Overconfidence and the Political and Financial Behavior of a Representative Sample *

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Abstract

We study the relationship between overconfidence and the political and financial behavior of a nationally representative sample. To do so, we introduce a new method of eliciting overconfidence that is simple to understand, quick to implement, and captures respondents' excess confidence in their own judgment. Our results show that, in line with theoretical predictions, an excessive degree of confidence in one's judgment is correlated with lower portfolio diversification, larger stock price forecasting errors, and more extreme political views. Additionally, we find that overconfidence is correlated with voting absenteeism. These results appear to validate our method and show how overconfidence is a bias that permeates several aspects of peoples' life.

Keywords Overconfidence, SOEP, Survey

JEL Classification C83 · D91 · G41

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

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

1 Introduction

Overconfidence is considered to be a pervasive and potent bias in human judgment (Mannes and Moore, 2013; Kahneman, 2013). It leads to fighting wars (Johnson, 2009), to excessive entry into markets (Camerer and Lovallo, 1999), or (less critically) for 80% of the population to think that they are above median 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, thinking that you are better than you really are. Overplacement has to do with relative values, thinking that your performance is better than that of others. Finally, overprecision has to do with the degree of certainty with which one judges her own knowledge. 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).

Of the three types of overconfidence, overprecision is the most persistent and least studied (Moore et al., 2015). 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 responsible for the under-diversification of portfolios as well as for asset price volatility (Goetzmann and Kumar, 2008; Scheinkman and Xiong, 2003) or systematic forecasting errors (Deaves et al., 2019). 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, 2020). However, even though overprecision has such negative consequences, we understand very little of it (Mannes and Moore, 2013).

One of the reasons for our lack of understanding of overprecision is that it is hard to measure since it deals with the second moment of the belief distribution. The most common measure, introduced by Alpert and Raiffa (1982), consists of asking respondents for the confidence intervals (CI) of a series of numerical questions (e.g., how long is the river Nile).[1] However, the literature has shown that this method creates implausibly high measures of overprecision as respondents do not fully understand how to use CIs (Moore et al., 2015). Other measures of overprecision are the two-alternative forced-choice (2AFC) (Griffin and Brenner, 2004) or the Subjective Probability Interval Estimate (SPIES) (Haran et al., 2010) which are either not fully suited to elicit individual-level measures of overprecision or too time-consuming (Moore et al., 2015).

In this paper, we study how overprecision correlates with the political and financial behavior of a nationally representative sample of the German population, the SOEP Innovation Sample (SOEP-IS). To do so, we introduce a new way of eliciting overprecision which we call the "Subjective Error Method." This method consists of a two-step procedure where we first ask participants a numerical question (e.g., in which year was Saddam Hussein captured by the US army?) and then ask them to estimate how "far away (in years)" their response to the first question is from the correct answer. In other words, in the second step, we ask respondents to report the *absolute error* they expect to make in the first question. The two questions are easy to understand and, by comparing the true "realized error" to their absolute subjective error, we can measure the degree of overprecision of respondents in a simple and direct way.

The richness of our data allows us to study the correlation of overprecision with both the socio-demographic measures of participants and their financial and political behavior. As a result, we observe that overprecision (as measured using the Subjective Error Method) is negatively correlated with age, years of education, and gross income, but does not differ across genders. We also find that overprecision has strong predictive power for several theoretical conjectures. For example, our measure is positively correlated with larger forecasting errors in respondents' stock price predictions and 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

[1]The idea behind this method is that a perfectly calibrated respondent should get nine out of ten correct answers within the CIs. An overprecise subject would get less than ten out of ten within her CI, while an underprecise respondent would get all ten questions within the CI's. In their seminal paper, the 98% CIs of their participants (MBA students) contain the correct answer only 60% of the time.

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 US.

There is only a small number of papers studying the effects of overprecision using a representative sample. Ortoleva and Snowberg (2015a,b) study the influence of overprecision on ideological extremeness, partisan identification, and voter turnout using a representative sample of the US population. Using the same data set, Stone (2019) studies partisan hostility. In the present paper, we go beyond the political dimensions studied in the existing literature by analyzing the financial behavior of our sample. Moreover, while Ortoleva and Snowberg (2015a,b) and Stone (2019) estimate the individual measure of overprecision of respondents, our new method allows us to directly elicit the overprecision of respondents.

