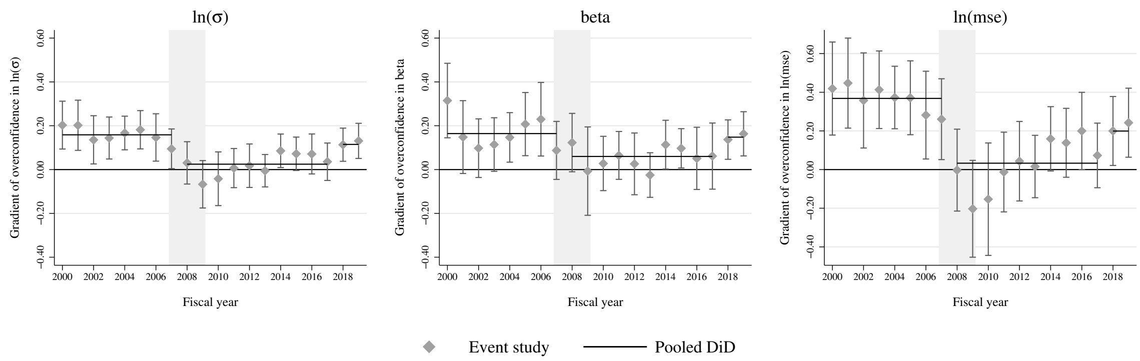


Figure 4.2: CEO overconfidence and risk-taking – dynamic results

This figure shows the gradient of overconfidence in risk-taking (diamonds), which is the linear combination of β_0 and β_j for each year j in the OLS estimation of Equation (4.1), along with the gradient of overconfidence of the pooled OLS estimation of Equation (4.2) (black line) for the three aggregate measures of risk-taking in the U.S. financial sector in the years 2000 to 2019 (natural logarithm of the standard deviation of daily stock returns (left), market beta (center), and the natural logarithm of the mean-squared-error of a single index model (right)). The vector of controls $\boldsymbol{X_{i,t}}$ includes the control variables size, return on assets, leverage, deposit ratio, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Variable definitions are in Table D.1.1. Hubert-White heteroskedasticity consistent standard errors are clustered at the firm level. 95% confidence intervals are shown. The shaded area indicates the crisis years.

of stricter regulation between 2008 and 2017. Albeit not formalized in legislation, the risk-decreasing effect is stronger during the period from 2008 to 2013 and weaker during the period from 2014 to 2017, reflected in a slight increase in overconfidence-induced risk-taking in the latter period. With deregulation in 2018 risk-taking again diverges with significantly higher risk at financial institutions with overconfident CEOs, which is consistent with an increase in the discretionary power of individual CEOs.

The results of the OLS regression of the pooled model in Equation (4.2) are summarized in Table 4.5. Columns (1) to (3) show the results excluding control variables and columns (4) to (9) including controls. In columns (7) to (9), I additionally split the regulation period into two separate periods lasting from 2010 to 2013 and from 2014 to 2017, based on the observation in Figure 4.2. In the period from 2000 to 2007, risk is significantly higher at financial institutions with overconfident CEOs across all risk measures as indicated by the positive and highly significant coefficient for the overconfidence dummy (β_0) in all specifications. Again, this is consistent with previous results in the literature for the financial sector (e.g., Ho et al., 2016). In terms of size, firms with overconfident CEOs had a 17.2% ($(e^{(0.159)} - 1) \times 100$) higher standard deviation of daily stock returns (column (4)) and a 44.5% higher loading of idiosyncratic risk (column (6)). Since the sample's average exposure to market risk is 1.19, the coefficient of the overconfidence dummy in column (5) indicates an additional market exposure of 13.8% for firms with overconfident CEOs.

The coefficient $\beta_{2008,2017}$ across all specifications indicates a risk-decreasing effect at financial institutions with overconfident CEOs in the period between 2008 and 2017 relative to financial institutions with non-overconfident CEOs. As mentioned before,

Table 4.5: CEO overconfidence and risk-taking – pooled results

This table presents the regression results of the OLS estimation of the fixed effects model in Equation (4.2) for risk-taking in the U.S. financial sector in the years 2000 to 2019. The dependent variables are the three aggregate measures of risk-taking, i.e., the natural logarithm of the standard deviation of daily stock returns, the market beta, and the natural logarithm of the mean-squared-error of a single index model. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Variable definitions are in Table D.1.1. Hubert-White heteroskedasticity consistent standard errors clustered at the firm level in parentheses. Stars indicate significance: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

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

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

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

4.3.3 Robustness Tests

In the following section, I test the robustness of the results of the previous analysis. The first set of robustness tests is concerned with a potentially endogenous selection of CEOs. In a second robustness test, I instrument CEO overconfidence with the age of the CEO. This is followed by further robustness tests concerning the inclusion of additional CEO and firm characteristics, the estimation methodology, and the sample. Throughout the section, I will focus on the pooled specification in Equation (4.2).

4.3.3.1 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., Hirshleifer et al., 2012; Aktas et al., 2019). If overconfident CEOs are replaced due to a change in the firm's strategy, this should particularly materialize in the first years of tenure. Therefore, I rerun the regression in Equation (4.2) for subsamples of CEOs with more than one, three, and five years of tenure.[17]

The results in Table 4.6 show that the baseline estimates remain robust to excluding the first years of tenure of a CEO. This further alleviates concerns that the results are driven by an endogenous selection of overconfident CEOs.

4.3.3.2 Instrumental Variable Analysis

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

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

Table 4.6: Robustness tests – tenure

This table presents the regression results of the OLS estimation of the fixed effects model in Equation (4.2) for risk-taking in the U.S. financial sector in the years 2000 to 2019 when excluding the first, the first three, and the first five years of tenure of each CEO. The dependent variables are the three aggregate measures of risk-taking, i.e., the natural logarithm of the standard deviation of daily stock returns, the market beta, and the natural logarithm of the mean-squared-error of a single index model. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Variable definitions are in Table D.1.1. 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)	(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}	0.186***	0.205***	0.418***	0.199***	0.224***	0.449***	0.186***	0.220***	0.408***
	(0.033)	(0.050)	(0.071)	(0.037)	(0.056)	(0.077)	(0.043)	(0.064)	(0.089)
$period_{2008,2017} \times OC_{t-1}$	-0.148***	-0.136**	-0.356***	-0.144***	-0.126**	-0.339***	-0.133***	-0.135*	-0.286***
	(0.041)	(0.053)	(0.092)	(0.044)	(0.061)	(0.097)	(0.048)	(0.069)	(0.103)
$period_{2018,2019} \times OC_{t-1}$	-0.0648	-0.0471	-0.207**	-0.0757	-0.0556	-0.234**	-0.0588	-0.0777	-0.177
	(0.045)	(0.060)	(0.104)	(0.048)	(0.065)	(0.109)	(0.052)	(0.072)	(0.120)
Observations	2255	2255	2255	1873	1873	1873	1531	1531	1531
Clusters	228	228	228	224	224	224	213	213	213
Mean	-3.93	1.20	-8.35	-3.95	1.19	-8.39	-3.96	1.19	-8.39
adj. 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

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:

$$Pr(OC_{i,t}=1|age_{i,t},\boldsymbol{X_{i,t}}) = \Phi(\delta_0+\delta_1 age_{i,t}+\boldsymbol{\gamma'}\boldsymbol{X_{i,t}}+\mu_t), \tag{4.3}$$

where $age_{i,t}$ is the age of the CEO in tenure.[18] Then, I use the fitted values of overconfidence $\widehat{OC}_{i,t}$ from Equation (4.3) as instruments in a linear 2SLS estimation of Equation (4.2).[19] This three-step procedure avoids the so-called 'forbidden regression', which uses predicted values from a non-linear first stage directly in a linear second stage regression (Angrist and Pischke, 2009), and has previously been applied in related contexts (e.g., Adams et al., 2009; Huang et al., 2018). The advantages of the approach are twofold. First, the procedure considers the non-linear nature of the endogenous variable. Second, the non-linear first step is not required to be correctly specified. It only requires the instrument to be correlated with the probability of the CEO being overconfident. As a result of this procedure, the standard errors of the 2SLS estimation remain valid (see Wooldridge, 2002, procedure 18.2).

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

[19]Moreover, I use the interaction of the fitted values of overconfidence $\widehat{OC}_{i,t}$ with the different periods as instruments for the interaction terms in Equation (4.2).

Table 4.7: 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 4.3.3.2. The first step (column (1)) regresses the overconfidence dummy on the instrument $age_{i,t}$, which denotes the age of the CEO in tenure, and the control variables in the probit model in Equation (4.3). The fitted values of the first step are then used as instruments in a 2SLS estimation of the fixed effects model in Equation (4.2) (second stage results in columns (2) to (4)). The dependent variables are the three aggregate measures of risk-taking, i.e., the natural logarithm of the standard deviation of daily stock returns, the market beta, and the natural logarithm of the mean squared error of a single index model. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Variable definitions are in Table D.1.1. *KP F-stat* denotes the Kleibergen-Paap Wald test statistic for multiple instruments and *SW F-stat* denotes the Sanderson-Windmeijer F-statistic for individual instruments. Hubert-White heteroskedasticity consistent standard errors clustered at the CEO level (column (1)) and at the firm level (columns (2)-(4)) in parentheses. Stars indicate significance: $^{*}p < 0.1$,** $p < 0.05$,*** $p < 0.01$.

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

Table 4.7 summarizes the results of the three-step instrumental variable estimation. Column (1) displays the results for the non-linear probit regression. The coefficient of age shows that age is a significant predictor for the overconfidence dummy and thus confirms earlier findings in the literature. The results of the second stage of the 2SLS in columns (2) to (4) do not change qualitatively compared to the fixed effects regression in Section 4.3.2. While overconfidence increases risk-taking in the period prior to 2008, the coefficients of the overconfidence dummy and the interaction term indicate a convergence in the risk-taking behavior in the period between 2008 and 2017 and again a significant difference in the period after 2018. The coefficients are larger than in the OLS estimation pointing towards an underestimation of the effect in the fixed effects regression.

4.3.3.3 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 D.1.2 in the appendix shows the results for the estimation of Equation (4.2), with the baseline results in column (1).

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

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

In column (5), I include the price and volatility sensitivity of the CEOs' stock option portfolio (e.g., Fahlenbrach and Stulz, 2011). I follow Core and Guay (2002) and Coles et al. (2006) in constructing the option portfolio *Delta* (sensitivity of the option portfolio to changes in the stock price) and the option portfolio *Vega* (sensitivity of the option portfolio to changes in the volatility of the stock price). Including both measures decreases the sample size due to data availability. To further rule out that compensation is confounding the results, I follow Correa and Lel (2016) and construct a measure for excessive compensation, which I include in column (6). For that, I regress total compensation on return on assets, annualized excess returns over the risk-free rate, market-to-book value, the annualized standard deviation of the daily stock returns, book leverage, and time and industry fixed effects. I then subtract the predicted values of income from the actual values of total income to derive a measure of excessive compensation. In column (7), I additionally control for the number of exercisable options, which influences the measure of overconfidence. In the specification in column (8), I predict the wealth of the CEO using age and income instead of using inside wealth, which disregards any outside wealth.[20]

For all the specifications mentioned above, the results in Table D.1.2 remain qualitatively and quantitatively similar.

[20]This choice is justified with the observation that in the U.S., for the income distribution observed in the sample, net worth and income are highly correlated. Using the 2016 Survey of Consumer Finances (SCF), the raw correlation of income and net worth between the 1st and 99th percentile in logarithmic terms is highly significant with a correlation coefficient of .77. Moreover, regression results of net worth on income in Table D.1.3 in the appendix reveal an elasticity of close to one. Since including age in the predictions of wealth in Table D.1.3 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 D.1.3.

4.3.3.4 Firm Characteristics

The next robustness tests are concerned with the potential omission of additional firm characteristics. Table D.1.4 in the appendix shows the results for the estimation of Equation (4.2), with the baseline results in column (1).

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

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

Again, the results for all changes to the specification as outlined above and shown in Table D.1.4 remain qualitatively and quantitatively similar.

4.3.3.5 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 D.1.5 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 (4.2) using industry fixed effects instead of firm fixed effects.

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

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

Since overconfidence is modeled as a semi-fixed effect, there is relatively little variation in the variable itself. The identification in the firm fixed effect model relies on within-CEO variation, i.e., CEOs who become overconfident during tenure, and within-firm variation, i.e., a replacement of a CEO. This might lead to a sample selection bias. Using industry fixed effects allows for across-firm identification. The results remain robust to these changes.

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

The robustness tests in columns (5) to (7) are concerned with a change in the composition of the CEO sample and only focus on those CEOs who were in tenure in all of the years between 2007 and 2010. In column (6) I re-estimate the model in Equation (4.2) only using CEOs who were replaced during the financial crisis, including their replacement, while in column (7) I re-estimate the model only using CEOs who were not replaced during the crisis to examine the source of variation more closely. Column (5) takes both groups together. Financial institutions with overconfident CEOs who were replaced during the financial crisis increased risk-taking more before the financial crisis than financial institutions with overconfident CEOs who were not replaced. Despite this difference before the financial crisis, risk at financial institutions with both replaced and non-replaced overconfident CEOs decreases to the same levels as the risk at financial institutions with non-overconfident CEOs during the period between 2008 and 2017. Hence, the disciplining effect after 2008 is similar for newly hired CEOs as well as for CEOs who remained in office. By focusing only on non-turnover CEOs in column (7), I ensure that the effects are not only driven by the replacement of CEOs further alleviating concerns about the strategic selection of CEOs. Since I am excluding variation that is driven by the replacement of CEOs, the statistical power decreases. The results do not change qualitatively.

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

Taken together, the robustness tests in this section deliver evidence that the results from the baseline estimation of Equation (4.2) are robust.

4.3.4 Lending Behavior

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

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

Since the analysis so far is at the financial holding company level and these parent companies usually do not directly issue mortgages, I link the respective holding companies to their direct subsidiaries. To do so, I use detailed bank relationship information from the Federal Reserve System.[23] When linking the subsidiaries to the parent companies, I only keep direct relationships and controlled subsidiaries. If several parent

[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). 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 4.3.2 was re-estimated using the matched sample only. The untabulated results show similar results.

companies overlap within a certain time period, I drop these observations. Since the HMDA data is only recorded at an annual frequency, I only keep parent-subsidiary pairs that were active for at least half a year in a respective calendar year.

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

To assess the riskiness of a loan, I compute the loan-to-income ratio of the borrower using the information provided by the loan application. A higher loan-to-income ratio increases the risk of not being able to service the debt and thus proxies for creditworthiness of the borrower. I winsorize the loan-to-income ratio at the 0.01% and 99.99% levels to exclude implausibly large outliers. Since this is the variable of interest, I only keep observations with data on the loan-to-income ratio. The final sample amounts to 7,062,126 observations for 321 direct subsidiaries at 163 holding companies for the years 2005-2019 with all necessary information provided.[24] To differentiate between credit demand and active lending decisions, I follow Duchin and Sosyura (2014) and estimate the following model:

$$\begin{aligned} y_{i,b,m,t} =& \alpha + \beta_0 OC_{b,t-1} + \sum_{p\neq\{2000,2007\}} \beta_p OC_{b,t-1} \times \mathbb{1}[t\in p]_{i,t} \\ &+ \eta_0 lti_{i,b,m,t} + \sum_{p\neq\{2000,2007\}} \eta_j lti_{i,b,m,t} \times \mathbb{1}[t\in p]_{i,t} \\ &+ \lambda_0 OC_{b,t-1} \times lti_{i,b,m,t} + \sum_{p\neq\{2000,2007\}} \lambda_j OC_{b,t-1} \times \mathbb{1}[t\in p]_{i,t} \times lti_{i,b,m,t} \\ &+ \boldsymbol{\gamma' X_{b,t}} + \boldsymbol{\delta' X_{i,t}} + \nu_i + \nu_b + \nu_m + \mu_t + \nu_m \times \mu_t + \epsilon_{i,b,m,t}, \end{aligned} \tag{4.4}$$

where $y_{i,b,c,t}$ is a binary that equals one if a loan application i at bank b for a property in metropolitan statistical area (MSA) m during year t was approved, $OC_{b,t-1}$ is a binary variable which is one if a financial institution has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p, $lti_{i,b,m,t}$ is the loan-to-income ratio of the borrower of loan i at bank b for a property in MSA m in year t. The vector of bank controls ($\boldsymbol{X_{b,t}}$) includes the standard controls as in the baseline estimation (size, return on assets, leverage,

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

deposit ratio, liquidity, inside wealth, and the fiscal year-end stock price). The vector of loan controls ($\boldsymbol{X_{i,t}}$) includes the loan amount. Furthermore, ν_i denotes categorical borrower characteristics (i.e., gender, race, ethnicity, and co-applicant status) as well as categorical loan characteristics such as, in the full specification, loan type (insured loans), property type, and occupancy, ν_b denotes bank holding company fixed effects, ν_m MSA fixed effects and μ_t year fixed effects. I include the interaction of MSA and year fixed effects to account for MSA characteristics that are varying with time. The standard errors are clustered at the bank holding company level to allow for within-bank correlation of residuals. I estimate Equation (4.4) using OLS.

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

The results are shown in Table 4.8. Column (1) shows the results when only controlling for bank characteristics, borrower characteristics, and firm, MSA, and year fixed effects. Column (2) includes MSA times year fixed effects. Column (3) adds categorical loan characteristics and column (4) adds additional loan characteristics. Column (5) excludes all observations where a parent-subsidiary relationship was non-existent for the entire calendar year.

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

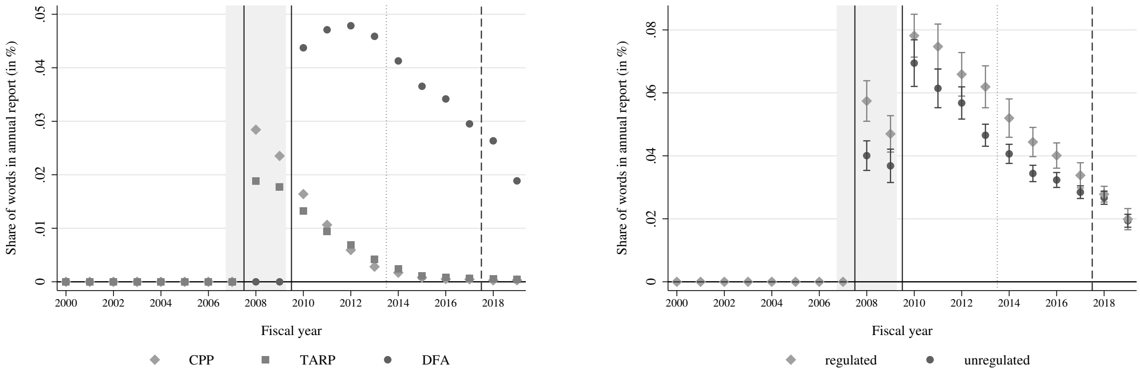
Table 4.8: Overconfidence and approval of mortgage applications

This table presents the regression results of the OLS estimation of the HMDA loan-level estimation in Equation (4.4) for the U.S. financial sector for the years 2004 to 2019. The dependent variable is a binary variable which is one if a loan application i at bank b for a property in metropolitan statistical area (MSA) m during year t was approved. $OC_{b,t-1}$ is a binary variable which is one if a financial institution b has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. $lti_{i,b,m,t}$ is the loan-to-income ratio of the borrower of loan i at bank b for a property in MSA m in year t. Variable definitions are in Table D.1.1. Standard errors clustered at the bank holding company level in parentheses. Stars indicate significance: $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

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

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

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



(a) Full sample (b) By group

Figure 4.3: Importance of regulatory provisions in annual reports

This figure plots the share of words referring to either of the three regulatory frameworks DFA, TARP, and CPP. Panel a) plots the average share for each of the regulatory frameworks separately for the full sample. Panel b) plots the average share for the three frameworks together split by regulated and non-regulated financial institutions as discussed in Section 4.4. The error bars show a one standard deviation from the mean. The shaded area indicates the crisis years. The solid vertical lines denote the timing of the respective regulatory frameworks and the dashed vertical line the timing of deregulation.

4.4 The Role of Stricter Financial Regulation

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

As already introduced in Section 4.2, the period between 2008 and 2017 was characterized by stricter financial regulation in the U.S. financial sector. The main regulatory frameworks introduced during that period were the DFA in 2010 and the rules and regulations associated with the CPP and TARP in 2008. To get a feeling about the importance of these regulatory provisions, I examine the number of references to either of them in the annual reports of the financial institutions in the sample. Figure 4.3a shows the average share of words referring to either of the three regulatory frameworks within the annual reports of the financial institutions in the sample. There was a strong focus on these frameworks during the period from 2008 to 2013 with a swift decline starting in 2014. Consistent with the official end of TARP/CPP in 2014 and the deregulation by the EGRRCPA in 2018, which repealed parts of the DFA, the share of words referring to either the TARP/CPP or the DFA declines further.

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

The first group includes smaller depository institutions ($< \$10bn$ in total assets) and non-depository institutions.[25] Depository institutions, in general, are overseen by depository regulators such as the Federal Reserve (FED), the Office of the Comptroller of the Currency (OCC), the Federal Deposit Insurance Corporation (FDIC), or the National Credit Union Administration (NCUA) depending on the status of the holding company (for an overview see, e.g., Labonte, 2020), and are, thus, subject to deposit insurance requirements, safety and soundness regulations, such as capital requirements, and consumer compliance regulations (Demyanyk and Loutskina, 2016). However, the smaller depository institutions were not subject to enhanced regulation after the financial crisis. Non-depository institutions, or shadow banks, are not subject to the same regulation that applies to depository institutions. As Demyanyk and Loutskina (2016) and Buchak et al. (2018) document, these financial institutions enjoyed laxer regulation before the financial crisis than depository institutions since they were neither overseen by the aforementioned institutional regulators nor strictly by the functional regulators such as the Securities and Exchange Commission (SEC) (for an overview see, e.g., Labonte, 2020). For example, non-depository institutions did not have to meet the same capital requirements as depository institutions. Despite acknowledging the risks stemming from this laxer regulation and the implementation of the Financial Stability Oversight Council (FSOC), the post-crisis regulation remained lax for non-depository institutions which were not designated to be systemically important by the FSOC (Acharya and Richardson, 2012).

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

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

Table 4.9: Regulated und unregulated financial institutions – summary statistics

This table presents summary statistics for the main variables used in this study in the year 2007 for the two groups as described in Section 4.4 separately. Variable definitions are in Table D.1.1. Stars indicate significance of a paired t-test: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

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

measures, might have contained the scope of overconfident CEOs.

Table 4.9 shows summary statistics for both groups for the year 2007. As expected, the financial institutions subject to stricter regulation are, on average, larger, have a higher share of deposits, a higher stock price, and, associated with that, a higher level of inside wealth of the CEO.

Figure 4.3b, depicting the average share of words referring to either of the three regulatory frameworks after 2008 for both groups separately, shows a higher importance within the group of stricter regulated financial institutions. Despite the sample split not perfectly reflecting the take-up of TARP and, thus, the exact treatment status in the years 2008 and 2009, Figure 4.3b shows that even during this time, on average, there seems to be a higher importance of the provisions for the stricter regulated group. A misclassification during this time, however, would only lead to an underestimation of the effects of stricter regulation. With deregulation in 2018, the difference between the two groups disappears.

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

Table 4.10: Regulated financial institutions – crisis exposure

This table presents the regression results of the OLS estimation of the cross-sectional model in Equation (4.5) for crisis exposure. The dependent variable $exp_{i,\tau}$ is one of the following measures of exposure to the financial crisis: i) the percent decline in the fiscal year-end stock price from the year 2006 to the year 2009, ii) the amount of write-offs accumulated during the crisis years 2007-2009 as a share of total assets in 2006, iii) the cumulative net income during the crisis years over assets in 2006, and iv) the share of mortgage loans in total lending in the year 2006. $\mathbb{1}[regulated = 1]_i$ is a binary variable that equals one for regulated financial institutions as described above. The vector of controls $\boldsymbol{X_{i,2006}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price as of 2006. Variable definitions are in Table D.1.1. Hubert-White heteroskedasticity consistent standard errors in parentheses. Stars indicate significance: $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

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

about by self-selection.

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

$$exp_{i,\tau} = \alpha + \beta_1 \mathbb{1}[regulated = 1]_i + \boldsymbol{\gamma}' \boldsymbol{X_{i,2006}} + \varepsilon_i, \tag{4.5}$$

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

The results in Table 4.10 show no significant difference in the stock price decline after the crisis with the average decline in stock prices amounting to 48% (column (1)). Furthermore, the regulated financial institutions neither experienced a significantly larger share of write-offs (column (2)) nor a lower return on assets (column (3)) during the crisis. The share of mortgage loans in total lending shows no significantly different

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

direct exposure to the mortgage market in the year prior to the financial crisis (column (4)). Taken together, the results suggest that the regulated financial institutions, on average, were not significantly more exposed to and adversely affected by the financial crisis than the other financial institutions.

To estimate the heterogeneous effect of the different regulatory environments, I re-estimate the event study model in Equation (4.1) interacted with a binary variable for the regulatory status of the financial institution as described above of the form:

$$\begin{aligned}
risk_{i,t} =& \alpha + \sum_{j \neq 2006} \mu_j \mathbb{1}[t=j]_{i,t} \\
& + \delta_0 \mathbb{1}[regulated=1]_i + \sum_{j \neq 2006} \delta_j \mathbb{1}[t=j]_{i,t} \times \mathbb{1}[regulated=1]_i \\
& + \beta_0 OC_{i,t-1} + \sum_{j \neq 2006} \beta_j OC_{i,t-1} \times \mathbb{1}[t=j]_{i,t} \\
& + \eta_0 OC_{i,t-1} \times \mathbb{1}[regulated=1]_i \\
& + \sum_{j \neq 2006} \eta_j OC_{i,t-1} \times \mathbb{1}[t=j]_{i,t} \times \mathbb{1}[regulated=1]_i \\
& + \boldsymbol{\gamma' X_{i,t}} + \nu_i + u_{i,t},
\end{aligned} \tag{4.6}$$

where $\mathbb{1}[regulated = 1]_i$ is an indicator variable that equals one for financial institutions in the stricter regulated group. In a similar way, I re-estimate the fixed effects model in Equation (4.2) interacted with the indicator variable for the regulatory status. Unregulated financial institutions serve as the base category. The coefficient of interest, η_j denotes the change in the difference between the groups relative to the difference in the base year 2006. If stricter regulation is indeed one of the mechanisms behind the decline observed in Figure 4.2, one would expect η_j to be significantly negative in the period between 2008 and 2017.

The coefficients η_j and η_p shown in Figure 4.4, with the corresponding values of η_p in columns (1) to (3) in Table 4.11, confirm the conjecture as outlined above. The decrease in overconfidence-induced risk during the period of stricter regulation is attributable only to financial institutions subject to enhanced regulation, as shown by significantly negative coefficients η_j and η_p and the insignificant and close to zero coefficients β_j and β_p for the period between 2008 and 2017.[27] The result that unregulated financial institutions remain largely unaffected supports the hypothesis that the regulatory intervention is the mechanism behind the decline in risk-taking during the period of stricter regulation. After deregulation in 2018, there is again no significant difference

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

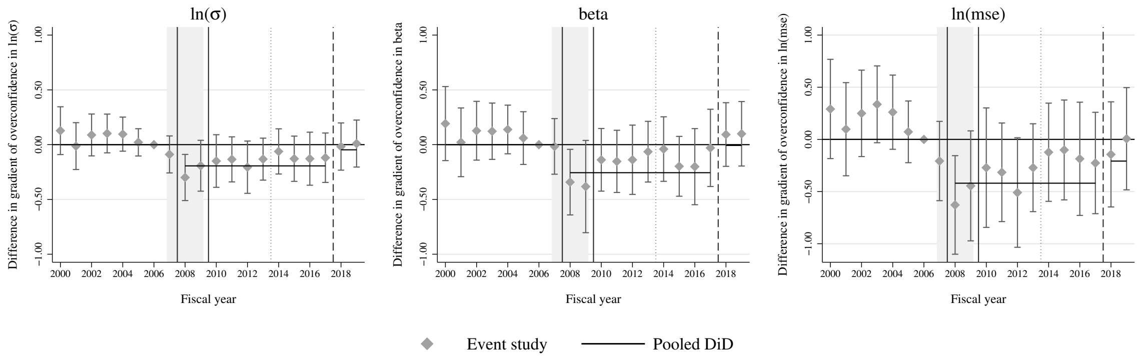


Figure 4.4: The role of stricter regulation – dynamic results

This figure shows the coefficients η_j in the OLS estimation of Equation (4.6) (diamonds) along with the coefficients η_p of the pooled model (black line) for the three aggregate measures of risk-taking in the U.S. financial sector in the years 2000 to 2019 (natural logarithm of the standard deviation of daily stock returns (left), market beta (center), and the natural logarithm of the mean-squared-error of a single index model (right)). The vector of controls $\boldsymbol{X_{i,t}}$ includes the control variables size, return on assets, leverage, deposit ratio, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Variable definitions are in Table D.1.1. Hubert-White heteroskedasticity consistent standard errors are clustered at the firm level. 90% confidence intervals are shown. The shaded area indicates the crisis years. The solid vertical lines denote the timing of the respective regulatory frameworks and the dashed vertical line the timing of deregulation.

between the two groups.

Columns (4)-(6), excluding financial institutions crossing the size threshold during the period from 2008 to 2017, show that the results are not affected by financial institutions that select into our out of stricter regulation. Excluding the largest financial institutions that are still subject to stricter regulation after 2008 in columns (7)-(9) does not change the results qualitatively but amplifies the effect during the period of deregulation after 2018. Excluding the financial institutions subject to the SCAP in columns (10)-(12) does not change the results qualitatively either.

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

4.5 Conclusion

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

Table 4.11: The role of stricter regulation – pooled results

This table presents the regression results of the OLS estimation of the fixed effects model in Equation (4.2) interacted with a binary variable for the regulatory status of a financial institution for risk-taking in the U.S. financial sector in the years 2000 to 2019. The dependent variables are the three aggregate measures of risk-taking, i.e., the natural logarithm of the standard deviation of daily stock returns, the market beta, and the natural logarithm of the mean-squared-error of a single index model. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. $\mathbb{1}[regulated = 1]_i$ is a binary variable that equals one for regulated financial institutions as described above. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Variable definitions are in Table D.1.1. Hubert-White heteroskedasticity consistent standard errors clustered at the firm level in parentheses. Stars indicate significance: $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

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

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

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

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

Conclusion

Overconfidence, a pervasive and potent bias in human judgment, has been the core of this dissertation. While the first two chapters focused on the implications of overconfidence on the individual level, the last two chapters focused on the implications on an economy-wide level and examined the role of financial regulation.

On the individual level, Chapter 1 highlights that overprecision, a form of overconfidence in one's judgment, distorts belief formation. This leads overprecise individuals to update their priors less than well-calibrated individuals. Since overprecision also distorts the trade-off between the costs and benefits of new information, overprecise individuals are more sensitive to cognitive processing costs and, thus, more susceptible to rational inattention. Chapter 2 shows that overprecision is a personality trait that is robust within individuals across different domains and that can have consequences on the financial and political behavior of individuals. The results indicate that overprecise individuals make larger forecast errors and diversify their portfolios less. Furthermore, they tend to hold more extreme political views and tend to vote less. On the economy-wide level, the results in Chapter 3 and Chapter 4 show that, if not sufficiently well regulated, managerial overconfidence increases risk-taking of financial institutions, which can be exploited by shareholders.

The results of this dissertation imply that policymakers have to take the contribution of overconfidence to systemic risks and to the fragility in the financial system into account when designing financial regulation. This dissertation provides several potential starting points for policy interventions. The first is to address the decision-making process of individuals operating in financial markets. The results in Chapter 1 suggest that informing individuals using less complex information or assessments of potential risks can in part address the underreaction of individuals to this information. Thus, increasing the attentiveness of individuals to potential risks in the financial system could prevent the underestimation of risks and thereby reduce systematic errors in forecasts and risk-taking. The second is to improve the incentive systems in place. While it is important that financial institutions align the manager's interests with the shareholders' interests by the means of incentive compensation, overconfident managers react more to incentive compensation and take higher risks. Bonus taxation that is linked to overconfidence can mitigate these adverse effects of overconfidence on risk-taking. The third is to improve governance in the financial sector. Implementing a system of checks and balances within financial institutions and also between financial institutions and the regulation entities can align risk-taking of overconfident CEOs with that of non-overconfident CEOs.

The recent collapse of Silicon Valley Bank (SVB) on March 10, 2023, after a bank run on its deposits, provides anecdotal evidence that the topic of CEO overconfidence is still relevant today. Following a drastic increase in deposits in 2020/21, SVB invested large parts of the raised deposits in long-term bonds and risky mortgage-backed securities in the search of yields. With rising interest rates in 2022/23, the valuation of these bonds decreased while depositors in need of liquidity started to withdraw their deposits. The resulting shortage in liquidity led the management to the fatal decision to sell $21 billion of bonds at a $1.8 billion loss. This decision, which was meant as a positive signal, surprised the market and led to a run on the deposits and ultimately to the collapse of the bank. The underlying 'bad bet' on interest rates is considered to be one of the roots of the collapse (Bloomberg, 2023; The New York Times, 2023).

Several indicators, which are also used in this dissertation, suggest that the (former) CEO of SVB, Greg Becker, can be regarded as overconfident. First, the moneyness of his aggregate option portfolio (see Chapter 4) exceeded 100% in 50% of the time between 2011 and 2019. Second, the use of optimistic language in the MD&A section of the annual reports (see Chapter 4) is among the top 5% over the same period, based on the data of Chapter 4. Last, several interviews with Greg Becker at the beginning of 2023 suggest a substantial degree of overconfidence (e.g., CNBC, 2023). Until 2018, SVB was subject to enhanced regulation under the Dodd-Frank Act. However, given a balance sheet sum between $50 billion and $250 billion, SVB was effectively deregulated when the size threshold for enhanced financial regulation was increased with the Economic Growth, Regulatory Relief, and Consumer Protection Act in 2018.[29] Based on the results in Chapter 4, it is likely that CEO overconfidence at least partly contributed to the risk-taking in the run-up to the collapse, which stricter financial regulation might have prevented.

This dissertation also offers interesting avenues for future research. First, rational inattention has so far only been examined in isolation. Chapter 1 shows that one of the assumptions of the benchmark model, which is the optimal reaction to information, is violated if individuals are overconfident. Combining rational inattention with

[29] As a matter of fact, Greg Becker was a strong proponent of increasing the size threshold for stricter financial regulation effectively deregulating SVB (see U.S. Government Publishing Office, 2015).

further individual biases contributes to a nascent literature. Second, while Chapter 2 shows that overprecision is robust within individuals across domains, it is yet unclear, whether overprecision is a stable personality trait or whether it varies over time. Contributing to the further understanding of overprecision offers an interesting field of research. Third, the empirical literature on the effectiveness of incentive compensation regulation specifically in the context of overconfidence is scarce. While the theoretical literature, as in Chapter 3, advocates the positive effects of regulating incentive compensation on risk-taking, it has yet to be demonstrated empirically. Empirical studies examining such reforms should take the heterogeneous effects on overconfident individuals into account. Last, while Chapter 4 shows that financial regulation in general can mitigate overconfidence-induced risk-taking, more research on the effectiveness of specific aspects and measures of financial regulation on overconfidence-induced risk-taking is needed. Overall, overconfidence and its consequences as well as potential remedies remain an interesting research topic in the foreseeable future.

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Appendices

A Appendix to Chapter 1

A.1 Additional Tables

Table A.1.1: Treatment text of the experiment in German

This table presents the treatment text of the experiment in German presented to respondents for each treatment. The text has been colored in this table to reduce the information processing cost of the reader. Respondents in the survey did not have differently colored text.

Treatment	**Text**
Control	*Bevor wir fortfahren, möchten wir Ihnen die folgende Information geben.* *Das Statistische Bundesamt hat vor Kurzem veröffentlicht, dass das Bevölkerungswachstum in Deutschland zwischen 1990 und 2020 4,3% betrug.*
Easy	*Bevor wir fortfahren, möchten wir Ihnen die folgende Information geben.* *Das Statistische Bundesamt hat vor Kurzem veröffentlicht, dass die Inflation in Deutschland im Oktober im Vergleich zum Vorjahresmonat 4,5% betrug*
Hard	*Bevor wir fortfahren, möchten wir Ihnen die folgende Information geben.* *Das Statistische Bundesamt (inzwischen häufig Destatis nach seiner Internetadresse) ist eine deutsche Bundesoberbehörde im Geschäftsbereich des Bundesministeriums des Innern. Sie erhebt, sammelt und analysiert statistische Informationen zu Wirtschaft, Gesellschaft und Umwelt. Die aufbereiteten Informationen werden tagesaktuell in rund 390 amtlichen Statistiken veröffentlicht.* *Zu den Aufgaben des Statistischen Bundesamtes gehört die Bereitstellung objektiver, qualitativ hochwertiger und unabhängiger Informationen für Politik, Regierung, Verwaltung, Wirtschaft und Bürger. Weiterhin ist es für die methodisch-technische Vorbereitung einer Vielzahl von Statistiken verantwortlich und sorgt dafür, dass diese koordiniert, nach einheitlichen Methoden und terminge-recht erstellt werden. Hierfür arbeitet das Statistische Bundesamt gemäß dem föderalen Staatsprinzip der Bundesrepublik Deutschland eng mit den Statistischen Ämtern der 16 Bundesländer zusammen.* *Das Statistische Bundesamt hat vor Kurzem veröffentlicht, dass die Inflation in Deutschland im Oktober im Vergleich zum Vorjahresmonat 4,5% betrug. Die Verpflichtung zur Objektivität, Neutralität und wissenschaftlichen Unabhängigkeit sowie die Aufgaben des Statistischen Bundesamtes und die Vorschriften zur statistischen Geheimhaltung sind im Gesetz über die Statistik für Bundeszwecke geregelt.*

Table A.1.2: Overview of the main variables used in the analysis.

Variable	Definition
Beliefs:	
prior	Point estimate of the 12-month-ahead inflation expectation question elicited before the treatment.
posterior	Most likely expected inflation rate of 12-month-ahead inflation expectation question elicited after the treatment.
Control variables:	
age	Reported age.
gender	=1 if female.
education	Categorical variable. =1 if no university degree and =2 if university degree. =0 if no answer was given.
income	Monthly gross labor income in thousands, reported in bins. =0 if no answer was given.
region	Categorical variable for region within Germany (north, east, south, west).
GDR 1989	Categorical variable whether respondent lived in the GDR in 1989. = 1 if lived in GDR in 1989. =0 if no answer was given.

A.2 Additional Figures

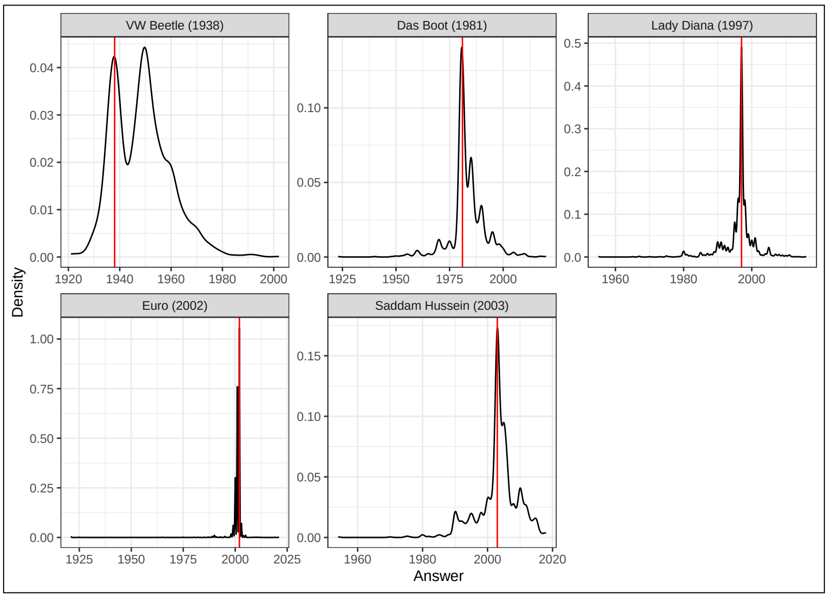


Figure A.2.1: Distributions of the answers to each history question

This figure shows the density of the answers ($a_{i,j}$) to each history question. The vertical red line marks the correct answer. Note that the vertical axis differs for each question.