To summarize, our paper contributes to the existing literature on overprecision in three dimensions: first, we introduce a novel technique, the Subjective Error Method, which gives a direct measure of overprecision, is easy to understand, and can be quickly implemented in surveys. Second, we show that, in line with the theoretical predictions, our measure shows that a higher degree of overprecision results in lower portfolio diversification and larger stock price forecasting errors, as well as 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 the theoretical predictions on a representative sample of the German population.

Our paper proceeds as follows: Section 2 discusses the notion of overprecision, introduces our measure of overprecision, the Subjective Error Method, and presents the SOEP-IS data set. In Section 3 we correlate overprecision with various socio-demographic measures. In Section 4 we 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. The last section concludes.

2 Overprecision, the Subjective Error Method, and Data Details

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 judgment (Moore et al., 2015). It relates to the second moment of the belief distribution, directly affecting how information is processed. Therefore it is widely used in finance and political science to model overconfident agents. For example, in Odean (1998) overconfident traders trade excessively and hold underdiversified portfolios because they believe their private signals to be more precise than they really are. Scheinkman and Xiong (2003) combine a constraint on short sales and overprecise traders to explain the formation of asset market bubbles.[2] In the political science literature, Ortoleva and Snowberg (2015b) show that more overprecise people tend to vote more, hold more extreme political views, and show stronger partisan identification. In this line, Stone (2019) suggests that overprecision increases partisanship through excessively strong inferences from (biased) information sources. More recently, literature has begun to study the role that overprecision plays in the dissemination of fake news (Pennycook et al., 2020; Thaler, 2020).

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 is by asking for 90% confidence intervals (CI) for a series of numerical questions (e.g., how long is the river Nile). 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 such a method creates implausible high measures of overprecision, with the stated 90% CI's of respondents containing the correct answer only 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 acquainted with CIs and do not fully grasp what they are being asked (Moore et al., 2015). This was made clear by Teigen and Jørgensen (2005) who

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

show that the elicited intervals resulting from asking 90% CI's are practically identical to those resulting from asking for 50% CI's.

While there are some alternatives to CI's to measure overprecision, these tend to be either time-consuming or limited in the information they provide. For example, the two-alternative forced-choice (2AFC) by Griffin and Brenner (2004) has respondents 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 if, 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); Griffin and Brenner (2004) for a further discussion of the 2AFC method and its statistical limitations). Another approach to measure overprecision is the Subjective Probability Interval Estimates (SPIES) method by Haran et al. (2010). The SPIES method elicits complete probability distributions from respondents. While it seems to measure overprecision more accurately than CI's (Moore et al., 2015), it is time-consuming as it requires respondents to understand the concept of probability distributions to then build such distributions for each question. 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.

2.2 The Subjective Error Method

In contrast to the methods listed in the previous section, we introduce the Subjective Error Method, which allows us to directly measure respondents' overprecision in a way that is both easy to understand and simple to implement. 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.[3] The second question (b) asks respondents how far away they expect their answer to question (a) to be from the true

[3]Some examples of numerical questions are the result multiplying 385 times 67, the length of the Nile, 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.

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 river Nile?*

(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 (b) to the realized *true error* in question (a), we get a measure of how over-/underprecise the 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 blue curve in Figure 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 of most respondents might not necessarily coincide with the true distribution. If the respondent is overprecise, then her perceived variance $\hat{\sigma}^2$ is smaller than the true variance of the error, i.e., the precision $\rho = 1/\hat{\sigma}^2$ is larger (red curve in Figure 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.[4]

Formally, call the answer of respondent i to question j $a_{i,j}$, her subjective error for question j $se_{i,j}$, and the true answer to the question ta_j. Hence, our measure of overprecision for respondent i for question j is:

$$error_{i,j} = |a_{i,j} - ta_j|, \tag{1}$$

$$overprecision_{i,j} = error_{i,j} - se_{i,j}, \tag{2}$$

where equation (1) measures the realized true error ($error_{i,j}$) of respondent i to question j. Notice, that this equation calculates the *absolute error*, that is, we do not care about the direction of the error, but rather the size of the error. In equation (2), we calculate

[4]Notice that the difference between the realized error and the absolute subjective error which would realize with the same cumulative probability is directly proportional to the difference in the precision of the underlying distributions.