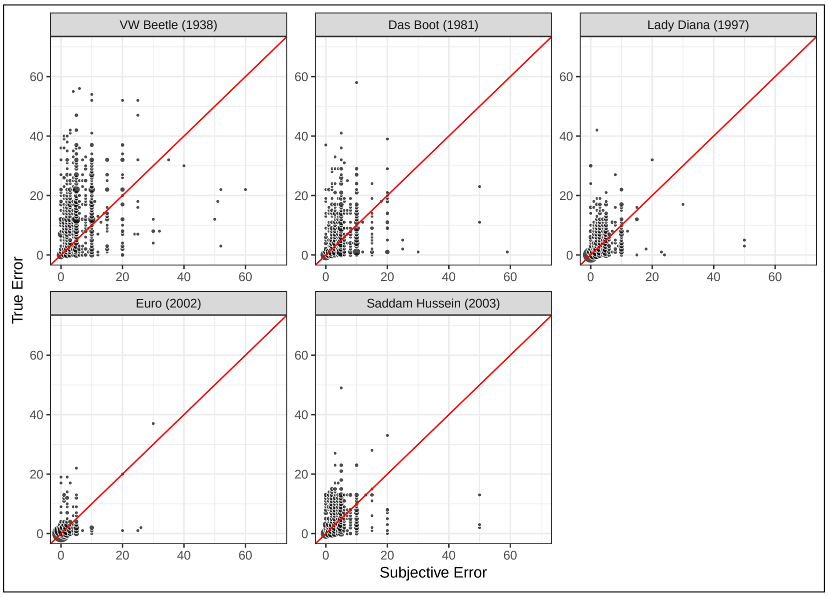


Figure A.2.2: Relation between the true error and the subjective error

This figure shows the relation between the realized true error ($error_{i,j}$) in the vertical axis and the subjective error ($se_{i,j}$) in the horizontal axis. Any dot above (below) the 45-degree red line is an overprecise (underprecise) answer by the individual.

A.3 Mapping Between Theoretical and Empirical Model

We start from the theoretical expression in (1.1), which we derived for the posterior:

$$E[\theta|s_{i,j}] = \beta_{i,j} \cdot (\theta + \epsilon_j + \psi_i) + (1 - \beta_{i,j}) \cdot \mu_{\theta,i}. \tag{A.3.1}$$

To map the theoretical model to the simple empirical model in (1.14), let us rewrite the model in terms of prior weights and define the prior weight as $\alpha_{i,j} = 1 - \beta_{i,j}$, and hence, $\alpha_{i,j} = 1 - \frac{\tilde{\sigma}^2_{\theta,i}}{\tilde{\sigma}^2_{\theta,i}+\sigma^2_{\epsilon,j}} + \frac{\lambda}{2\phi\tilde{\sigma}^2_{\theta,i}}$. The cognitive costs λ enter the expression only linearly. Thus, we can decompose the prior weight into a cost-independent part and a cost-dependent part. Then

$$E[\theta|s_{i,j}] = \underbrace{(1 - \alpha_{i,j}) \cdot (\theta + \epsilon_j + \psi_i)}_{a} + \left(1 - \frac{\tilde{\sigma}^2_{\theta,i}}{\tilde{\sigma}^2_{\theta,i} + \sigma^2_{\epsilon,j}}\right) \cdot \mu_{\theta,i} + \frac{1}{2\phi\tilde{\sigma}^2_{\theta,i}} \cdot \lambda \cdot \mu_{\theta,i}. \tag{A.3.2}$$

Equation (A.3.2) shows that, when increasing the cognitive costs λ by $\Delta\lambda$, the weight on the prior increases by $\frac{1}{2\phi\tilde{\sigma}^2_{\theta,i}} \cdot \Delta\lambda$. We summarize all components regarding the signal in a constant a.

Now we turn to overprecision. Since overprecision ω_i enters both expressions of the prior weight in a non-linear way, we use Taylor approximations to linearize the equation. The first-order Taylor approximation for a function $f(x)$ is defined as $f(x) = f(a)+f'(a)\cdot(x-a)$. Here, we approximate around $\omega_i = 0$, hence, $f(\omega_i) = f(0)+f'(0)\cdot\omega_i$. We define overprecision as $f(\omega_i) = \tilde{\sigma}^2_{\theta,i}$ with $f' < 0$ and $f(0) = \sigma^2_{\theta,i}$.

Let us start with the first term, the cost-independent part of the prior weight:

$$1 - \frac{\tilde{\sigma}^2_{\theta,i}}{\tilde{\sigma}^2_{\theta,i} + \sigma^2_{\epsilon,j}} \approx 1 - \frac{\sigma^2_{\theta,i}}{\sigma^2_{\theta,i} + \sigma^2_{\epsilon,j}} - \frac{\sigma^2_{\epsilon,j}}{(\sigma^2_{\theta,i} + \sigma^2_{\epsilon,j})^2} \cdot \frac{\partial\tilde{\sigma}^2_{\theta,i}}{\partial\omega_i}|_{\omega_i=0} \cdot \omega_i. \tag{A.3.3}$$

Equation (A.3.3) shows that the cost-independent part of the prior weight increases in overprecision ω_i since the last part of the equation is positive as $\frac{\partial\tilde{\sigma}^2_{\theta,i}}{\partial\omega_i} < 0$.

Let us continue with the second term, the cost-dependent part of the prior weight:

$$\frac{1}{2\phi\tilde{\sigma}^2_{\theta,i}} \approx \frac{1}{2\phi\sigma^2_{\theta,i}} - \frac{1}{2\phi(\sigma^2_{\theta,i})^2} \cdot \frac{\partial\tilde{\sigma}^2_{\theta,i}}{\partial\omega_i}|_{\omega_i=0} \cdot \omega_i. \tag{A.3.4}$$

Equation (A.3.4) shows that the cost-dependent part of the prior weight also increases in overprecision ω_i since the last part of the equation is positive. Note that this positive relationship between cognitive costs (rational inattention) and overprecision is the interaction term that our model posits.

Putting the previously derived expressions together, we arrive at the following linear model:

$$
\begin{aligned}
E[\theta|s_{i,j}] = a& \\
&+ \left(1 - \frac{\sigma^2_{\theta,i}}{\sigma^2_{\theta,i} + \sigma^2_{\epsilon,j}}\right) \cdot \mu_{\theta,i} + \left(-\frac{\sigma^2_{\epsilon,j}}{(\sigma^2_{\theta,i} + \sigma^2_{\epsilon,j})^2} \cdot \frac{\partial \tilde{\sigma}^2_{\theta,i}}{\partial \omega_i}|_{\omega_i=0}\right) \cdot \omega_i \cdot \mu_{\theta,i} \\
&+ \left(\frac{1}{2\phi\sigma^2_{\theta,i}}\right) \cdot \lambda \cdot \mu_{\theta,i} + \left(-\frac{1}{2\phi(\sigma^2_{\theta,i})^2} \cdot \frac{\partial \tilde{\sigma}^2_{\theta,i}}{\partial \omega_i}|_{\omega_i=0}\right) \cdot \lambda \cdot \omega_i \cdot \mu_{\theta,i}
\end{aligned}
\tag{A.3.5}
$$

However, with the treatment, we also vary the informativeness of the signal and, hence, the variance of the signal $\sigma^2_{\epsilon,j}$. Therefore, we also apply a Taylor approximation for this part. To do so, we evaluate the approximation at $\sigma^2_{\epsilon,0}$. Equation (A.3.5) shows that the cost-dependent part of the equation is independent of $\sigma^2_{\epsilon,j}$. Therefore, we focus on the cost-independent part only.

Let us start with the first term, the cost- and overprecision-independent part of the prior weight:

$$
1 - \frac{\sigma^2_{\theta,i}}{\sigma^2_{\theta,i} + \sigma^2_{\epsilon,j}} \approx 1 - \frac{\sigma^2_{\theta,i}}{\sigma^2_{\theta,i} + \sigma^2_{\epsilon,0}} + \frac{\sigma^2_{\theta,i}}{(\sigma^2_{\theta,i} + \sigma^2_{\epsilon,0})^2} \cdot (\sigma^2_{\epsilon,j} - \sigma^2_{\epsilon,0}). \tag{A.3.6}
$$

Equation (A.3.6) shows that the cost- and overprecision-independent part of the prior weight decreases if the variance of the signal $\sigma^2_{\epsilon,j}$ is decreased and, hence, if the signal is more informative.

Assuming $\frac{\partial(\tilde{\sigma}^2_{\theta,i})^2}{\partial\omega_i\partial\sigma^2_{\epsilon,j}} = 0$, we continue with the second term, the cost-independent but overprecision-dependent part:

$$
\begin{aligned}
-\frac{\sigma^2_{\epsilon,j}}{(\sigma^2_{\theta,i} + \sigma^2_{\epsilon,j})^2} \cdot \frac{\partial \tilde{\sigma}^2_{\theta,i}}{\partial \omega_i}|_{\omega_i=0} \approx &- \frac{\sigma^2_{\epsilon,0}}{(\sigma^2_{\theta,i} + \sigma^2_{\epsilon,0})^2} \cdot \frac{\partial \tilde{\sigma}^2_{\theta,i}}{\partial \omega_i}|_{\omega_i=0} \\
&- \frac{\sigma^2_{\theta,i} - \sigma^2_{\epsilon,0}}{(\sigma^2_{\theta,i} + \sigma^2_{\epsilon,0})^3} \cdot \frac{\partial \tilde{\sigma}^2_{\theta,i}}{\partial \omega_i}|_{\omega_i=0} \cdot (\sigma^2_{\epsilon,j} - \sigma^2_{\epsilon,0}).
\end{aligned}
\tag{A.3.7}
$$

Equation (A.3.7) shows that the effects of a decrease in the variance of the signal $\sigma^2_{\epsilon,j}$ in this part of the prior weight is ambiguous, depending on the relative size of $\sigma^2_{\theta,i}$ and $\sigma^2_{\epsilon,0}$.

Combining all of the equations, the linearized model is the following:

$$\begin{aligned}
E[\theta|s_{i,j}] = a& \\
&+ \left(1 - \frac{\sigma^2_{\theta,i}}{\sigma^2_{\theta,i} + \sigma^2_{\epsilon,0}}\right) \cdot \mu_{\theta,i} \\
&+ \left(\frac{\sigma^2_{\theta,i}}{(\sigma^2_{\theta,i} + \sigma^2_{\epsilon,0})^2}\right) \cdot (\sigma^2_{\epsilon,j} - \sigma^2_{\epsilon,0}) \cdot \mu_{\theta,i} \\
&+ \left(-\frac{\sigma^2_{\epsilon,0}}{(\sigma^2_{\theta,i} + \sigma^2_{\epsilon,0})^2} \cdot \frac{\partial \tilde{\sigma}^2_{\theta,i}}{\partial \omega_i}|_{\omega_i=0}\right) \cdot \omega_i \cdot \mu_{\theta,i} \\
&+ \left(-\frac{\sigma^2_{\theta,i} - \sigma^2_{\epsilon,0}}{(\sigma^2_{\theta,i} + \sigma^2_{\epsilon,0})^3} \cdot \frac{\partial \tilde{\sigma}^2_{\theta,i}}{\partial \omega_i}|_{\omega_i=0}\right) \cdot (\sigma^2_{\epsilon,j} - \sigma^2_{\epsilon,0}) \cdot \omega_i \cdot \mu_{\theta,i} \\
&+ \left(\frac{1}{2\phi\sigma^2_{\theta,i}}\right) \cdot \lambda \cdot \mu_{\theta,i} + \left(-\frac{1}{2\phi(\sigma^2_{\theta,i})^2} \cdot \frac{\partial \tilde{\sigma}^2_{\theta,i}}{\partial \omega_i}|_{\omega_i=0}\right) \cdot \lambda \cdot \omega_i \cdot \mu_{\theta,i}
\end{aligned} \tag{A.3.8}$$

Combining the linearized theoretical model in with the coefficients in the empirical model

$$\begin{aligned}
posterior_i = a_0 + &\sum_{j=1}^{2} a_j \cdot \mathbb{1}\{i \in Treat_j\} \\
+ b_0 \cdot prior_i + &\sum_{j=1}^{2} b_j \cdot \mathbb{1}\{i \in Treat_j\} \cdot prior_i \\
+ c_0 \cdot sop_i + &\sum_{j=1}^{2} c_j \cdot \mathbb{1}\{i \in Treat_j\} \cdot sop_i \\
+ d_0 \cdot prior_i \cdot sop_i + &\sum_{j=1}^{2} d_j \cdot \mathbb{1}\{i \in Treat_j\} \cdot prior_i \cdot sop_i \\
&+ \mathbf{X}' \cdot \delta + \varepsilon_i
\end{aligned} \quad , \tag{A.3.9}$$

we can derive the following mapping between the theoretical parameters and the estimated coefficients of our linear regression model:

$$
\begin{aligned}
\hat{b}_0 &= \left(1 - \frac{\sigma^2_{\theta,i}}{\sigma^2_{\theta,i} + \sigma^2_{\epsilon,0}}\right) > 0, \\
\hat{b}_1 &= \left(\frac{\sigma^2_{\theta,i}}{(\sigma^2_{\theta,i} + \sigma^2_{\epsilon,0})^2}\right) \cdot (\sigma^2_{\epsilon,1} - \sigma^2_{\epsilon,0}) < 0, \\
\hat{b}_2 &= \hat{b}_1 + \left(\frac{1}{2\phi\sigma^2_{\theta,i}}\right) \cdot (\lambda_2 - \lambda_1) \lesseqgtr 0, \\
\hat{b}_2 - \hat{b}_1 &= \left(\frac{1}{2\phi\sigma^2_{\theta,i}}\right) \cdot (\lambda_2 - \lambda_1) > 0, \\
\hat{d}_0 &= \left(-\frac{\sigma^2_{\epsilon,0}}{(\sigma^2_{\theta,i} + \sigma^2_{\epsilon,0})^2} \cdot \frac{\partial\tilde{\sigma}^2_{\theta,i}}{\partial\omega_i}|_{\omega_i=0}\right) > 0, \\
\hat{d}_1 &= \left(-\frac{\sigma^2_{\theta,i} - \sigma^2_{\epsilon,0}}{(\sigma^2_{\theta,i} + \sigma^2_{\epsilon,0})^3} \cdot \frac{\partial\tilde{\sigma}^2_{\theta,i}}{\partial\omega_i}|_{\omega_i=0}\right) \cdot (\sigma^2_{\epsilon,1} - \sigma^2_{\epsilon,0}) \lesseqgtr 0, \\
\hat{d}_2 &= \hat{d}_1 + \left(-\frac{1}{2\phi(\sigma^2_{\theta,i})^2} \cdot \frac{\partial\tilde{\sigma}^2_{\theta,i}}{\partial\omega_i}|_{\omega_i=0}\right) \cdot (\lambda_2 - \lambda_1) \lesseqgtr 0, \\
\hat{d}_2 - \hat{d}_1 &= \left(-\frac{1}{2\phi(\sigma^2_{\theta,i})^2} \cdot \frac{\partial\tilde{\sigma}^2_{\theta,i}}{\partial\omega_i}|_{\omega_i=0}\right) \cdot (\lambda_2 - \lambda_1) > 0.
\end{aligned}
\tag{A.3.10}
$$

B Appendix to Chapter 2

B.1 Additional Figures

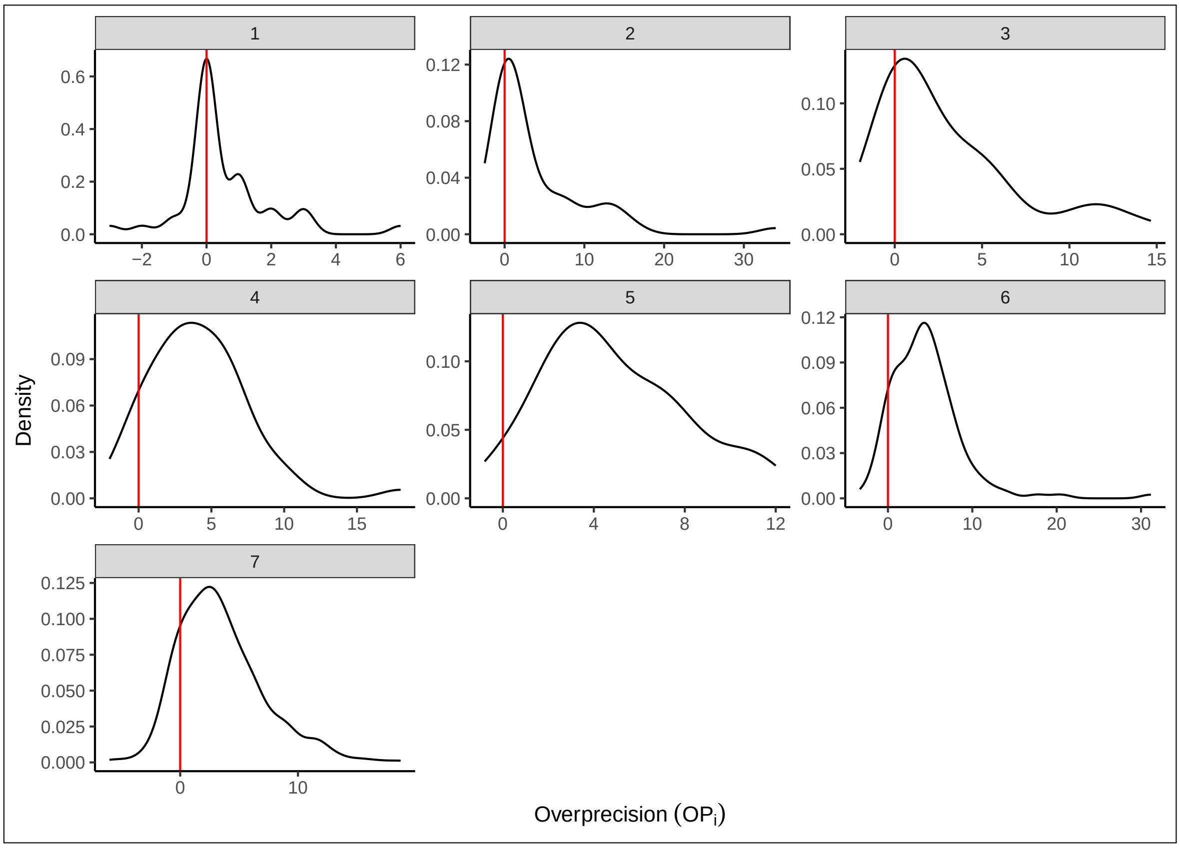


Figure B.1.1: Distribution of overprecision for different numbers of answers (SOEP-IS)

This figures shows the density of overprecision (op_i) for each of the subsets of questions answered. We plot from left to right the densities of op_i for those respondents who answered from the minimum number of answers (1) to the maximum number of answers (7). In the title, we report the number of respondents for each density. Notice that the scale of the Y-axis changes across panels.

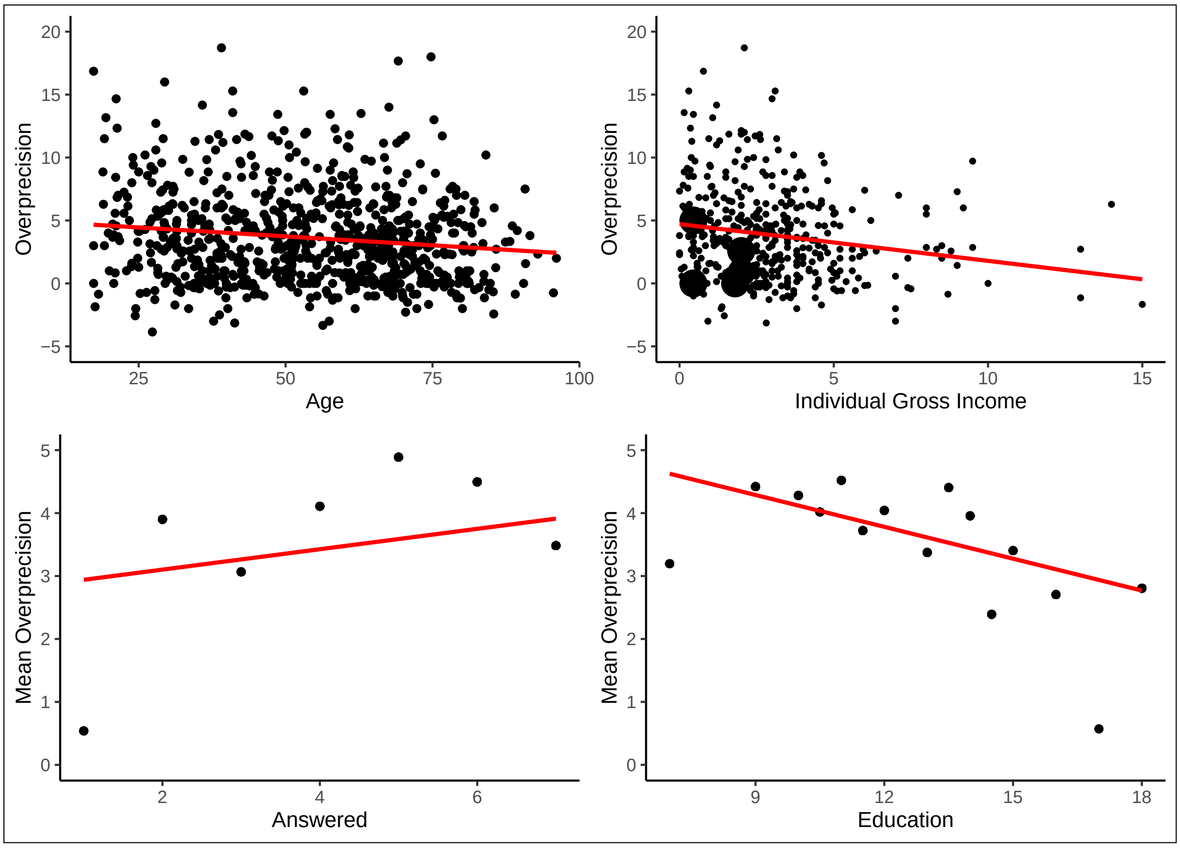


Figure B.1.2: Correlation of overprecision with selected control variables (SOEP-IS)

This figure shows the correlation of overprecision with selected control variables. In the vertical axis of each panel, we plot the overprecision (upper row) and mean overprecision across all groups which we plot in the horizontal axis (lower row). In all four cases, the red line is the fitted linear regression. We dropped one individual outlier in all cases to make the graphs more readable.

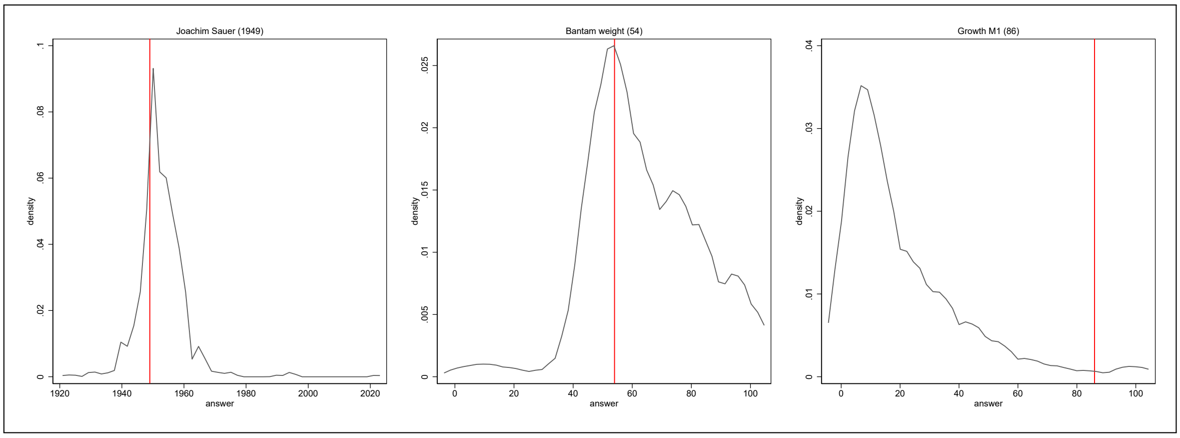


Figure B.1.3: Distributions of the answers to each question (survey)

This figure shows the density of the answers ($a_{i,j}$) for each of the questions which we use to detect respondents who we assume to have used search engines. The vertical line marks the correct answer. Note that the vertical axis is different for each question.

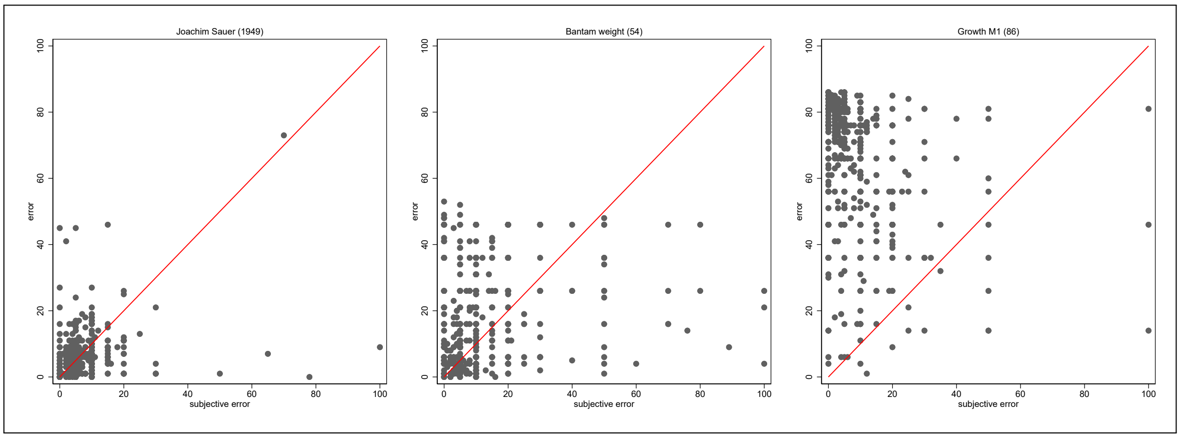


Figure B.1.4: Relation between the true error and the subjective error (survey)

This figure shows the relation between the realized true error ($error_{i,j}$) in the vertical axis and the subjective error ($se_{i,j}$) in the horizontal axis for each of the questions which we use to detect respondents who we assume to have used search engines. Any dot above (below) the 45-degree red line is an overprecise (underprecise) answer by the respondent.

B.2 Additional Tables

Table B.2.1: Original history questions in English from the 2018 SOEP-IS

SOEP-IS Code	Question (a)	Answer
Q467 - IGEN02a	In which year were euro notes and coins introduced?	2002
Q470 - IGEN03a	In which year was Microsoft (Publisher of the software package Windows) founded?	1975
Q473 - IGEN04a	In which year was the movie "Das Boot" (directed by Wolfgang Peterson) first shown in German cinemas?	1981
Q476 - IGEN05a	In which year was Saddam Hussein captured by the US army?	2003
Q479 - IGEN06a	In which year was the first Volkswagen Type 1 (also known as "Volkswagen Beetle") produced?	1938
Q482 - IGEN07a	In which year did the Korean War end with a truce?	1953
Q485 - IGEN08a	In which year did Lady Diana, Prince Charles' first wife, die?	1997
	Question (b)	
	What do you think: How far is your answer off the correct answer?	

Table B.2.2: Original history questions in German from the 2018 SOEP-IS

SOEP-IS Code	Questions (a)	Answer
Q467 - IGEN02a	In welchem Jahr wurden Euro-Geldscheine und -Münzen eingeführt?	2002
Q470 - IGEN03a	In welchem Jahr wurde das Unternehmen Microsoft (Herausgeber des Betriebssystems Windows) gegründet?	1975
Q473 - IGEN04a	In welchem Jahr kam der Film "Das Boot" (Regie: Wolfgang Petersen) in die deutschen Kinos?	1981
Q476 - IGEN05a	In welchem Jahr wurde Saddam Hussein von der US-Armee gefangen genommen?	2003
Q479 - IGEN06a	In welchem Jahr wurde der erste Volkswagen Typ 1 (auch bekannt als "Käfer") produziert?	1938
Q482 - IGEN07a	In welchem Jahr endete der Korea-Krieg mit einem Waffenstillstand?	1953
Q485 - IGEN08a	In welchem Jahr starb Lady Diana, die erste Frau von Prinz Charles?	1997
	Question (b)	
	Was schätzen Sie: wie viele Jahre liegt Ihre Antwort von der richtigen Antwort entfernt?	

Table B.2.3: Overview of the variables from the SOEP-IS used in the analysis.

Variable	Definition
Financial Behavior:	
DAX forecast error	Principal component of the absolute distance between one- and two-year-ahead prediction of the DAX realization and the actual realization over the horizon. The closing price of the date of the respective interview was used. Standardized to have mean 0 and standard deviation 1.
portfolio diversification	Aggregate diversification measure over five asset classes. For each asset class, a penalty score is calculated expressing the distance to an equally diversified portfolio. Diversification equals the maximum attainable penalty score less the actual penalty. The diversification measure is standardized to have mean 0 and standard deviation 1.
Political Behavior:	
extremeness	Absolute distance to the center of an ideology scale from 0 (left) to 10 (right). Standardized to have mean 0 and standard deviation 1.
left-right	Location on an ideology scale from 0 (left) to 10 (right). Standardized to have mean 0 and standard deviation 1.
non-voter	=1 if respondent indicated not to vote in the Sonntagsfrage (ex-post) for the Bundestagswahl 2017.
Controls:	
age	Difference between interview month/year and birth month/year in years.
gender	=1 if female.
GDR 1989	=1 if living in East Germany in 1989.
years education	Years of education (including any further education after primary and secondary education)=.
gross income	Monthly gross labor income in thousands. Missings are coded with a zero.
missing income	=1 if missing gross income.
fin. literacy	Share of correct answers to 6 questions related to financial knowledge.

Table continued on next page

Table B.2.3 cont.: Overview of the variables from the SOEP used in the analysis

Variable	Definition
risk aversion	Location on a risk scale from 0 (risk avers) to 10 (risk loving). Standardized to have mean 0 and standard deviation 1.
narcissism	Average narcissism measure over 6 items on a scale from 1 to 6. Standardized to have mean 0 and standard deviation 1.
impulsivity	Location on impulsivity scale from 0 (not impulsive) to 10 (fully impulsive). Standardized to have mean 0 and standard deviation 1.
patience	Location on the patience scale from 0 (not patient) to 10 (fully patient). Standardized to have mean 0 and standard deviation 1.
employed	=1 if employed.
unemployed	=1 if unemployed.
nonwork	=1 if non-working.
matedu	=1 if on maternity, educational, or military leave.
retired	=1 if retired.
answered	Number of questions answered for overprecision.
Additional Controls:	
assets	=1 if owning financial assets.
pol. interest	Political interest on a scale from 1 (high) to 4 (low). Reversed and standardized to have mean 0 and standard deviation 1.

Table B.2.4: Representativeness of the SOEP-IS subsample

This table presents the representativeness of the SOEP-IS subsample by showing the descriptives of selected personal characteristics of the respondents for the subsample of the SOEP-IS and the SOEP-Core. The results for the SOEP-IS in Columns (1) and (2) are unweighted whereas the results for the SOEP-Core in Columns (3) and (4) are weighted using the sampling weights provided. Columns (5) and (6) show a simple t-test on the difference between the means. Column (7) shows the sample size of the SOEP-Core. The sample size varies due to missing observations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	SOEP-IS		SOEP Core		Difference		
	mean	sd	mean	sd	difference	p-value	N[Core]
age	53.914	(0.627)	50.535	(0.180)	-3.379	0.000	30,997
gender (female=1)	0.508	(0.018)	0.508	(0.005)	0.000	0.989	30,997
german	0.933	(0.009)	0.877	(0.003)	-0.056	0.000	30,997
east (current)	0.174	(0.013)	0.172	(0.003)	-0.001	0.916	30,997
GDR 1989	0.186	(0.014)	0.198	(0.004)	0.012	0.404	24,591
years education	12.704	(0.098)	12.276	(0.027)	-0.428	0.000	28,482
employed	0.534	(0.018)	0.593	(0.005)	0.058	0.001	30,967
retired	0.229	(0.015)	0.221	(0.004)	-0.007	0.627	30,967
gross income	2.943	(0.112)	2.837	(0.029)	-0.106	0.359	17,829
married	0.568	(0.017)	0.521	(0.005)	-0.047	0.009	30,896
N[SOEP-IS]	805						

Table B.2.5: Results of the baseline analysis including Big 5

This table presents the estimation results as described in Section 2.3.4 including the Big Five personality traits. Each row is a separate analysis with the respective dependent variable listed in the left column. The number of observations (Column (7)) varies due to missing observations in the outcome variable. The maximum number of observations is 750. Column (1) lists the point estimate of the standardized overprecision measure *sop* from the full regression as specified in Section 2.3.4.1 along with the unadjusted p-value (Column (2)) and the Sidak-Holm adjusted p-value for multiple hypothesis testing (Column (3)). Column (4) displays the result from the R^2 procedure as specified in Section 2.3.4.1 along with the maximum possible variables to be included in the model. The regressions with political outcomes as dependent variable additionally include a self-reported measure of political interest. Column (5) specifies the result of the LASSO procedure as specified in Section 2.3.4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)). Stars indicate significance: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Dependent variable	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) R^2	(7) N
Financial Behavior:							
DAX forecast error	0.104**	0.024	0.071	4/46	yes/13	0.09	510
1-year ahead	*0.631*	*0.251*		10/46	yes/18	0.14	*537*
2-year ahead	*3.944****	*0.004*		4/46	no/0	0.00	*519*
portfolio diversification	-0.12***	0.002	0.009	4/46	yes/15	0.13	719
Political Behavior:							
extremeness	0.077*	0.059	0.115	8/47	yes/18	0.07	716
left-right	-0.019	0.643	0.643	24/47	no/17	0.10	716
non-voter	0.029**	0.015	0.060	3/47	yes/10	0.12	706

Table B.2.6: Results of the baseline analysis including assets

This table presents the estimation results as described in Section 2.3.4 including asset ownership as control. Each row is a separate analysis with the respective dependent variable listed in the left column. The number of observations (Column (7)) varies due to missing observations in the outcome variable. The maximum number of observations is 791. Column (1) lists the point estimate of the standardized overprecision measure *sop* from the full regression as specified in Section 2.3.4.1 along with the unadjusted p-value (Column (2)) and the Sidak-Holm adjusted p-value for multiple hypothesis testing (Column (3)). Column (4) displays the result from the R^2 procedure as specified in Section 2.3.4.1 along with the maximum possible variables to be included in the model. The regressions with political outcomes as dependent variable additionally include a self-reported measure of political interest. Column (5) specifies the result of the LASSO procedure as specified in Section 2.3.4.1 along with the R^2 of the estimated model (Column (6)). Stars indicate significance: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Dependent variable	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) R^2	(7) N
Financial Behavior:							
DAX forecast error	0.081*	0.065	0.125	6/42	yes/16	0.10	545
1-year ahead	*0.477*	*0.360*		8/42	yes/24	0.17	*574*
2-year ahead	*3.044***	*0.018*		5/42	no/0	0.00	*553*
portfolio diversification	-0.131***	0.000	0.002	4/42	yes/18	0.13	763
Political Behavior:							
extremeness	0.082*	0.057	0.161	6/43	yes/14	0.06	706
left-right	-0.002	0.966	0.966	18/43	no/14	0.08	706
non-voter	0.031**	0.014	0.054	3/43	yes/10	0.10	694

Table B.2.7: Original questions in English from the online survey

Qualtrics Code	Question (a)	Answer
PX110 a	How many black triangles were in the matrix?	70
PX110 b	How many black triangles were in the matrix?	120
PX110 c	How many black triangles were in the matrix?	195
PX110 d	How many black triangles were in the matrix?	280
PX110 e	How many black triangles were in the matrix?	330
PX120 a	In which year were euro notes and coins introduced?	2002
PX120 b	In which year was Microsoft (Publisher of the software package Windows) founded?	1975
PX120 c	In which year was Saddam Hussein captured by the US army?	2003
PX120 d	In which year was the first Volkswagen Type 1 (also known as "Volkswagen Beetle") produced?	1938
PX120 e	In which year did Lady Diana, King Charles' first wife, die?	1997
PX120 f	In which year was Joachim Sauer (husband of Angela Merkel) born?	1949
PX120 g	Which year is between 1993 and 1995?	1994
PX130 a	How many teeth does an adult polar bear have?	42
PX130 b	How many keys (black AND white) does a grand piano have?	88
PX130 c	How high (in meters) is the Reichstag building in Berlin?	47
PX130 d	What percentage of seats in the 20th German Bundestag (elected on September 26, 2021) are occupied by female members of the Bundestag	35
PX130 e	How many countries on the African continent are members of the United Nations?	54
PX130 f	What is the upper bantamweight limit in women's Olympic boxing weight classes?	54
PX130 g	What whole number is between 83 and 85?	84
PX140 a-e	What do you estimate: Where (in euros) will the share price be in exactly four weeks?	+ 28 days
PX140 f	In this question, the graph is empty. Please just enter the number 42 as your answer. What do you estimate: where (in euros) will the share price be in exactly four weeks?	42

Table continued on next page

Table B.2.7 cont.: Original questions in English language from the online survey

Qualtrics Code	Question (a)	Answer
PX150 a	The Consumer Price Index (CPI) is a measure of the average percentage change in the price level of certain goods and services purchased by households for consumption. The change in the consumer price index compared to the same month of the previous year or the previous year is also referred to as the rate of inflation. By how much (in percent) did the German CPI increase from the beginning of 2011 to the end of 2021?	17
PX150 b	The gross domestic product (GDP) indicates the total value of all goods and services that were produced as end products within the national borders of an economy during a year, after deduction of all intermediate consumption. By how much (in percent) is the German GDP at market prices (nominal) increased from 2006 to 2021?	51
PX150 c	The DAX (Deutscher Aktienindex) is a stock index that measures the performance of the 40 largest companies in the German stock market. By how much (in percent) did the DAX rise from the beginning of 2014 to the end of 2021?	65
PX150 d	The middle income or median income in a society or group describes the income level at which the number of households (or persons) with lower incomes is equal to the number of households with higher incomes. By how much (in percent) did median income in Germany increase from 1991 to 2018?	22
PX150 e	A census is a legally ordered survey of statistical population data. The last census in Germany took place in 2022. By how much (in percent) did the German population grow from 1991 to 2021?	4
PX150 f	M1 money supply describes the amount of cash in circulation and the amount of sight deposits (e.g., savings accounts). By how much (in percent) did the M1 money supply in the euro zone increase from the beginning of 2015 to the end of 2021?	86
	Question (b)	
	What do you think: How many [unit] is your answer away from the correct answer?	

Table B.2.8: Original questions in German from the online survey

Qualtrics Code	Question (a)	Answer
PX110 a	Wie viele schwarze Dreiecke waren in der Matrix?	70
PX110 b	Wie viele schwarze Dreiecke waren in der Matrix?	120
PX110 c	Wie viele schwarze Dreiecke waren in der Matrix?	195
PX110 d	Wie viele schwarze Dreiecke waren in der Matrix?	280
PX110 e	Wie viele schwarze Dreiecke waren in der Matrix?	330
PX120 a	In welchem Jahr wurden Euro-Geldscheine und -Münzen eingeführt?	2002
PX120 b	In welchem Jahr wurde das Unternehmen Microsoft (Herausgeber des Betriebssystems Windows) gegründet?	1975
PX120 c	In welchem Jahr wurde Saddam Hussein von der US-Armee gefangen genommen?	2003
PX120 d	In welchem Jahr wurde der erste Volkswagen Typ 1 (auch bekannt als "Käfer") produziert?	1938
PX120 e	In welchem Jahr starb Lady Diana, die erste Frau von König Charles III.?	1997
PX120 f	In welchem Jahr wurde Joachim Sauer (Ehemann von Angela Merkel) geboren?	1949
PX120 g	Welches Jahr liegt zwischen 1993 und 1995?	1994
PX130 a	Wie viele Zähne hat ein ausgewachsener Eisbär?	42
PX130 b	Wie viele Tasten (schwarz UND weiß) hat ein Konzertflüegel?	88
PX130 c	Wie hoch (in Metern) ist das Berliner Reichstagsgebäude?	47
PX130 d	Wie viel Prozent der Sitze im 20. Deutschen Bundestag (gewählt am 26. September 2021) sind durch weibliche Bundestagsabgeordnete besetzt?	35
PX130 e	Wie viele Staaten auf dem Afrikanischen Kontinent sind Mitglied der Vereinten Nationen?	54
PX130 f	Bei wie viel Kilogramm liegt die Obergrenze des Bantamgewichts in den Gewichtsklassen der Frauen beim Olympischen Boxen?	54
PX130 g	Welche ganze Zahl liegt zwischen 83 und 85?	84
PX140 a-e	Was schätzen Sie: wo (in Euro) liegt der Aktienkurs in genau vier Wochen?	+28 Tage

Table continued on next page

Table B.2.8 cont.: Original questions in German language from the online survey

Qualtrics Code	Question (a)	Answer
PX140 f	In dieser Frage ist die Grafik leer. Bitte geben Sie einfach die Zahl 42 als Antwort ein. Was schätzen Sie: wo (in Euro) liegt der Aktienkurs in genau vier Wochen?	42
PX150 a	Der Verbraucherpreisindex (VPI) ist ein ist ein Maß der durchschnittlichen prozentualen Veränderung des Preisniveaus bestimmter Waren und Dienstleistungen, die von privaten Haushalten für Konsumzwecke gekauft werden. Die Veränderung des Verbraucherpreisindex zum Vorjahresmonat bzw. zum Vorjahr wird auch als Teuerungsrate oder als Inflationsrate bezeichnet. Um wie viel (in Prozent) ist der deutsche VPI von Anfang 2011 bis Ende 2021 gestiegen?	17
PX150 b	Das Bruttoinlandsprodukt (BIP) gibt den Gesamtwert aller Waren und Dienstleistungen an, die während eines Jahres innerhalb der Landesgrenzen einer Volkswirtschaft als Endprodukte hergestellt wurden, nach Abzug aller Vorleistungen. Um wie viel (in Prozent) ist das deutsche BIP zu Marktpreisen (nominal) von 2006 bis 2021 gestiegen?	51
PX150 c	Der DAX (Deutscher Aktienindex) ist ein Aktienindex, der die Wertentwicklung der 40 größ ten Unternehmen des deutschen Aktienmarkts misst. Um wie viel (in Prozent) ist der DAX von Anfang 2014 bis Ende 2021 gestiegen?	65
PX150 d	Das mittlere Einkommen oder Medianeinkommen in einer Gesellschaft oder Gruppe bezeichnet die Einkommenshöhe, von der aus die Anzahl der Haushalte (bzw. Personen) mit niedrigeren Einkommen gleich groß ist wie die der Haushalte mit höheren Einkommen. Um wie viel (in Prozent) ist das Medianeinkommen in Deutschland von 1991 bis 2018 gestiegen?	22
PX150 e	Eine Volkszählung oder auch Zensus ist eine gesetzlich angeordnete Erhebung statistischer Bevölkerungsdaten. Der letzte Zensus in Deutschland fand 2022 statt. Um wie viel (in Prozent) ist die deutsche Bevölkerung von 1991 bis 2021 gewachsen?	4

Table continued on next page

Table B.2.8 cont.: Original questions in German language from the online survey

Qualtrics Code	Question (a)	Answer
PX150 f	Die Geldmenge M1 bezeichnet die Menge an Bargeld im Umlauf sowie die Höhe an Sichteinlagen (bspw. Sparkonten). Um wie viel (in Prozent) ist die Geldmenge M1 in der Eurozone von Anfang 2015 bis Ende 2021 gestiegen?	86
	Question (b)	
	Was schätzen Sie: wie viele [Einheit] liegt Ihre Antwort von der richtigen Antwort entfernt?	