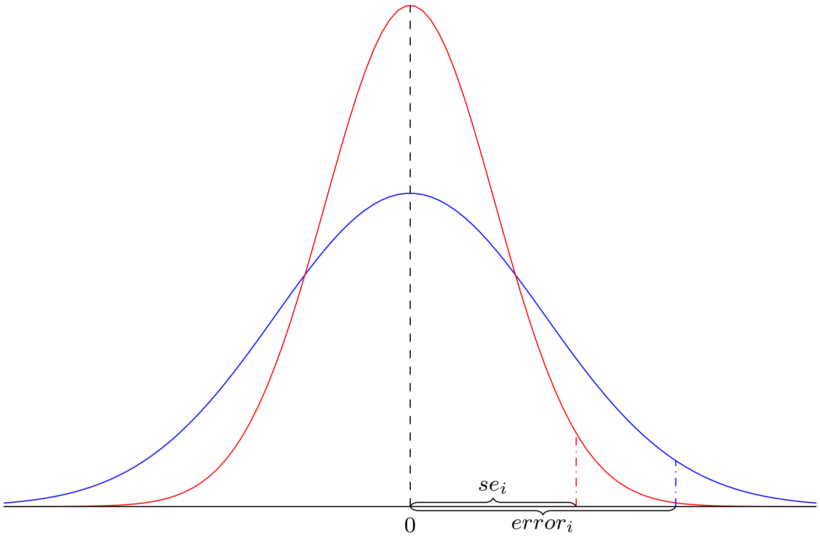


Figure 1: The figure shows two hypothetical normal distributions of the error. The blue curve shows the true distribution of the error with a standard deviation of 2 (precision of .25). The red curve shows the perceived distribution by an overprecise respondent with a standard deviation of 1.25 (precision of .64). The dashed vertical lines indicate the subjective error se_i and the realized true errors $error_i$ resulting with the same cumulative probability.

the difference between the subjective error ($se_{i,j}$) and the realized true error ($error_{i,j}$) of respondents i to question j. This time 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 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.

Eliciting overprecision using the Subjective Error Method rather than CI's 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, 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 as one can put a payment mechanism such as a quadratic scoring rule (Brier, 1950) or the binarized scoring rule (Hossain and Okui, 2013) on top of each question, and then pay randomly only one of the two outcomes to avoid hedging across questions. This stands in contrast with the more complicated scoring rules necessary to make CIs incentive-compatible (e.g., Jose and Winkler, 2009).

In a recent paper, Enke and Graeber (2019) 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, allowing 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 of Enke and Graeber (2019) 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 Data

We use data from the Innovation Sample of the German Socio-Economic Panel (SOEP-IS). The Innovation Sample is a subset of the larger SOEP-Core panel (approximately 30,000 individual respondents) and it is designed to host and test novel survey items (see, Richter et al., 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.

For the construction of our measure, 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 further away than 100 years, and (b) the distance (in years) between their answer to (a) and the correct answer to (a).[5] In other words, we ask respondents to answer a general knowledge question and then we ask them to report the absolute error they expect to make, i.e., their subjective error (see Section 2.2).

We asked seven different questions about events taking place between 1938 and 2003. The questions were 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.1 in the appendix for all questions and their correct answers).[6] These questions were asked to a subset (902) of the respondents in the SOEP-IS 2018 who joined the panel

[5]The precise formulation was 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?*.

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

in 2016. We supplement the data with additional 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.[7]

3 Socio-Demographic Determinants of Overprecision

In Figure 2, we plot the density of the 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 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 overprecise in their answers across all questions, independent of the difficulty.

Since overprecision is measured across seven different questions, internal consistency is important. To measure such consistency, we use congeneric reliability, which is commonly referred to as coefficient omega (see e.g., Cho, 2016). The congeneric reliability measure is defined as $T_i = \mu_i + \lambda_i F + e_i$, where T_i is the outcome of item i with mean μ_i, e_i is the score error and λ_i is the factor loading on the latent common factor F (Morera and Sotkes, 2016). It is a generalized version of the Cronbach α (Cronbach, 1951), but allowing for different factor loadings of the latent common factor.[8] To construct the congeneric reliability measure, we estimate the factor loadings, $\hat{\lambda}_i$, for the overprecision measure of each question with respect to a common factor (i.e., overprecision) and estimate the

[7]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.4 in the appendix show that our sub-sample is at large still representative of the larger SOEP-Core with only some significant but small and non-meaningful differences. When applying the sampling weights to our estimation sample as well, the differences disappear.