Table B.2.9: Overview of the variables from the survey used in the analysis

Variable	Definition
Controls:	
age	Reported age.
gender	=1 if female.
education	Years of primary and secondary education.
gross income	Monthly gross labor income in thousands, reported in bins.
nationality	Reported primary nationality.
location	Reported current Bundesland in Germany.
math. literacy	Share of correct answers to three statistical problems.
expertise	Self-reported expertise on specific domain on a scale from 0 to 100.

Table B.2.10: Summary statistics of selected variables in the companion survey

This table presents summary statistics for the main variables in the survey. *Full sample* describes the entire collected sample while *Subsample* describes the sample after the exclusions following the pre-registration. The analysis is conducted using the subsample. Variable definitions are in Table B.2.9 in the appendix.

	count	mean	sd	p25	p50	p75
Full sample						
age	1000	44.950	14.315	33.000	46.000	58.000
gender (female=1)	998	0.489	0.500	0.000	0.000	1.000
german	1000	0.962	0.191	1.000	1.000	1.000
east (current)	1000	0.200	0.400	0.000	0.000	0.000
education	988	10.685	1.871	10.000	10.000	12.000
gross income	924	2.456	1.856	1.500	2.500	4.000
N	1000					
Subsample						
age	839	44.897	14.213	33.000	46.000	57.000
gender (female=1)	837	0.483	0.500	0.000	0.000	1.000
german	839	0.969	0.173	1.000	1.000	1.000
east (current)	839	0.203	0.402	0.000	0.000	0.000
education	831	10.693	1.863	10.000	10.000	12.000
gross income	778	2.485	1.898	1.500	2.500	4.000
N	839					

B.3 Alternative Measures of Overprecision

To test the robustness of our overprecision measure, in Section B.3.1 we discuss five alternative measures of overprecision, which are variations of our measure. In Section B.3.2 we use these alternative measures to test the robustness of our results from Section 2.3.3 regarding the socio-demographic characteristics and Section B.3.3 the robustness of the predictions in Section **??**.

B.3.1 Alternative Measures

Standardized measure (op_i'): Since the overprecision measure of Ortoleva and Snowberg (2015b) standardizes the measure with respect to the entire population, we further construct a *standardized* measure op_i' of overprecision where we standardize the absolute measure op_i of the respective question to be mean zero and standard deviation one before aggregation to avoid the aggregated measure to be biased by a specific question and to relate the level to the entire population. The mean is used again to aggregate across the seven questions.

Centered measure (op_i''): Respondents might not only differ with respect to the perceived variance of the distribution of the error to their answer, but also with respect to the mean of the distribution. Hence, the baseline overprecision measure might capture both overprecision and a miscalibration of the mean. To separate both of them, we construct a *centered* measure of overprecision. To correct for the difference in the means of the distributions and center the distributions around zero, for each question, we subtract the sample mean from the true and subjective error. Any remaining systematic deviation of the subjective error from the realized true error should be exclusively due to over- or underprecision.

Relative measure (op_i'''): To circumvent the classification problem of the residual approach (op_i''''') we compute a *relative* measure op_i''' by dividing the absolute measure op_i in a specific question with the respective subjective error. Taking the relative distance into account makes the measure more comparable across respondents while still keeping the relative distance between the subjective error and the realized true error (see Figure B.3.1).

Assume that, similar to the example in Figure 2.1, the true error is normally distributed with mean 0 and variance σ^2 (solid curve). Moreover, the perceived distribution by the respondents might not necessarily coincide with the true distribution. If the perceived variance $\hat{\sigma}^2$ is smaller, i.e., the precision $\rho = 1/\hat{\sigma}^2$ is larger, then we call this respondent overprecise (dashed curve). As long as respondents have the same idea in mind when asking for the error they expect to make, the absolute overprecision measure is comparable across subjects. However, when respondents substantially dif-

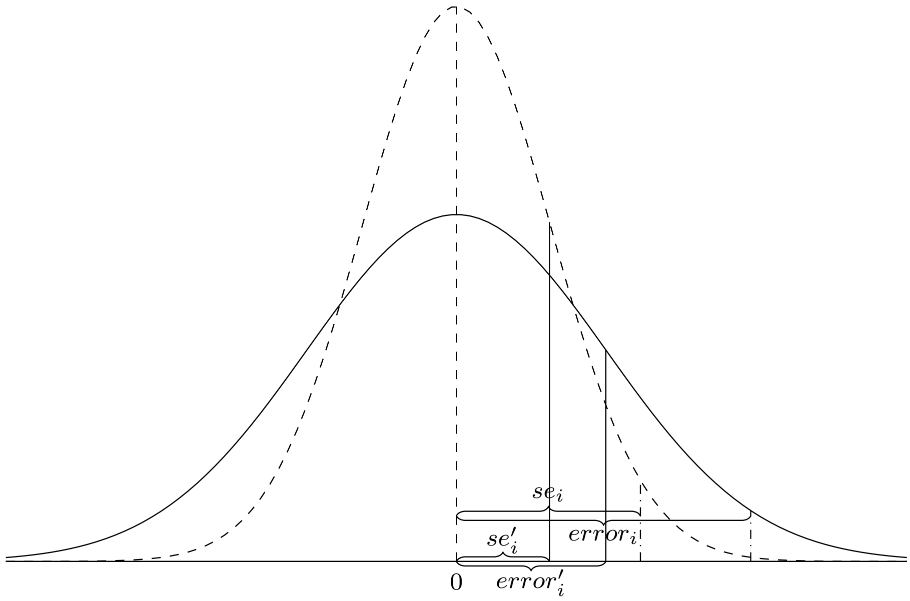


Figure B.3.1: Two hypothetical distributions of the (subjective) error

This figure shows two hypothetical distributions of the (subjective) error. The solid curve shows the true distribution of the error with a standard deviation of 2 (precision of .25). The dashed curve shows the perceived distribution by an overprecise respondent with a standard deviation of 1.25 (precision of .64). The solid and dash-dotted vertical lines indicate the subjective errors (*se*) and the realized true errors (*error*) resulting from respondents with two different ideas about the nature of the subjective error asked in the second question.

fer, e.g., by having different confidence intervals in mind, the ranking as computed with the absolute measure might not be consistent anymore whilst the sign of the deviation still being correct. Taking the example in Figure B.3.1, where the respondents have the same degree of overprecision since the perceived precision of .64 deviates from the true precision of .25, for a respondent with having 95% confidence in mind (*se* and *error*) the absolute overprecision measure would yield 1.47 whereas for the respondent with having 68% confidence in mind (se' and $error'$) it would yield .75. Thus, the second respondent would incorrectly be classified as less overprecise.

The relative measure corrects this inconsistency by scaling the absolute overprecision measure with the subjective absolute error, making the measure comparable across subjects. In the above example, the relative measure yields .6 in both cases, which is precisely the relative difference between the standard deviations of the respective distributions and, thus, directly proportional to the relative difference between the degree of precision.

Turning to the SOEP data, the correlation between the absolute and relative measure across the seven questions ranges from $\rho^{Spearman} = .91$ to $\rho^{Spearman} = .96$ which is consistent with the respondents interpreting the subjective error question in the same way.[1] Given the high correlation between both approaches, using the absolute mea-

[1]Note that the relationship between the absolute and the relative measure is non-linear. Therefore, we report the Spearman correlation coefficient only.

sure is preferable as it avoids having to drop the observations of respondents whose subjective error is zero.

Age-robust measure (op_i''''): The negative correlation between age and overprecision in our sample is likely to be driven by the type of questions that were asked in the survey. Since we asked about specific historical events within the last 100 years, respondents who lived during these events might be better calibrated. This becomes obvious in Figure B.3.2 where, for every question, we split the density of our overprecision measure $op_{i,j}$ between those respondents born before and after the event. As expected, those subjects born before the event are better calibrated than those born after. As a robustness test, we construct, for every respondent, an *age-robust* measure of overconfidence (op_i''''). We construct this measure following the formulation described in Section 2.2.1, but using only those questions about events that happened *after* the respondent was born. The drawback of this approach is that we lose a substantial amount of information and give more weight to events that occurred later in time. Taking fewer questions into account also comes at the risk that the aggregate measure is biased by one specific question.

Residual measure (op_i'''''): The *residual* measure is a measure of overprecision obtained by the estimation method of Ortoleva and Snowberg (2015b). Ortoleva and Snowberg (2015b) construct their measure of overconfidence by asking respondents about their assessment of the current and one year-ahead inflation rate and the unemployment rate as well as their confidence about the respective answers using a six-point scale. They then regress participants' confidence on a fourth-order polynomial of accuracy to isolate the effect of knowledge. The principal component of the four residuals is then used as their measure of overconfidence. To replicate their approach as closely as possible, we construct a measure of respondent confidence by inverting the reported subjective error and computing quintiles. We then regress the respondents' "confidence" about the answer on a fourth-order polynomial of the realized true error and take the principal component of the residuals across all seven questions to create our new individual measure of overprecision op_i'''''.

The residual measure of overprecision (op_i''''') mechanically differs from our baseline measure (op_i) because it effectively calculates the distance between the subjective error and the fitted fourth-order polynomial instead of the distance between the subjective error and the realized *true error*. This approach comes with the caveat that, if a respondents deviation is small relative to that of the population, then, when computing the residuals for the seven questions, the measure classifies the respondent as underconfident even if her realized true error is larger than her subjective error (for an illustrative example see Figure B.3.3). Thus, for every measure of op_i''''', the resid-

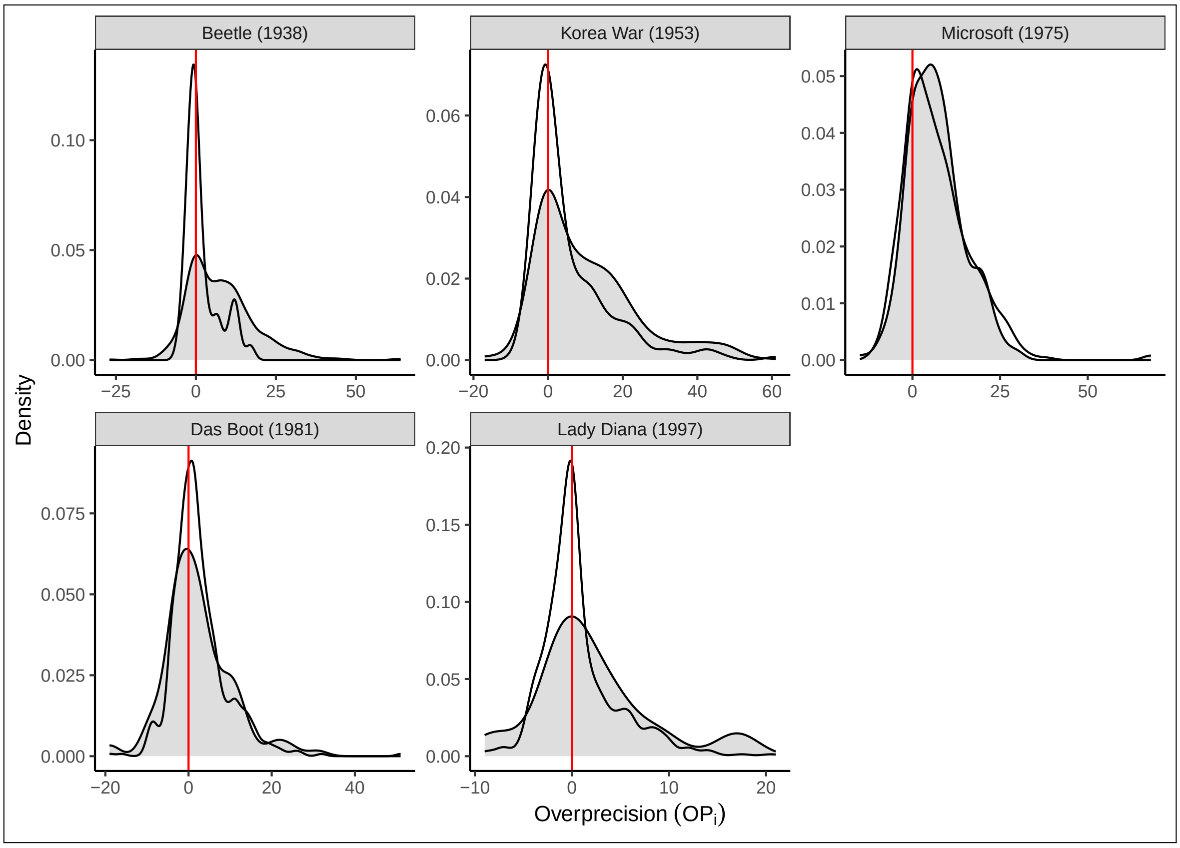


Figure B.3.2: Distribution of overprecision depending on age (SOEP-IS)

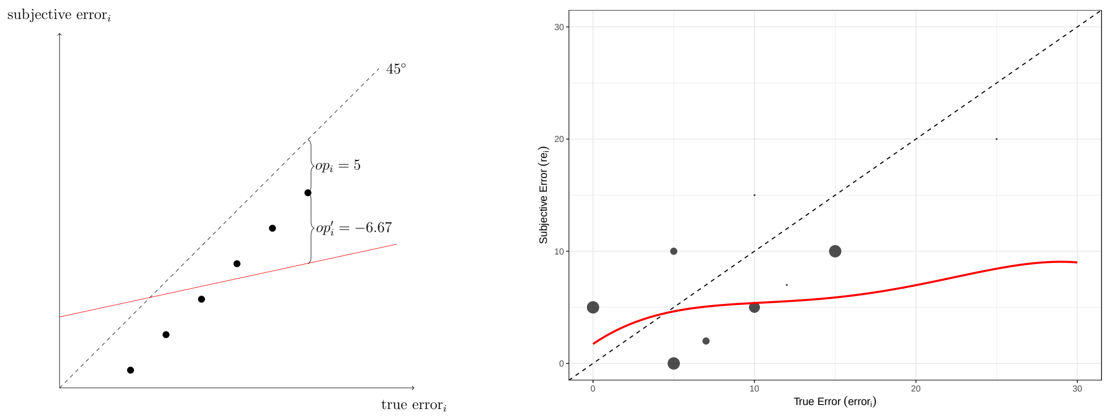
This figure shows the density of overprecision (op_{ij}) and age. From left (less recent) to right (more recent) We plot the density of the measured overprecision ($op_{i,j}$) for each question j. In gray, we plot the density of the measured overprecision for the question ($op_{i,j}$) of those subjects that were born after the event took place. With no color, we plot the density of all respondents born at the year of the event or before. Note that the scale of the vertical axis is different across the five plots. Questions with (correct) answers after 2000 are omitted as there were no underage respondents.

ual measure takes into account the relationship between the subjective error and the realized true error for the entire *population* of respondents. In contrast, our approach focuses on the respondent's signal processing only by comparing the realized true error with the subjective error.

B.3.2 Robustness of Descriptive Results

In Table B.3.1 we replicate Table 2.1 using each of the measures described in Section B.3.1 (Columns (2) to (6)) and our baseline measure sop_i in Column (1).

Column (2) of Table B.3.1 shows the results for the *standardized* measure (op_i'). The results show no qualitative changes with respect to the baseline except for the coefficient of the number of questions that were answered. However, the results are less significant. Column (3) shows the results using the *centered* measure (op_i''). The results remain largely robust with the coefficient for *gender* becoming larger and the coefficient for *answered* turning negative and insignificant.



(a) Illustration (b) Data

Figure B.3.3: Misspecification of participants

This figure shows the misspecification of participants, which is the difference between the Subjective Error Method and the *residual* approach for a theoretical illustration in (a) and for the answers to one of the overprecision questions in (b). Any observation in both panels above the 45° line represents underprecise individuals and any observation below represents overprecise individuals. Note that the axes are changed as compared to Figure 2.3. In panel (a), the dots represent observations for respondents for whom, in the example, the Subjective Error Method yields $op_i = error_i - se_i = 5$ in a specific question in the set of questions. The red line illustrates the fitted line of a simplified version of the *residual* approach using only a first order polynomial ($se_i = \alpha + \beta error_i + \epsilon_i$). In panel (b), the dots represent respondents for whom the Subjective Error Method yields an overprecision of 5 and -5 respectively. The red line indicates the fitted line of the *residual* approach using a fourth-order polynomial.

Column (4) replicates the baseline estimations using the *relative* approach (op_i'''). The qualitative results remain similar except for less precisely estimated coefficients which can be explained by the decreased sample size. Column (5) uses the *age-robust* measure (op_i''''). The results show that, if we exclude the mechanical effect of age, then overprecision and age are positively correlated which is consistent with the earlier results from the literature (e.g., Ortoleva and Snowberg, 2015a,b; Prims and Moore, 2017). Otherwise, all of our results remain robust.

Column (6) of Table B.3.1 shows the results for the *residual* approach (op_i'''''). For the most part, the outcome replicates the results of Ortoleva and Snowberg (2015b), with females being less overprecise and income and education not showing up as statically relevant. Moreover, age is positively correlated with the estimated overprecision. Surprisingly, the number of answered questions has a negative effect on overprecision. In other words, contrary to the observed measure of overprecision, if we estimate overprecision using the methodology of Ortoleva and Snowberg (2015b), then the more questions a respondent answers, the less overprecise she is.

Given the results in Table B.3.1, we believe that our baseline measure is the best alternative. It is a simple and straightforward approach that can easily be implemented and which does not require the specification of an econometric model such as the approach of Ortoleva and Snowberg (2015b). It does not miss-classify respondents and uses all of the available information into account. Moreover, it is highly correlated to both the standardized measure ($\rho^{Pearson} = .85$; $\rho^{Spearman} = .86; N = 805$), the relative measure ($\rho^{Pearson} = .68$; $\rho^{Spearman} = .82; N = 801$), as well as the centered measure ($\rho^{Pearson} = .96$; $\rho^{Spearman} = .93; N = 801$) and therefore robust to transformations. All of these results are confirmed in Appendix B.3.3 where we test the predictive power of all robustness measures.

Table B.3.1: Socio-economic determinants of overprecision using alternative measures

This table presents the determinants of overprecision using alternative measures of overprecision. In all Columns, we run an OLS with standardized overprecision measure *sop* as the dependent variable. For comparison, in Column (1) we run an OLS with the baseline measure. In Column (2) - (6), we run an OLS using the *standardized* measure, the *centered* measure, the *relative* measure, the *age-robust* measure, and the *residual* measure respectively. All include dummies for the labor force status (employed, unemployed, retired, maternity leave, non-working), whether the respondent was a GDR citizen before 1989, and further personal characteristics. We also control for the federal state (*Bundesland*) where the respondent lives and the time at which he/she responded to the questionnaire. Standard errors in parentheses. Stars indicate significance: $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Dependent variable: *sop*	Baseline (1)	Standardized (2)	Centered (3)	Relative (4)	Age robust (5)	Residual (6)
age	-0.005*	-0.000	-0.005*	0.003	0.018***	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
gender (female=1)	0.111	0.087	0.177**	0.079	-0.013	-0.199***
	(0.075)	(0.076)	(0.075)	(0.083)	(0.074)	(0.074)
years education	-0.037***	-0.014	-0.037***	-0.003	-0.008	0.002
	(0.014)	(0.014)	(0.014)	(0.016)	(0.014)	(0.014)
answered	0.085***	-0.031	-0.010	0.033	0.075***	-0.104***
	(0.021)	(0.022)	(0.021)	(0.027)	(0.021)	(0.021)
gross income	-0.039*	-0.040*	-0.033	-0.019	-0.032	0.010
	(0.023)	(0.024)	(0.023)	(0.025)	(0.023)	(0.023)
fin. literacy	-0.398**	-0.306*	-0.364**	-0.469***	-0.347**	-0.149
	(0.155)	(0.158)	(0.155)	(0.175)	(0.154)	(0.153)
risk aversion	0.048	0.037	0.036	-0.016	0.017	0.007
	(0.037)	(0.038)	(0.037)	(0.043)	(0.037)	(0.037)
impulsivity	-0.014	-0.005	-0.018	-0.006	0.020	0.034
	(0.037)	(0.038)	(0.037)	(0.041)	(0.037)	(0.037)
patience	0.038	0.042	0.038	0.058	0.033	0.044
	(0.035)	(0.036)	(0.035)	(0.039)	(0.035)	(0.035)
narcissism	0.100***	0.079**	0.098***	0.118***	-0.003	0.042
	(0.037)	(0.038)	(0.037)	(0.041)	(0.037)	(0.037)
N	805	805	805	702	800	805
adj. R^2	0.098	0.066	0.100	0.045	0.121	0.117
Constant Term	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Employment Status Dummy	Yes	Yes	Yes	Yes	Yes	Yes

B.3.3 Predictions Using Alternative Overprecision Measures

In the following, we will show the results for the *residual* approach following Ortoleva and Snowberg (2015b), the *relative* measure, the *standardized*, the *age-robust* measure, and the *centered* measure of overprecision. Table B.3.2 shows the results from the predictions using the *standardized* measure of overprecision instead. The results only slightly change with respect to the baseline, with the coefficients for the prediction errors becoming insignificant. However, the sign of the coefficient remains unchanged. The predictive power with respect to the LASSO estimations remains strong despite a slight decrease in the ranking as calculated by the R^2 method.

Table B.3.3 shows the results from the predictions using the *centered* measure of overprecision. Since the correlation between the centered and the baseline measure is .96, the results remain mostly unchanged.

Table B.3.4 shows the results from the predictions using the *relative* measure of overprecision instead. The advantage is that it makes the measure more comparable across subjects. However, we lose those observations with a reported zero subjective error due to mathematical reasons. The results, as compared to those in the baseline in Table 2.2, remain qualitatively similar.

Table B.3.5 shows the results from the predictions using the *age-robust* measure of overprecision instead. The results are at large in line with the results of the baseline estimations. The *age-robust* overprecision measures still predicts the outcomes according to the LASSO estimations. The point estimates slightly decrease in size and significance. However, as pointed out above, this measure considers fewer answers of the respondents and puts more weight on the more recent events since it only considers the questions on events after the respondent was born. Thus, the aggregate measure is calculated across fewer answers which might bias the measure. Therefore, these results have to be taken with a grain of salt.

Table B.3.6 shows the results from the predictions using the residual approach. Compared to the baseline measure, the alternative measure does not significantly predict any of the predictions derived from the theory. This is most likely because, applied to our data, this approach misclassifies certain respondents in the data as discussed in Appendix B.3.1.

Table B.3.2: Results of the analysis using the *standardized* measure

This table presents the estimation results as described in Section 2.3.4 using the *standardized* overprecision measure. Each row is a separate analysis with the respective dependent variable listed in the left column. The number of observations (Column (7)) varies due to missing observations in the outcome variable. The maximum number of observations is 805. Column (1) lists the point estimate of the standardized overprecision measure *sop* from the full regression as specified in Section 2.3.4.1 along with the unadjusted p-value (Column (2)) and the Sidak-Holm adjusted p-value for multiple hypothesis testing (Column (3)). Column (4) displays the result from the R^2 procedure specified in Section 2.3.4.1 along with the maximum possible variables to be included in the model. The regressions with political outcomes as dependent variable additionally include a self-reported measure of political interest. Column (5) specifies the result of the LASSO procedure as specified in Section 2.3.4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)). Stars indicate significance: $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Dependent variable	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) R^2	(7) N
Financial Behavior:							
DAX forecast error	0.11***	0.010	0.039	3/41	yes/15	0.10	548
1-year ahead	*0.382*	*0.450*		*19/41*	*no/15*	*0.14*	*578*
2-year ahead	*4.776****	*0.000*		*1/41*	*no/0*	*0.00*	*557*
portfolio diversification	-0.104***	0.004	0.019	3/41	yes/18	0.13	774
Political Behavior:							
extremeness	0.09**	0.025	0.072	3/42	yes/13	0.06	716
left-right	-0.017	0.662	0.662	18/42	no/14	0.08	716
non-voter	0.026**	0.025	0.050	4/42	yes/19	0.13	706

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3.3: Results of the analysis using the *centered* measure

This table presents the estimation results as described in Section 2.3.4 using the *centered* overprecision measure. Each row is a separate analysis with the respective dependent variable listed in the left column. The number of observations (Column (7)) varies due to missing observations in the outcome variable. The maximum number of observations is 805. Column (1) lists the point estimate of the standardized overprecision measure *sop* from the full regression as specified in Section 2.3.4.1 along with the unadjusted p-value (Column (2)) and the Sidak-Holm adjusted p-value for multiple hypothesis testing (Column (3)). Column (4) displays the result from the R^2 procedure specified in Section 2.3.4.1 along with the maximum possible variables to be included in the model. The regressions with political outcomes as dependent variable additionally include a self-reported measure of political interest. Column (5) specifies the result of the LASSO procedure as specified in Section 2.3.4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)). Stars indicate significance: $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Dependent variable	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) R^2	(7) N
Financial Behavior:							
DAX forecast error	0.08*	0.066	0.127	4/41	yes/14	0.10	548
1-year ahead	*0.387*	*0.456*		*12/41*	*yes/21*	*0.16*	*578*
2-year ahead	*3.202***	*0.012*		*4/41*	*no/1*	*0.00*	*557*
portfolio diversification	-0.125***	0.001	0.003	3/41	yes/19	0.13	774
Political Behavior:							
extremeness	0.081*	0.059	0.166	6/42	yes/14	0.05	716
left-right	0.003	0.944	0.944	18/42	no/14	0.08	716
non-voter	0.026**	0.034	0.128	4/42	yes/18	0.13	706

Table B.3.4: Results of the analysis using the *relative* measure

This table presents the estimation results as described in Section 2.3.4 using the *relative* overprecision measure. Each row is a separate analysis with the respective dependent variable listed in the left column. The number of observations (Column (7)) varies due to missing observations in the outcome variable. The maximum number of observations is 805. Column (1) lists the point estimate of the standardized overprecision measure *sop* from the full regression as specified in Section 2.3.4.1 along with the unadjusted p-value (Column (2)) and the Sidak-Holm adjusted p-value for multiple hypothesis testing (Column (3)) which is slightly less conservative than the Bonferroni adjustment. Column (4) displays the result from the R^2 procedure specified in Section 2.3.4.1 along with the maximum possible variables to be included in the model. The regressions with political outcomes as dependent variable additionally include a self-reported measure of political interest. Column (5) specifies the result of the LASSO procedure as specified in Section 2.3.4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)). Stars indicate significance: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Dependent variable	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) R^2	(7) N
Financial Behavior:							
DAX forecast error	0.062	0.166	0.421	3/41	yes/16	0.11	501
1-year ahead	*0.19*	*0.721*		*9/41*	*no/20*	*0.16*	*530*
2-year ahead	*2.822***	*0.033*		*2/41*	*no/1*	*0.01*	*510*
portfolio diversification	-0.068*	0.080	0.284	18/41	yes/14	0.11	681
Political Behavior:							
extremeness	0.113***	0.007	0.033	2/42	yes/15	0.06	624
left-right	-0.03	0.465	0.713	18/42	no/15	0.08	624
non-voter	0.003	0.800	0.800	3/42	no/4	0.09	616

Table B.3.5: Results of the analysis using the *age-robust* measure

This table presents the estimation results as described in Section 2.3.4 using the *age-robust* overprecision measure. Each row is a separate analysis with the respective dependent variable listed in the left column. The number of observations (Column (7)) varies due to missing observations in the outcome variable. The maximum number of observations is 805. Column (1) lists the point estimate of the standardized overprecision measure *sop* from the full regression as specified in Section 2.3.4.1 along with the unadjusted p-value (Column (2)) and the Sidak-Holm adjusted p-value for multiple hypothesis testing (Column (3)). Column (4) displays the result from the R^2 procedure specified in Section 2.3.4.1 along with the maximum possible variables to be included in the model. The regressions with political outcomes as dependent variable additionally include a self-reported measure of political interest. Column (5) specifies the result of the LASSO procedure as specified in Section 2.3.4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)). Stars indicate significance: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Dependent variable	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) R^2	(7) N
Financial Behavior:							
DAX forecast error	0.036	0.399	0.399	8/41	no/8	0.07	546
1-year ahead	*-0.442*	*0.379*		*4/41*	*no/16*	*0.15*	*576*
2-year ahead	*2.868***	*0.021*		*5/41*	*no/0*	*0.00*	*555*
portfolio diversification	-0.048	0.200	0.359	6/41	yes/16	0.12	769
Political Behavior:							
extremeness	0.065	0.102	0.350	5/42	yes/13	0.05	712
left-right	-0.061	0.119	0.315	6/42	no/11	0.07	712
non-voter	0.026**	0.022	0.106	3/42	yes/19	0.14	701

Table B.3.6: Results of the analysis using the *residual* measure

This table presents the estimation results as described in Section 2.3.4 using the *residual* aggregation method of Ortoleva and Snowberg (2015a). Each row is a separate analysis with the respective dependent variable listed in the left column. The number of observations (Column (7)) varies due to missing observations in the outcome variable. The maximum number of observations is 805. Column (1) lists the point estimate of the standardized overprecision measure *sop* from the full regression as specified in Section 2.3.4.1 along with the unadjusted p-value (Column (2)) and the Sidak-Holm adjusted p-value for multiple hypothesis testing (Column (3)). Column (4) displays the result from the R^2 procedure specified in Section 2.3.4.1 along with the maximum possible variables to be included in the model. The regressions with political outcomes as dependent variable additionally include a self-reported measure of political interest. Column (5) specifies the result of the LASSO procedure as specified in Section 2.3.4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)). Stars indicate significance: $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Dependent variable	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) LASSO R^2	(7) N
Financial Behavior:							
DAX forecast error	-0.021	0.626	0.948	14/41	no/12	0.09	548
1-year ahead	*-0.269*	*0.606*		*9/41*	*no/20*	*0.16*	*578*
2-year ahead	*-0.267*	*0.835*		*12/41*	*no/7*	*0.04*	*557*
portfolio diversification	-0.029	0.440	0.902	13/41	no/19	0.12	774
Political Behavior:							
extremeness	-0.046	0.256	0.773	8/42	yes/13	0.05	716
left-right	-0.008	0.831	0.831	17/42	no/14	0.08	716
non-voter	-0.003	0.798	0.959	18/42	no/17	0.13	706

B.4 Comparing the Survey Data to the SOEP-IS Data

In the following, we compare the Subjective Error Method answers to the history questions for the online survey with those in the SOEP-IS survey. To avoid any distortion from outliers, all variables are trimmed at the 1 and 99 percentile.

Figure B.4.1 plots the distributions of answers to the history questions in the SOEP and the online survey. With the exception of the Beetle, the distributions are relatively similar across samples. Table B.4.1 shows the results of a standard two-sided t-test on the difference between the means and of a test on the equality of the standard deviations of both samples. Except for the mean of the question regarding the VW Beetle (1938), the means of the answers to the questions differ by little, even if this difference is statistically significant in most cases. Interestingly, in most cases, the SOEP sample is closer to the correct answer. This could be explained by more effort of the respondents in the face-to-face interviews than in the online survey and speaks in favor of the '*Google*' filters we introduced to filter our online sample. The dispersion of the answers around the mean is relatively similar for both samples except for the question regarding Hussein (2003) where SOEP respondents are more closely around the mean. However, the analysis suggests that knowledge about contemporary history is relatively similarly distributed among both samples.

Figure B.4.2 plots the distributions of the overprecision measure for the respective history questions contained in both the SOEP survey and the companion online survey. The distributions are graphically relatively similar in both samples. The statistical tests in Table B.4.2, however, show that the respondents in the SOEP sample, on average, tend to be slightly more overprecise for most of the questions. One explanation for this result could be that respondents try to show off in front of the interviewers in the face-to-face interviews by stating lower subjective errors. Taken together, the distributions of the overprecision measures only marginally differ among both samples.

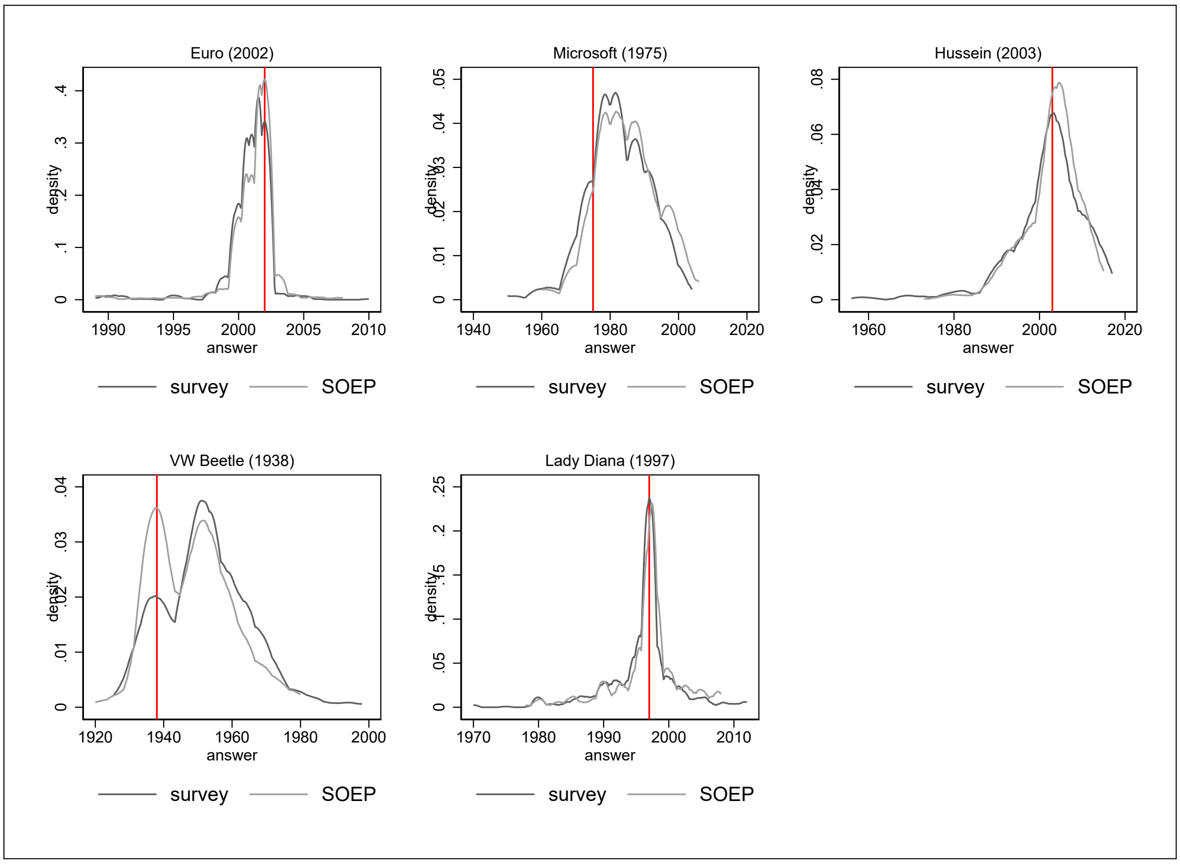


Figure B.4.1: Comparing the distributions of the answers to each history question

This figure shows the density of the answers ($a_{i,j}$) for each of the history questions contained in both the SOEP survey and the companion online survey. The vertical line marks the correct answer. Note that the vertical axis is different for each question.

Table B.4.1: Statistical comparison of the answers to each history question

This table presents the statistical comparison of the answers to the history questions between the survey and the SOEP sample. The p-values are the results from a two-sided t-test on the difference between the means Δ and from a test on the equality of the standard deviations of both samples, respectively.

	mean				standard deviation			
Question	mean (survey)	mean (SOEP)	Δ	p	sd (survey)	sd (SOEP)	Δ	p
Euro (2002)	2000,835	2001,124	-0,289	0,004	1,980	2,055	-0,075	0,294
Microsoft (1975)	1982,691	1984,929	-2,237	0,000	8,974	9,108	-0,134	0,697
Hussein (2003)	2002,212	2002,955	-0,742	0,077	8,718	6,568	2,150	0,000
VW Beetle (1938)	1952,268	1948,535	3,734	0,000	12,561	11,502	1,059	0,016
Lady Diana (1997)	1995,975	1996,680	-0,704	0,010	5,367	5,141	0,226	0,240

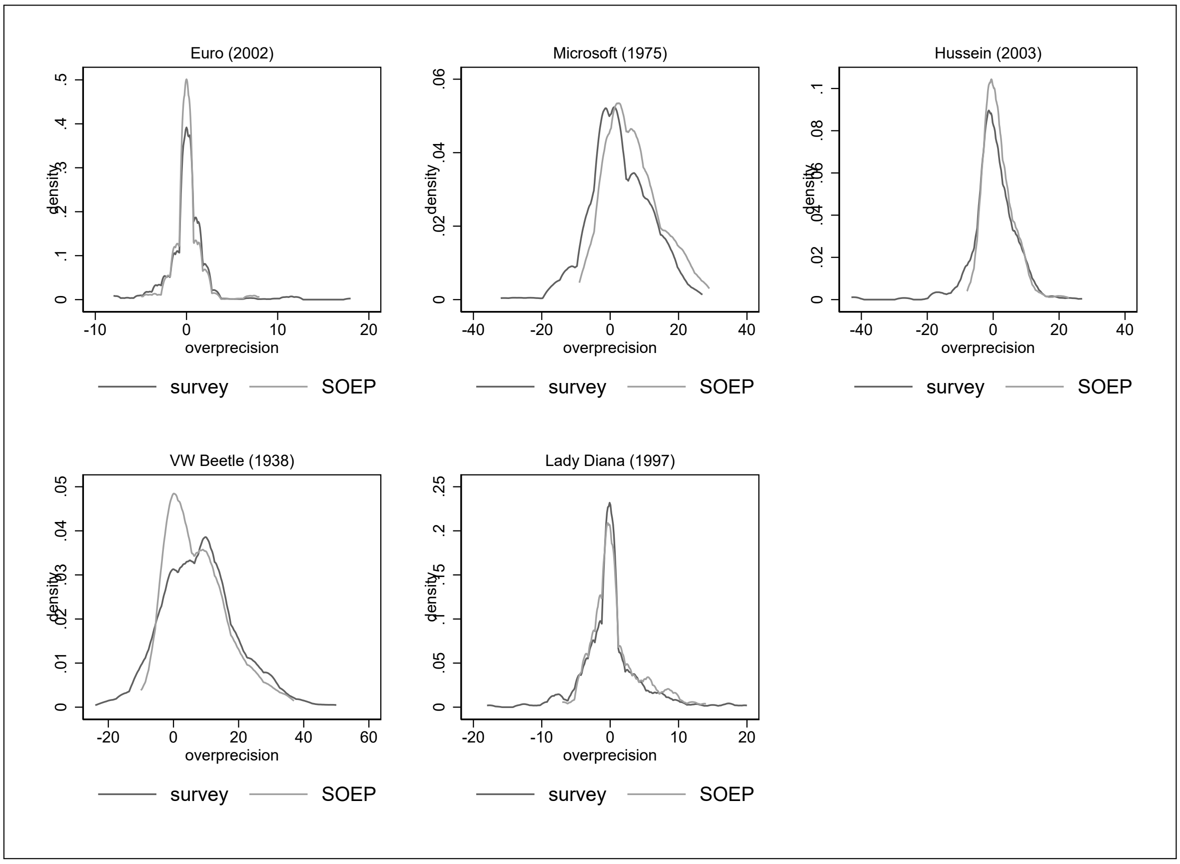


Figure B.4.2: Comparing the distributions of the overprecision measures

This figure shows the density of the overprecision measure ($op_{i,j}$) for each of the history questions contained in both the SOEP survey and the companion online survey. Note that the vertical axis is different for each question.