[8]For the case of τ-equivalence, i.e., $\lambda_i = \lambda_j \ \forall i, j$, all factor loadings are equal and both measures coincide.

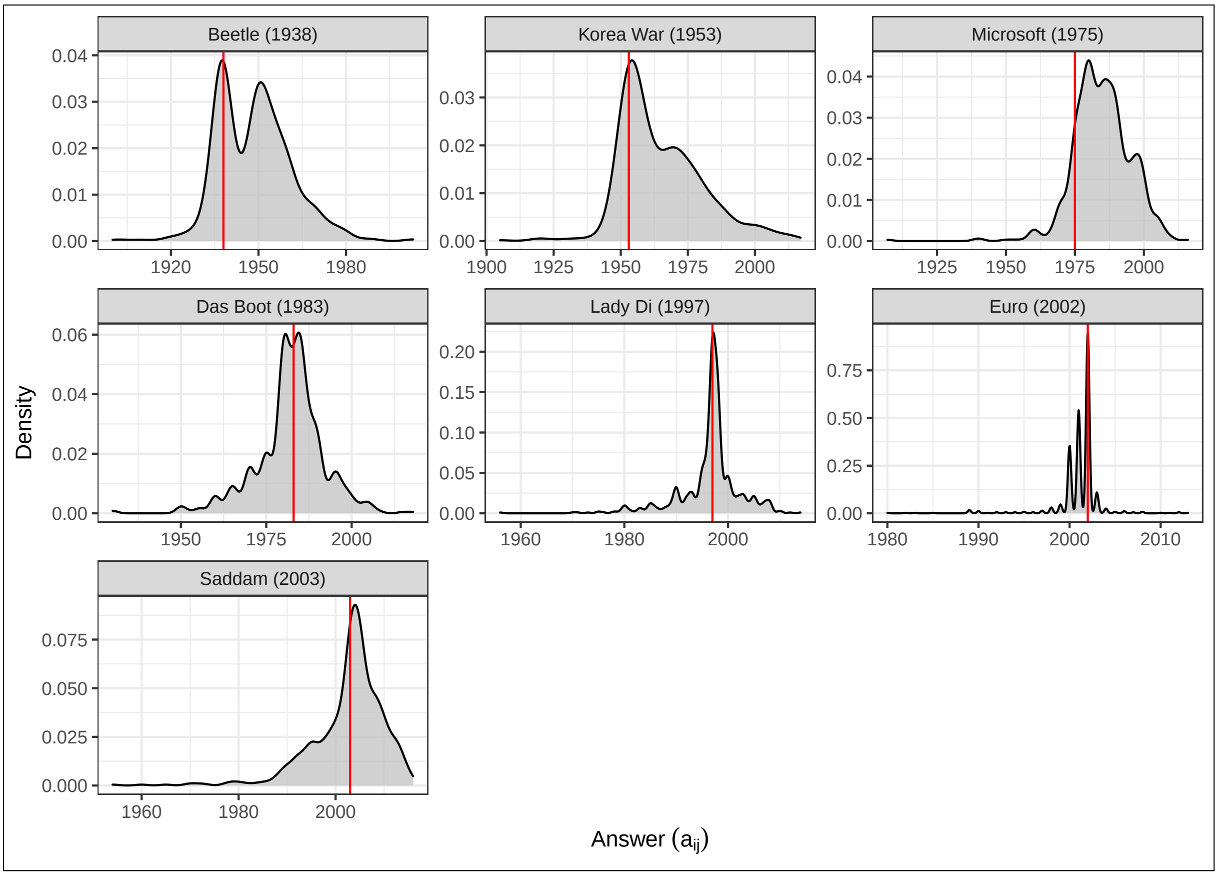


Figure 2: Density of the answers ($a_{i,j}$) for each question. The red vertical line marks the correct answer. Note that the vertical axis is different for each question.

congeneric reliability according to the formula $\frac{(\sum \hat{\lambda}_i)^2}{(\sum \hat{\lambda}_i)^2 + \sum \hat{\sigma}^2_{e_i}}$, where $\hat{\sigma}^2_{e_i}$ is the estimated variance of the error. This results in a congeneric reliability of .76.