Table B.4.2: Statistical comparison of the overprecision measures

This table presents the statistical comparison of the overprecision measures by question between the survey and the SOEP sample. The p-values are the results from a two-sided t-test on the difference between the means Δ and from a test on the equality of the standard deviations of both samples, respectively.

	mean				standard deviation			
Question	mean (survey)	mean (SOEP)	Δ	p	sd (survey)	sd (SOEP)	Δ	p
Euro (2002)	0,143	0,106	0,037	0,728	2,474	1,562	0,913	0,000
Microsoft (1975)	2,953	6,662	-3,708	0,000	8,687	7,979	0,708	0,031
Hussein (2003)	0,293	1,562	-1,269	0,000	6,707	4,554	2,153	0,000
VW Beetle (1938)	8,222	7,238	0,984	0,076	11,352	9,290	2,062	0,000
Lady Diana (1997)	0,096	0,663	-0,567	0,008	4,412	3,622	0,790	0,000

B.5 Robustness Tests in the Companion Survey

In the following, we test the robustness of the analyses of the online experiment as outlined in the pre-registration. All robustness tests are concerned with the exclusion restrictions specified in the pre-analysis plan. In the baseline analysis, we exclude all respondents who admit to using a third party to answer our questions and respondents who we identify as '*Googlers*' by using our control questions. We do so by excluding those respondents who answer the *Google* controls correctly and state a subjective error of zero while displaying the same behavior for at least three other questions within the same domain. The respondent is then excluded from the entire analysis if this behavior is detected in any domain. Additionally, we exclude the lowest five percentiles on the self-reported effort measure to ensure data quality.

Robustness tests (1) and (2) change the exclusion restriction to detect '*Googlers*'. Robustness test (1) drops all respondents that have one of the *Google* control questions correct while stating a subjective error of zero. Robustness test (2) instead drops all respondents who get at least four of the five answers in any domain correct. Robustness test (3) additionally excludes all respondents who are in the lowest decile of time spent on each survey question at least 20% of the time across the entire survey, while robustness test (4) repeats the same for the highest decile. Robustness test (5) increases the threshold of self-reported quality to 10% and robustness test (6) to 20%. Robustness test (7) additionally excludes those respondents who gave the same answer to more than two of the respective first questions within a domain to control for response patterns.

Table B.5.1 shows the robustness test results for the factor analysis, Table B.5.2 for the partial correlation analysis, and Table B.5.3 for the leave-one-out analysis. The results show that by adding more stringent exclusion restrictions concerning '*Googlers*' does not substantially change the results. Adding further restrictions, which improve the quality of answers but reduced the number of observations, only marginally changes the results, predominantly improving the results.

Table B.5.1: Robustness of the factor analysis

This table presents the robustness test of the factor analysis. Column (Baseline) shows the baseline results with the exclusion restrictions specified in Section 2.4.2. Each of the robustness tests changes one of the exclusion restrictions. Robustness tests (1) and (2) change the exclusion restriction to detect '*Googlers*'. Robustness test (1) drops all respondents that have one of the hard questions, which we use to detect respondents who we assume to have used search engines, correct while stating a subjective error of zero. Robustness test (2) drops all respondents who get at least four of the five answers in any domain correct. Robustness test (3) additionally excludes all respondents who are in the lowest decile of time spent on each survey question at least 20% of the time across the entire survey, while robustness test (4) repeats the same for the highest decile. Robustness test (5) increases the threshold of self-reported quality to 10% and robustness test (6) to 20%. Robustness test (7) additionally excludes those respondents who gave the same answer to more than two of the respective first questions within a domain to control for response patterns.

		Robustness						
	Baseline	1	2	3	4	5	6	7
Eigenvalue	2.29	2.30	2.28	2.34	2.23	2.27	2.32	2.25
Loading neutral	0.52	0.52	0.52	0.53	0.60	0.51	0.49	0.48
Loading history	0.76	0.76	0.76	0.76	0.72	0.76	0.78	0.77
Loading knowledge	0.74	0.75	0.74	0.75	0.72	0.73	0.75	0.74
Loading stocks	0.69	0.69	0.68	0.71	0.68	0.68	0.67	0.68
Loading economics	0.65	0.65	0.65	0.65	0.61	0.66	0.67	0.65
N	552	544	547	487	440	535	476	500

Table B.5.2: Robustness of the partial correlation analysis

This table presents the robustness test of the partial correlation coefficients ρ between the aggregate overprecision measures across the five domains. The control variables are age, gender, education, income, nationality, state, mathematical literacy, and a measure of self-reported knowledge on the topic of the domain. Variable definitions are in Table B.2.9 in the appendix. Column (Baseline) shows the baseline results with the exclusion restrictions specified in Section 2.4.2. Each of the robustness tests changes one of the exclusion restrictions. Robustness tests (1) and (2) change the exclusion restriction to detect '*Googlers*'. Robustness test (1) drops all respondents that have one of the hard questions, which we use to detect respondents who we assume to have used search engines, correct while stating a subjective error of zero. Robustness test (2) drops all respondents who get at least four of the five answers in any domain correct. Robustness test (3) additionally excludes all respondents who are in the lowest decile of time spent on each survey question at least 20% of the time across the entire survey, while robustness test (4) repeats the same for the highest decile. Robustness test (5) increases the threshold of self-reported quality to 10% and robustness test (6) to 20%. Robustness test (7) additionally excludes those respondents who gave the same answer to more than two of the respective first questions within a domain to control for response patterns.

				Robustness													
		Baseline		1		2		3		4		5		6		7	
Domain 1	Domain 1	ρ	N	ρ	N	ρ	N	ρ	N	ρ	N	ρ	N	ρ	N	ρ	N
Neutral	History	0.17	688	0.17	680	0.17	679	0.18	588	0.19	560	0.16	658	0.18	578	0.16	632
Neutral	Knowledge	0.21	626	0.22	618	0.20	617	0.23	539	0.22	503	0.19	603	0.18	538	0.18	570
Neutral	Stocks	0.30	676	0.30	668	0.29	670	0.32	577	0.33	546	0.28	648	0.24	575	0.25	619
Neutral	Economics	0.18	639	0.18	632	0.18	633	0.17	552	0.20	518	0.17	613	0.19	542	0.17	580
History	Knowledge	0.52	609	0.52	600	0.52	600	0.52	531	0.49	488	0.52	586	0.55	522	0.53	554
History	Stocks	0.35	638	0.35	629	0.35	632	0.37	557	0.29	514	0.35	614	0.37	544	0.35	584
History	Economics	0.37	620	0.37	612	0.37	614	0.37	542	0.31	499	0.37	596	0.38	526	0.37	565
Knowledge	Stocks	0.34	591	0.34	582	0.33	585	0.37	516	0.32	471	0.33	573	0.34	509	0.32	537
Knowledge	Economics	0.32	580	0.33	572	0.32	574	0.33	507	0.28	461	0.32	562	0.35	502	0.30	525
Stocks	Economics	0.28	618	0.28	610	0.27	613	0.30	540	0.24	500	0.29	594	0.29	529	0.28	561

Table B.5.3: Robustness of the leave-one-out-analysis

This table presents the robustness tests of the leave-one-out analysis between the domains. *In sample* signifies the domain in which the quartiles based on overprecision were computed. The sample is then partitioned into the lower 75% and upper 25% group. *Out sample* signifies the domain in which overprecision is then measured and tested between both groups. *Lower 75%* shows the means, standard deviation, and the number of observations in the *Out sample* for the lower three quartiles of overprecision based on the *In sample* and *Upper 25%* the means, standard deviation, and the number of observations in the *Out sample* for the upper quartile. The last column reports the p-values from two-sided t-tests of the difference Δ against the value 0. Column (Baseline) shows the baseline results with the exclusion restrictions specified in Section 2.4.2. Each of the robustness tests changes one of the exclusion restrictions. Robustness tests (1) and (2) change the exclusion restriction to detect '*Googlers*'. Robustness test (1) drops all respondents that have one of the hard questions, which we use to detect respondents who we assume to have used search engines, correct while stating a subjective error of zero. Robustness test (2) drops all respondents who get at least four of the five answers in any domain correct. Robustness test (3) additionally excludes all respondents who are in the lowest decile of time spent on each survey question at least 20% of the time across the entire survey, while robustness test (4) repeats the same for the highest decile. Robustness test (5) increases the threshold of self-reported quality to 10% and robustness test (6) to 20%. Robustness test (7) additionally excludes those respondents who gave the same answer to more than two of the respective first questions within a domain to control for response patterns.

				Robustness													
		Baseline		1		2		3		4		5		6		7	
In	Out	Δ	p	Δ	p	Δ	p	Δ	p	Δ	p	Δ	p	Δ	p	Δ	p
Neutral	History	-0.348	< 0.01	-0.335	< 0.01	-0.363	< 0.01	-0.394	< 0.01	-0.335	< 0.01	-0.346	< 0.01	-0.352	< 0.01	-0.335	< 0.01
Neutral	Knowledge	-0.406	< 0.01	-0.422	< 0.01	-0.373	< 0.01	-0.519	< 0.01	-0.368	< 0.01	-0.397	< 0.01	-0.409	< 0.01	-0.396	< 0.01
Neutral	Stocks	-0.339	< 0.01	-0.343	< 0.01	-0.341	< 0.01	-0.354	< 0.01	-0.338	< 0.01	-0.301	< 0.01	-0.273	< 0.01	-0.328	< 0.01
Neutral	Economics	-0.323	< 0.01	-0.322	< 0.01	-0.340	< 0.01	-0.326	< 0.01	-0.338	< 0.01	-0.311	< 0.01	-0.364	< 0.01	-0.311	< 0.01
History	Neutral	-0.218	0.01	-0.184	0.03	-0.221	0.01	-0.243	0.01	-0.288	< 0.01	-0.207	0.02	-0.273	< 0.01	-0.163	0.07
History	Knowledge	-0.566	< 0.01	-0.572	< 0.01	-0.547	< 0.01	-0.605	< 0.01	-0.547	< 0.01	-0.549	< 0.01	-0.534	< 0.01	-0.556	< 0.01
History	Stocks	-0.432	< 0.01	-0.436	< 0.01	-0.453	< 0.01	-0.439	< 0.01	-0.477	< 0.01	-0.421	< 0.01	-0.368	< 0.01	-0.387	< 0.01
History	Economics	-0.385	< 0.01	-0.393	< 0.01	-0.383	< 0.01	-0.366	< 0.01	-0.439	< 0.01	-0.370	< 0.01	-0.405	< 0.01	-0.390	< 0.01
Knowledge	Neutral	-0.230	0.01	-0.244	< 0.01	-0.215	0.01	-0.247	0.01	-0.186	0.05	-0.206	0.02	-0.150	0.10	-0.213	0.02
Knowledge	History	-0.451	< 0.01	-0.480	< 0.01	-0.463	< 0.01	-0.381	< 0.01	-0.454	< 0.01	-0.468	< 0.01	-0.419	< 0.01	-0.488	< 0.01
Knowledge	Stocks	-0.323	< 0.01	-0.336	< 0.01	-0.314	< 0.01	-0.349	< 0.01	-0.341	< 0.01	-0.315	< 0.01	-0.271	< 0.01	-0.325	< 0.01
Knowledge	Economics	-0.301	< 0.01	-0.307	< 0.01	-0.291	< 0.01	-0.301	< 0.01	-0.308	< 0.01	-0.281	< 0.01	-0.320	< 0.01	-0.279	< 0.01
Stocks	Neutral	-0.449	< 0.01	-0.418	< 0.01	-0.436	< 0.01	-0.451	< 0.01	-0.467	< 0.01	-0.421	< 0.01	-0.406	< 0.01	-0.407	< 0.01
Stocks	History	-0.421	< 0.01	-0.408	< 0.01	-0.421	< 0.01	-0.416	< 0.01	-0.467	< 0.01	-0.416	< 0.01	-0.411	< 0.01	-0.361	< 0.01
Stocks	Knowledge	-0.368	< 0.01	-0.408	< 0.01	-0.360	< 0.01	-0.432	< 0.01	-0.381	< 0.01	-0.364	< 0.01	-0.352	< 0.01	-0.325	< 0.01
Stocks	Economics	-0.371	< 0.01	-0.395	< 0.01	-0.369	< 0.01	-0.437	< 0.01	-0.394	< 0.01	-0.397	< 0.01	-0.459	< 0.01	-0.348	< 0.01
Economics	Neutral	-0.338	< 0.01	-0.313	< 0.01	-0.358	< 0.01	-0.344	< 0.01	-0.346	< 0.01	-0.323	< 0.01	-0.302	< 0.01	-0.319	< 0.01
Economics	History	-0.384	< 0.01	-0.367	< 0.01	-0.386	< 0.01	-0.336	< 0.01	-0.445	< 0.01	-0.376	< 0.01	-0.359	< 0.01	-0.341	< 0.01
Economics	Knowledge	-0.292	< 0.01	-0.306	< 0.01	-0.277	< 0.01	-0.273	0.01	-0.320	< 0.01	-0.281	< 0.01	-0.301	< 0.01	-0.262	< 0.01
Economics	Stocks	-0.381	< 0.01	-0.386	< 0.01	-0.330	< 0.01	-0.364	< 0.01	-0.360	< 0.01	-0.363	< 0.01	-0.359	< 0.01	-0.340	< 0.01

B.6 Further Exploratory Analyses in the Companion Survey

Given the rich data we collect in the companion online survey, we conduct further exploratory analyses which have not been pre-registered in the pre-analysis plan.

B.6.1 Overprecision and Expertise

The literature on overconfidence and overprecision has shown that knowledge and expertise increase both the accuracy of answers and confidence in these answers at the same time. This cancels out the effect of expertise on overconfidence. Önkal et al. (2003), for example, show that newcomers and experts have similar levels of overconfidence when predicting foreign exchange rates. While the experts' predictions were more accurate, they also showed more confidence in their answers. McKenzie et al. (2008) show that the confidence intervals of experts were closer to the truth but also narrower than those of newcomers resulting in similar levels of overprecision.

In the following, we test this relationship in our data using a self-reported measure of expertise. To do so, we regress the mean error, the mean subjective error, and the aggregate measure of overprecision in each domain on self-reported expertise in the same domain. Since self-reported expertise itself is likely to be influenced by overprecision, we control for an aggregate measure of overprecision in the following analysis. That is, for each domain, we predict the first component of a principal component analysis of the standardized aggregate overprecision measures across all domains excluding the one that is analyzed.

The results in Table B.6.1 show that self-reported expertise is both associated with a decrease in the mean error and a decrease in the mean subjective error within the same domain. Importantly, the results in Columns (3) and (4) show that overprecision also affects self-reported expertise. Controlling for overprecision, the effects on the mean error and the mean subjective error are relatively similar. Therefore, consistent with the literature, we do not find an effect of expertise on the overprecision measure within the same domain.

Table B.6.1: Self-reported expertise and the overprecision measure

This table presents the relation between self-reported expertise and the overprecision measure, which is the result of regressing the mean error, the mean subjective error, and the overprecision measure of one domain on the self-reported expertise in the same domain. Expertise is reported on a scale from 0 to 100. Overprecision is the first component of a principal component analysis of the standardized aggregate overprecision measures across all domains excluding the one that is analyzed. In Columns (2), (4), and (6) we additionally control for overprecision, which is measured as the first component of a principal component analysis of the overprecision measures across all domains but the one that is analyzed. Robust standard errors in parentheses. Stars indicate significance: $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

	mean error		mean subjective error		mean overprecision	
	(1)	(2)	(3)	(4)	(5)	(6)
History:						
expertise	-0.036***	-0.039***	-0.044***	-0.041***	0.001	0.000
	(0.007)	(0.008)	(0.010)	(0.010)	(0.002)	(0.002)
overprecision		0.389**		-3.437***		0.581***
		(0.180)		(0.225)		(0.039)
N	703	552	703	552	703	552
adj. R^2	0.032	0.042	0.025	0.312	-0.001	0.291
Knowledge:						
expertise	-0.030**	-0.030*	-0.054***	-0.056***	0.002	0.002
	(0.015)	(0.016)	(0.013)	(0.012)	(0.002)	(0.002)
overprecision		1.288***		-4.277***		0.484***
		(0.336)		(0.248)		(0.034)
N	633	552	633	552	633	552
adj. R^2	0.005	0.028	0.023	0.370	0.001	0.272
Stocks:						
expertise	-0.026**	-0.028**	-0.058***	-0.046***	0.003**	0.002
	(0.012)	(0.014)	(0.013)	(0.013)	(0.002)	(0.002)
overprecision		0.984***		-3.655***		0.443***
		(0.316)		(0.313)		(0.036)
N	690	552	690	552	690	552
adj. R^2	0.005	0.020	0.024	0.214	0.004	0.219
Economics:						
expertise	-0.039***	-0.043***	-0.066***	-0.050***	0.002	0.001
	(0.011)	(0.011)	(0.015)	(0.014)	(0.002)	(0.002)
overprecision		0.429*		-3.839***		0.376***
		(0.250)		(0.316)		(0.033)
N	647	552	647	552	647	552
adj. R^2	0.019	0.025	0.030	0.230	0.002	0.188

C Appendix to Chapter 3

C.1 Bank's Maximization Problem

From eq. (3.16), the bank's maximization problem is given by

$$\begin{aligned}
&\max_{z_H, z_L, F} \Pi = \beta q_H^*[(y + x(\alpha, e_H)) - (1+t)z_H] + (1 - q_H^*)y + (1-\beta)q_H^* v_i sd - F - sd \\
&\text{s.t. (i) participation constraint: } \hat{u}_H^* = \hat{\beta}(\theta)q_H^* z_H + F - \varphi - \frac{\mu q_H^{*2}}{2} \geq \bar{u} \\
&\quad\text{(ii) incentive constraint: } \hat{\beta}(\theta)q_H^* z_H - \varphi - \frac{\mu q_H^{*2}}{2} \geq \hat{\beta}(\theta)q_L^* z_L - \frac{\mu q_L^{*2}}{2} \\
&\quad\text{(iii) } q_H^* = \arg\max_{q_H} \hat{u}_H = \hat{\beta}(\theta)q_H z_H + F - \varphi - \frac{\mu q_H^2}{2} \\
&\quad\text{(iv) } F \geq 0,\ z_H \geq 0,\ z_L \geq 0.
\end{aligned} \tag{C.1.1}$$

Using the equilibrium probabilities from eq. (3.13), we get the following Lagrangian:

$$\begin{aligned}
\max_{z_H, z_L, F} \mathcal{L} =& \beta\frac{\hat{\beta}(\theta)}{\mu} z_H[(y + x(\alpha, e_H)) - (1+t)z_H] + (1 - \frac{\hat{\beta}(\theta)}{\mu} z_H)y + (1-\beta)\frac{\hat{\beta}(\theta)}{\mu} z_H v_i sd \\
&- F - sd + \lambda_p\left[\frac{\hat{\beta}(\theta)^2}{2\mu} z_H^2 + F - \varphi - \bar{u}\right] + \lambda_k\left[\frac{\hat{\beta}(\theta)^2}{2\mu}(z_H^2 - z_L^2) - \varphi\right].
\end{aligned} \tag{C.1.2}$$

The four first order conditions are then given by

$$\begin{aligned}
\frac{\partial \mathcal{L}}{\partial z_H} =& \frac{\hat{\beta}(\theta)}{\mu}\left[r_H + (1-\beta)v_i sd - 2\beta(1+t)z_H\right] \\
&+ \lambda_p \frac{\hat{\beta}(\theta)^2}{\mu} z_H + \lambda_k \frac{\hat{\beta}(\theta)^2}{\mu} z_H \leq 0 \quad \wedge \quad \frac{\partial \mathcal{L}}{\partial z_H} z_H = 0,
\end{aligned} \tag{C.1.3}$$

$$\frac{\partial \mathcal{L}}{\partial z_L} = -\lambda_k \frac{\hat{\beta}(\theta)^2}{\mu} z_L \leq 0 \quad \wedge \quad \frac{\partial \mathcal{L}}{\partial z_L} z_L = 0, \tag{C.1.4}$$

$$\frac{\partial \mathcal{L}}{\partial F} = -1 + \lambda_p \leq 0 \quad \wedge \quad \frac{\partial \mathcal{L}}{\partial F} F = 0, \tag{C.1.5}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_p} = \frac{\hat{\beta}(\theta)^2}{2\mu} z_H^2 + F - \varphi - \bar{u} \geq 0, \tag{C.1.6}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda_k} = \frac{\hat{\beta}(\theta)^2}{2\mu}(z_H^2 - z_L^2) - \varphi \geq 0. \tag{C.1.7}$$

From eq. (C.1.4) it becomes clear that the bank will always set $z_L = 0$ if it wants to incentivize z_H. Furthermore, the bonus will always be used in equilibrium ($z_H > 0$) as the marginal costs of the bonus at $z_H = 0$ are zero, while the marginal benefits are positive due to the positive effect of the bonus on risk-taking.

Since we want to find an interior solution for the bonus in situations where the fixed wage is used, we want to rule out the cases where the incentive constraint is binding and the participation constraint is not binding or binding with $F = 0$. Since we assume $\bar{u} > 0$, this leaves us with four different cases:

- Case 1: $\lambda_k = 0$, $\lambda_p = 1$, $z_H > 0$, and $F > 0$. The bonus is determined by an interior solution and fixed wage is used to satisfy participation constraint.
- Case 2: $\lambda_k = 0$, $0 < \lambda_p < 1$, $z_H > 0$, and $F = 0$. The bonus is determined by the participation constraint.
- Case 3: $\lambda_k = 0$, $\lambda_p = 0$, $z_H > 0$, and $F = 0$. The bonus is so high that participation constraint is not binding.
- Case 4: $\lambda_k > 0$, $\lambda_p = 1$, $z_H > 0$, and $F > 0$. The bonus is determined by the incentive constraint and the fixed wage is used to satisfy participation constraint.

We want to focus on the case where the bonus and the fixed wage are used in equilibrium and where the incentive constraint is not binding (**Case 1**: $\lambda_k = 0$, $\lambda_p = 1$, $z_H > 0$, and $F > 0$). From the complementary slackness condition it follows that a positive fixed wage ($F > 0$) implies $\lambda_p = 1$ in eq. (C.1.5). Note also that for the fixed wage to be used ($F > 0$), the participation constraint must be binding (i.e., eq. (C.1.6) holds with equality). Otherwise profits could be increased by lowering the fixed wage.

Solving eq. (C.1.3) for z_H and using $\lambda_p = 1$ and $\lambda_k = 0$, we get the bank bonus z_H in eq. (3.19). Using the participation constraint in eq. (C.1.6) gives the bank's fixed wage F in eq. (3.20). The second order condition with respect to z_H is given by

$$\frac{\partial^2 \mathcal{L}}{\partial z_H^2} = -\frac{\hat{\beta}(\theta)}{\mu}[2\beta(1+t) - \hat{\beta}(\theta)] < 0. \tag{C.1.8}$$

In the two other possible cases under $\lambda_k = 0$, the fixed wage is not used. In **Case 2** ($\lambda_k = 0$, $0 < \lambda_p < 1$, $z_H > 0$, and $F = 0$) only the bonus is used and the participation constraint is binding. In **Case 3** ($\lambda_k = 0$, $\lambda_p = 0$, $z_H > 0$, and $F = 0$) only the bonus is used and the participation constraint is not binding.

Analyzing the conditions under which $\lambda_p = 0$, $\lambda_p = 1$, and $\lambda_k > 0$, we can derive the conditions for the four cases. Case 2 and 3 are ruled out if overconfidence is sufficiently low:

$$\hat{\beta}(\theta) < \frac{\sqrt{2\mu(\bar{u}+\varphi)}}{\Omega_H + \sqrt{2\mu(\bar{u}+\varphi)}} 2(1+t)\beta, \text{ where } \Omega_H \equiv r_H + (1-\beta)v_i sd. \tag{C.1.9}$$

Note that eq. (C.1.9) implies that $\hat{\beta}(\theta) < 2\beta(1+t)$, which ensures that there is an interior solution for the bonus (cf. eq. (C.1.8)). To rule out **Case 4** ($\lambda_k > 0$, $\lambda_p = 1$, $z_H > 0$, and $F > 0$), overconfidence must in addition not be too large, i.e.:

$$\frac{\sqrt{2\mu\varphi}}{\Omega_H + \sqrt{2\mu\varphi}} 2(1+t)\beta < \hat{\beta}(\theta). \tag{C.1.10}$$

Combining eq. (C.1.9) and eq. (C.1.10) yields the condition for Case 1 to hold:

$$\frac{\sqrt{2\mu\varphi}}{\Omega_H + \sqrt{2\mu\varphi}} 2(1+t)\beta < \hat{\beta}(\theta) < \frac{\sqrt{2\mu(\bar{u}+\varphi)}}{\Omega_H + \sqrt{2\mu(\bar{u}+\varphi)}} 2(1+t)\beta. \tag{C.1.11}$$

It can be shown that under the assumption $\bar{u} > 0$ a solution range for Case 1 exists. We assume that the fixed wage is used for any possible bonus tax (i.e., $t \geq 0$). This assumption can be derived by setting $t = 0$ in eq. (C.1.11), and is given in eq. (3.17).

Case 2 holds for $\frac{\sqrt{2\mu(\bar{u}+\varphi)}}{\Omega_H+\sqrt{2\mu(\bar{u}+\varphi)}}2(1+t)\beta < \hat{\beta}(\theta) < \frac{\sqrt{2\mu(\bar{u}+\varphi)}}{\Omega_H}2(1+t)\beta$. If overconfidence is very high, $\hat{\beta}(\theta) > \frac{\sqrt{2\mu(\bar{u}+\varphi)}}{\Omega_H}2(1+t)\beta$, the participation constraint does not bind and Case 3 holds. If overconfidence is very low, $\hat{\beta}(\theta) < \frac{\sqrt{2\mu\varphi}}{\Omega_H+\sqrt{2\mu\varphi}}2(1+t)\beta$, the incentive constraint is binding and Case 4 holds.

For the bank to prefer high effort over low effort, the following must hold (for Case 1, i.e. both bonus and fixed wage are used): For the bank to prefer e_H over e_L it must hold that $\Pi(e_H) \geq \Pi(e_L)$, i.e. the expected return when incentivizing e_H must be larger than under incentivizing e_L. Plugging in e_H and e_L as well as F from eq. (3.20) in eq. (3.15), the following holds:

$$\begin{aligned} &q_H[r_H + (1-\beta)v_i sd] - q_L[r_L + (1-\beta)v_i sd] - \beta(1+t)(q_H z_H - q_L z_L) \\ &+ \frac{\hat{\beta}(\theta)^2}{2\mu}(z_H^2 - z_L^2) - \varphi \geq 0. \end{aligned} \tag{C.1.12}$$

Eq. (C.1.12) implies that the benefit of high effort compared to low effort, i.e. a higher expected return, must outweigh the increased compensation costs. Using the optimal risk decision in eq. (3.12), eq. (C.1.12) can be further simplified.

$$\frac{\hat{\beta}(\theta)}{\mu}\left[z_H r_H - z_L r_L + (1-\beta)v_i sd(z_H - z_L) - \frac{1}{2}[2\beta(1+t) - \hat{\beta}(\theta)](z_H^2 - z_L^2)\right] - \varphi \geq 0. \tag{C.1.13}$$

Plugging in z_H and z_L from eq. (3.19) in the paper and rearranging yields:

$$\frac{\hat{\beta}(\theta)}{\mu\Psi}\left[\frac{1}{2}(r_H^2 - r_L^2) + (1-\beta)v_i sd(r_H - r_L)\right] - \varphi \geq 0. \tag{C.1.14}$$

The condition in eq. (C.1.14) simply states that the benefit which results from high effort outweighs the costs associated with high effort and which have to be compensated by the bank. Thus, assuming $x(\alpha, e_H) - x(\alpha, e_L)$ to be sufficiently large to outweigh the costs of effort φ ensures that the bank wants the manager to exert high effort. This holds, analogously, for the other cases.

C.2 Optimal Bonus Tax

Substituting the bank's bonus z_H^* from eq. (3.19) and $\frac{\partial z_H^*}{\partial t}$ into eq. (3.25), we get

$$\frac{\partial W}{\partial t} = \frac{\hat{\beta}(\theta)}{\mu}\left\{-\frac{2\beta r_H \Omega_H}{\Psi^2} + 2\beta\hat{\beta}(\theta)\frac{\Omega_H^2}{\Psi^3}\right\}. \tag{C.2.1}$$

Collecting terms in eq. (C.2.1) gives

$$\frac{\partial W}{\partial t} = \left[\frac{\hat{\beta}(\theta)}{\mu}\beta\frac{\Omega_H}{\Psi^3}\right]\{2\hat{\beta}(\theta)\Omega_H - [2\beta(1+t) - \hat{\beta}(\theta)]2r_H\}. \tag{C.2.2}$$

Setting $t = 0$ and summarizing terms in eq. (C.2.2), we get the first order condition at $t = 0$, as given in eq. (3.26).

Using the fact that $\frac{\hat{\beta}(\theta)}{\mu}\beta\frac{\Omega_H}{\Psi^3} > 0$ always holds, and collecting terms in eq. (C.2.2), we find that

$$\begin{aligned} sgn\left\{\frac{\partial W}{\partial t}\right\} = sgn\{&2[2\beta - \hat{\beta}(\theta)](1-\beta)v_i sd + 4\Omega_H(\hat{\beta}(\theta) - \beta) \\ &+ \beta t[4(1-\beta)v_i sd - 4\Omega_H]\}. \end{aligned} \tag{C.2.3}$$

The last term in brackets in eq. (C.2.3) shows that there exists no corner solution since by assumption

$$\beta(y + x(\alpha, e_H)) - y > 0. \tag{C.2.4}$$

More generally, corner solutions are ruled out if $r_H = \beta(y + x(\alpha, e_H)) - y > 0$. Otherwise, the last term in squared brackets in eq. (C.2.3) is positive. As all other terms in eq. (C.2.3) are positive as well, eq. (C.2.4) is thus a sufficient condition for a corner solution. Intuitively, this condition shows that if risk-shifting is only costly, the government optimally chooses $t^* \to \infty$ in order to minimize the costs.

If assuming $r_H = \beta(y+x(\alpha, e_H))-y > 0$, however, then there is an interior solution for the optimal bonus tax. Setting $\frac{\partial W}{\partial t}$ in eq. (C.2.2) equal to zero, dividing both sides by $\frac{\hat{\beta}(\theta)}{\mu}\beta\frac{\Omega_H}{\Psi^3}$, and solving for t, we get the optimal bonus tax in eq. (3.27). It is easy to show that $\beta(y+x(\alpha, e_H))-y > 0$ implies that $\frac{\partial W}{\partial t} > 0$ for $0 \leqslant t < t^*$, and that $\frac{\partial W}{\partial t} < 0$ for $t > t^*$. Hence, t^* in eq. (3.27) is a global maximum, if $\beta(y+x(\alpha, e_H))-y > 0$ holds.

C.3 Socially Optimal Bonus

In the absence of bonus taxes, social welfare is the (weighted) sum of bank profit $\Pi^* = \beta q_H^*[(y + x(\alpha, e_H)) - z_H] + (1 - q_H^*)y + (1 - \beta)q_H^* v_i sd - F - sd$, actual manager utility $u = \beta q_H^* z_H + F - \varphi - \frac{\mu q_H^{*2}}{2}$, and the bailout costs $B = (1 - \beta)q_H^* v_i sd$.

The social planer's maximization problem is then given by

$$\begin{aligned} \max_{z_H} W &= \Pi^* - B + u \\ &= \beta q_H^*(y + x(\alpha, e_H)) + (1 - q_H^*)y - \varphi - \frac{\mu q_H^{*2}}{2} - sd. \end{aligned} \tag{C.3.1}$$

Substituting (3.12) and (3.13) into eq. (C.3.1) and assuming $r_H = \beta(y+x(\alpha, e_H))-y > 0$, we get

$$W = \frac{\hat{\beta}(\theta)}{\mu} z_H r_H + y - sd - \varphi - \frac{\hat{\beta}(\theta)^2}{2\mu} z_H^2. \tag{C.3.2}$$

Differentiating eq. (C.3.2) with respect to z_H gives

$$\frac{\partial W}{\partial z_H} = \frac{\hat{\beta}(\theta)}{\mu} r_H - \frac{\hat{\beta}(\theta)^2}{\mu} z_H. \tag{C.3.3}$$

Setting (C.3.3) equal to zero, and solving for z_H, we get the socially optimal bonus in eq. (3.31).

The second order condition is given by

$$\frac{\partial^2 W}{\partial z_H^2} = -\frac{\hat{\beta}(\theta)^2}{\mu} < 0. \tag{C.3.4}$$

C.4 Internalized Risk-Shifting Incentives

We can derive the bonus of a bank that fully internalizes the government's bailout costs by adding the term $-(1 - \beta)q_H^* v_i sd$ to the bank profit in eq. (3.16). Setting $t = 0$, the bank's maximization problem is then given by

$$\max_{z_H,z_L,F} \Pi = \beta q_H^*[(y + x(\alpha, e_H)) - z_H] + (1 - q_H^*)y + (1 - \beta)q_H^* v_i sd - F - sd - (1 - \beta)q_H^* v_i sd$$

$$\begin{aligned}
\text{s.t. } &\text{(i) participation constraint: } \hat{u}_H^* = \hat{\beta}(\theta)q_H^* z_H + F - \varphi - \frac{\mu q_H^{*2}}{2} \geq \bar{u} \\
&\text{(ii) incentive constraint: } \hat{\beta}(\theta)q_H^* z_H - \varphi - \frac{\mu q_H^{*2}}{2} \geq \hat{\beta}(\theta)q_L^* z_L - \frac{\mu q_L^{*2}}{2} \\
&\text{(iii) } q_H^* = \arg\max_{q_H} \hat{u}_H = \hat{\beta}(\theta)q_H z_H + F - \varphi - \frac{\mu q_H^2}{2} \\
&\text{(iv) } F \geq 0,\ z_H \geq 0,\ z_L \geq 0.
\end{aligned} \tag{C.4.1}$$

Solving the maximization problem in (C.4.2), we get the bonus of a bank that fully internalizes the government's bailout costs

$$z_{R|t=0} = \frac{\Omega_H - (1 - \beta)v_i sd}{2\beta - \hat{\beta}(\theta)}. \tag{C.4.2}$$

The bonus simplifies to

$$z_{R|t=0} = \frac{r_H}{2\beta - \hat{\beta}(\theta)}. \tag{C.4.3}$$

Eq. (C.4.3) shows that the internalisation of bailout costs indeed reduces the bank's bonus, $z_{H,R|t=0}$. Comparing this bonus to the socially optimal bonus, we get

$$z_{H,R_{|t=0}} - z_{H,S_{|t=0}} = \frac{r_H}{2\beta - \hat{\beta}(\theta)} - \frac{r_H}{\hat{\beta}(\theta)} = \frac{2(\hat{\beta}(\theta) - \beta)r_H}{(2\beta - \hat{\beta}(\theta))\hat{\beta}(\theta)}. \tag{C.4.4}$$

It follows from eq. (C.4.4) that the bank's bonus, $z_{H,R_{|t=0}}$, equals the socially optimal bonus, $z_{H,S_{|t=0}}$, only if the manager is rational ($\theta = 0$). If the manager is overconfident $\theta > 0$, the bank's bonus will be higher than the socially optimal bonus. The reason is analogous to the argument why capital requirements alone cannot achieve the socially optimal bonus. If a bank internalizes the externalities of its risk-taking, then the bank chooses a lower bonus in order to reduce bailout costs. If the manager is overconfident, however, the participation constraint of a manager (cf. eq. (C.4.2)) provides an additional incentive for the bank to choose an excessive bonus in order to save compensation costs.

D Appendix to Chapter 4

D.1 Additional Tables

Table D.1.1: Overview of the variables used in the analysis

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 D.1.2: Robustness tests – CEO characteristics

This table presents the robustness test concerning CEO characteristics of the OLS estimation of the fixed effects model in Equation (4.2) for risk-taking in the U.S. financial sector in the years 2000 to 2019. The dependent variable is the natural logarithm of the standard deviation of daily stock returns. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Column (1) displays the baseline results. Column (2) excludes imputed CEO observations, column (3) excludes all observations with zero exercisable options from the construction of the overconfidence measure, column (4) additionally includes gender and tenure of the CEO, column (5) includes the price sensitivity (*Delta*) and the volatility sensitivity (*Vega*) of the CEOs option portfolio, column (6) includes a measure of excess compensation of the CEO, column (7) includes the number of exercisable options, and column (8) uses an alternative proxy of wealth. Variable definitions are in Table D.1.1. 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)	(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}	0.159***	0.159***	0.168***	0.165***	0.175***	0.159***	0.158***	0.138***
	(0.031)	(0.031)	(0.033)	(0.033)	(0.033)	(0.031)	(0.031)	(0.032)
$period_{2008,2017} \times OC_{t-1}$	-0.134***	-0.134***	-0.138***	-0.136***	-0.129***	-0.134***	-0.134***	-0.128***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.041)	(0.040)	(0.040)	(0.041)
$period_{2018,2019} \times OC_{t-1}$	-0.0438	-0.0438	-0.0762*	-0.0441	-0.0458	-0.0440	-0.0434	-0.0366
	(0.043)	(0.043)	(0.045)	(0.043)	(0.051)	(0.042)	(0.043)	(0.044)
Observations	2448	2447	2057	2385	1871	2448	2447	2448
Clusters	238	238	222	230	216	238	238	238
Mean	-3.94	-3.94	-3.92	-3.93	-3.90	-3.94	-3.94	-3.94
adj. R^2	0.85	0.85	0.86	0.85	0.86	0.85	0.85	0.85
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table D.1.3: Relation between 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 D.1.4: Robustness tests – firm characteristics

This table presents the robustness tests concerning firm characteristics of the OLS estimation of the fixed effects model in Equation (4.2) for risk-taking in the U.S. financial sector in the years 2000 to 2019. The dependent variable is the natural logarithm of the standard deviation of daily stock returns. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Column (1) displays the baseline results. Column (2) includes *Tobin's Q*, column (3) two lags and leads of the stock return, column (4) the size of the executive board, and column (5) a measure for market concentration. Variable definitions are in Table D.1.1. Hubert-White heteroskedasticity consistent standard errors clustered at the firm level in parentheses. Stars indicate significance: $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

	(1) $ln(\sigma_t)$	(2) $ln(\sigma_t)$	(3) $ln(\sigma_t)$	(4) $ln(\sigma_t)$	(5) $ln(\sigma_t)$
OC_{t-1}	0.159***	0.158***	0.143***	0.159***	0.159***
	(0.031)	(0.031)	(0.042)	(0.031)	(0.031)
$period_{2008,2017} \times OC_{t-1}$	-0.134***	-0.133***	-0.130***	-0.134***	-0.134***
	(0.040)	(0.040)	(0.046)	(0.040)	(0.039)
$period_{2018,2019} \times OC_{t-1}$	-0.0438	-0.0483		-0.0448	-0.0426
	(0.043)	(0.043)		(0.043)	(0.042)
Observations	2448	2448	1685	2448	2448
Clusters	238	238	214	238	238
Mean	-3.94	-3.94	-3.95	-3.94	-3.94
adj. 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 D.1.5: 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 (4.2) for risk-taking in the U.S. financial sector in the years 2000 to 2019. The dependent variable is the natural logarithm of the standard deviation of daily stock returns. $OC_{i,t-1}$ is a binary variable which is one if a firm has an overconfident CEO at time $t-1$, $\mathbb{1}[t \in p]_{i,t}$ is an indicator variable that equals one if the observation falls within one of the three periods p. The vector of controls $\boldsymbol{X_{i,t}}$ includes size, return on assets, leverage, deposits, liquidity, a proxy for CEO wealth, and the fiscal year-end stock price. Column (1) displays the baseline results. Column (2) uses weighted least squares (WLS), column (3) uses industry fixed effects, column (4) only keeps financial institutions which are in the sample over the entire sample period, column (5) only keeps CEOs who were in office either in 2007 or 2010, column (6) only keeps CEOs who were replaced between 2007 and 2010, column (7) only keeps CEOs who were in office both in 2007 and in 2010, column (8) omits the last year of each CEO's tenure, and column (9) the first year. Variable definitions are in Table D.1.1. Hubert-White heteroskedasticity consistent standard errors clustered at the firm level in parentheses. Stars indicate significance: $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$.

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

Eidesstattliche Versicherung

Ich versichere hiermit eidesstattlich, dass ich die vorliegende Arbeit selbständig und ohne fremde Hilfe verfasst habe. Die aus fremden Quellen direkt oder indirekt übernommenen Gedanken sowie mir gegebene Anregungen sind als solche kenntlich gemacht. Die Arbeit wurde bisher keiner anderen Prüfungsbehörde vorgelegt und auch noch nicht veröffentlicht. Sofern ein Teil der Arbeit aus bereits veröffentlichten Papers besteht, habe ich dies ausdrücklich angegeben.

München, 13. März 2023

Bernhard Kassner