To combine the overprecision measures across all seven questions into a unique value for each respondent (op_i), we average the measure of overprecision ($overprecision_{i,j}$) for each respondent (i) across all questions (j).[9] We plot the density of op_i in Figure 4a. In line with Figure 3, Figure 4a shows that the large 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 4a) in the aggregate measure. Of these 56 respondents, 88% are perfectly calibrated

[9] An alternative would be to construct the composite measure op_i using a principal component approach as in Ortoleva and Snowberg (2015b). The result of using such an approach is very similar to using the average ($\rho^{Pearson} = .88; \rho^{Spearman} = .84; N = 805$).

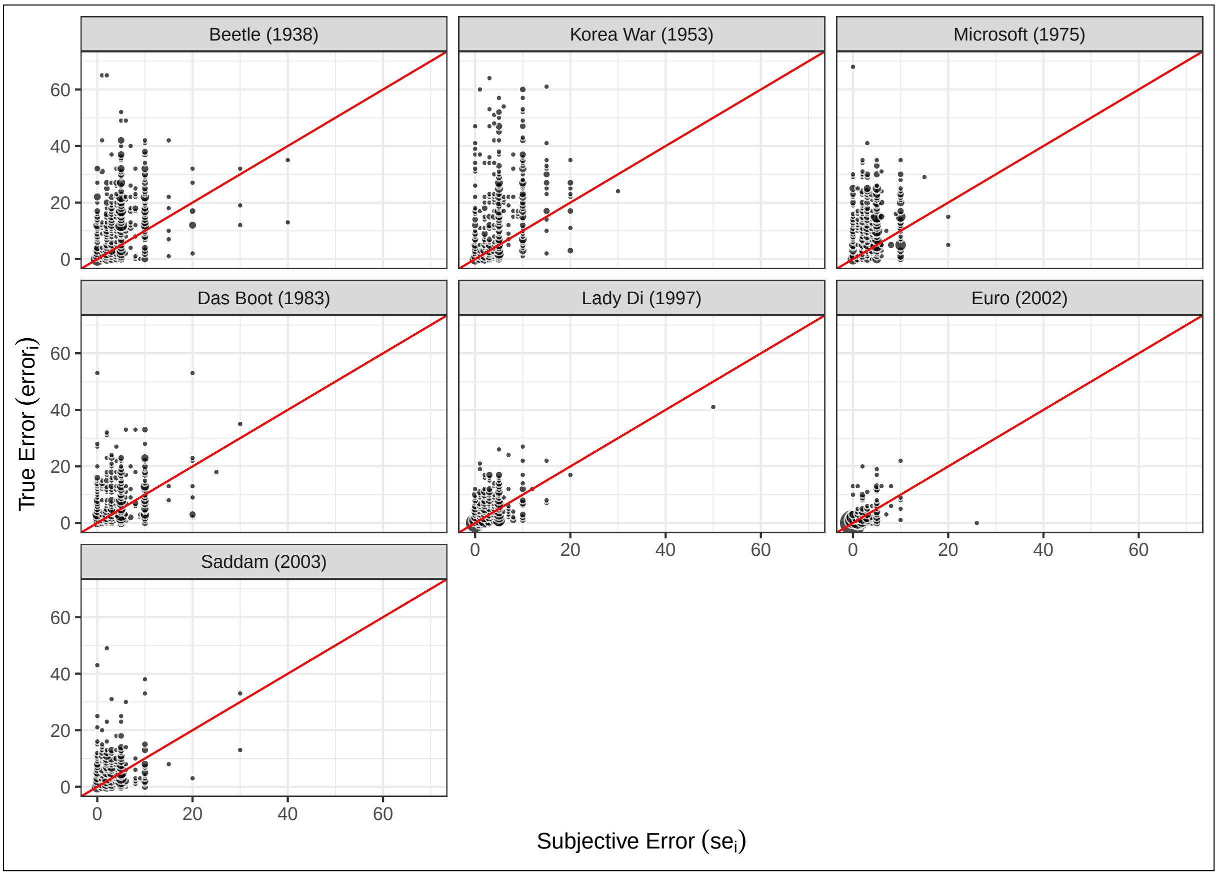
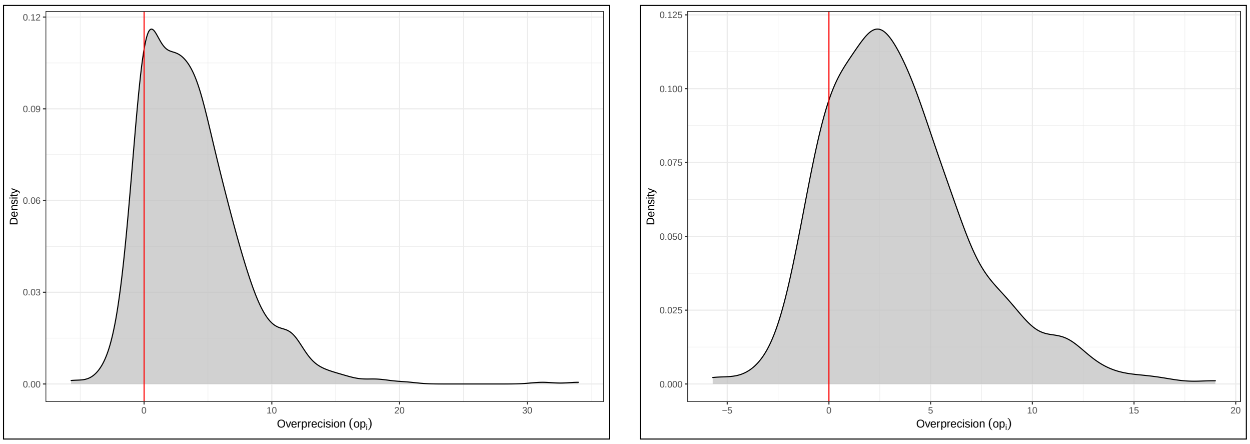


Figure 3: Relation between the realized true error ($error_{i,j}$) in the vertical axis and the subjective error ($se_{i,j}$) in the horizontal axis. Any dot above (below) the 45-degree red line is an overprecise (underprecise) answer by the respondent.

across all the questions they answer. However, one should consider that respondents could decide not to answer a question; 51% of the respondents answered all questions, with 5% answering only one (see Figure A.2 in the appendix for a detailed breakdown). Of those respondents that are perfectly calibrated, 39% answered only one question, and only 7% answered all seven. This means that what we see in Figure 4a is an "upper bound" of perfectly calibrated respondents. As can be seen in Figure 4b, once we plot the density function for the subset of respondents that answered *all questions*, then respondents are substantially less calibrated, with the mode of op_i shifting to the right and leaving only 1% of the respondents perfectly calibrated, while, at the same time, having 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). In Table 1 we regress sop_i on a series of socio-demographic variables using four different OLS models. In all models, we control for age, gender,



(a) Density of op_i for all respondents (N=805) **(b)** Density of op_i for subset (N=410)

Figure 4: Density of Overprecision (op_i). In the left panel we plot the density of op_i, which is the average overprecision for each respondent i across all questions j. In the right panel we plot the density of op_i only for those respondents who answered all questions in the survey.

and years of education. In Column (2) we add the number of overprecision questions answered. In Columns (3) and (4), we add the monthly gross individual income (*Gross Income*) measured in thousands of euros as well as dummies for the labor force status (e.g., employed, unemployed, maternity leave, etc.) and a dummy for those respondents that were living in East Germany in 1989.[10] Finally, in Column (4) we add federal state (Bundesland) and time of interview fixed effects.

The results show that age, education, and income are negatively correlated with overprecision. These correlations seem to be quantitatively large, as, for example, every two thousand euros of gross income reduce overprecision by almost one-tenth of a standard deviation, and every two years of education reduce overprecision by about one-tenth of a standard deviation. 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 A.1 and A.2 in the appendix for a graphical overview of these results). In all of the subsequent analysis, we use the above-mentioned variable as controls.

The results from Table 1 are in contrast to 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

[10]Since *Gross Income* is only available for employed individuals, we code missing variables as 0 and include a dummy that is one for missing observations.

Dependent Variable: *sop*	(1)	(2)	(3)	(4)
age	-0.008***	-0.007***	-0.007**	-0.007**
	(0.002)	(0.002)	(0.003)	(0.003)
female	0.085	0.132*	0.103	0.082
	(0.069)	(0.070)	(0.073)	(0.072)
years education	-0.053***	-0.063***	-0.050***	-0.044***
	(0.013)	(0.013)	(0.014)	(0.014)
answered		0.063***	0.066***	0.070***
		(0.020)	(0.020)	(0.021)
gross income			-0.051**	-0.051**
			(0.023)	(0.023)
constant	1.056***	0.772***	0.652**	0.502
	(0.209)	(0.227)	(0.311)	(0.377)
N	805	805	805	805
adj. R^2	0.035	0.046	0.060	0.083
Fixed Effects	No	No	No	Yes
Employment Status Dummy	No	No	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1: Determinants of overprecision. In Columns (1) - (4) we run an OLS with *Sop* as the dependent variable. In Column (3) we include dummies for the labor force status (employed, unemployed, retired, maternity leave, non-working), and whether the respondent was a citizen of the GDR before 1989. In Column (4) we also include fixed effects for the federal state (Bundesland) where the respondent lives and the time at which he/she responded to the questionnaire.

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.

In Appendix C we test the robustness of our measure of overprecision by comparing it to five alternative approaches. These are i) a *residual* approach following the regression methodology of Ortoleva and Snowberg (2015b), ii) a *relative* approach, which takes into account the relative distance between the subjective error and the realized true error, iii) a *standardized* measure, which standardizes each question before aggregating them, iv) an *age-robust* measure, which is constructed using only those questions of events which occurred after the respective respondent was born, and v) 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.

For all five alternative measures, we run the same OLS models as in Table 1. The results can be found in Table C.1 in the appendix, and show that the impact of the socio-demographic characteristics is overall robust across the different measures of overprecision we build.[11] Furthermore, there is a high correlation between our measure and most of the alternative measures, a result which we take as a validation of our approach.

4 Overprecision and Behavior

This section examines how overprecision correlates with the behavior of respondents in the political and financial domains. In Section 4.1 we describe the empirical methodology and in Section 4.2 we present the results.

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:

$$y_i = \alpha + \beta sop_i + \boldsymbol{\gamma' X_i} + \epsilon_i, \tag{3}$$

where sop_i denotes the standardized overprecision measure, $\boldsymbol{X_i}$ a vector of control variables, and ϵ_i is the random error term. We include all possible control variables we assume to be correlated either with the dependent variable or with overprecision. These are age, gender, years of education (which serves as a proxy for cognitive ability), the 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, as well as interview date (month and year) and state fixed effects. Additionally, we include a measure of political interest in the political analyses.[12] A test for

[11] There are a few exceptions such as being female, which has a negative effect on overprecision only in one of the five measures.

[12] In Table B.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.

multicollinearity shows no strong linear dependencies across explanatory variables. We estimate (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.[13] 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 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 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 by minimizing the sum of squared residuals and a penalty term for the sum of the coefficients.[14] 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.[15] If sop_i is included in the model, then it has

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

[14] 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.

[15] The algorithm proceeds step-wise and estimates the model for each λ starting at the smallest λ that

	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) LASSO R^2	(7) N
A Prediction error:							
err_dax	1.153**	0.022	0.105	2/38	yes/15	0.15	578
opt_dax	0.091***	0.009	0.061	3/38	yes/11	0.39	578
err_rent	0.348*	0.051	0.145	2/38	yes/13	0.07	670
err_buy	0.160	0.264	0.458	9/38	no/0	0.00	644
B Portfolio Diversification:							
std_divers	-0.129***	0.000	0.000	3/38	yes/19	0.13	774
C Ideological Positioning:							
std_extreme	0.091**	0.032	0.122	6/39	yes/13	0.05	716
std_lr	-0.011	0.801	0.801	18/39	no/11	0.07	716
D Voting behavior:							
non_voter	0.032***	0.010	0.059	3/39	yes/18	0.14	706

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: This table shows the estimation results of Section 4. 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 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 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 4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)).

predictive power for the outcome. We report the results in Column (5) of Table 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.[16]

4.2 Prediction Results

The results of our three analytical approaches are summarized in Table 2. We first discuss financial market outcomes and then outcomes regarding political behavior.

Financial Behavior Outcomes

The first set of predictions concerns the forecast errors of asset price predictions in the stock market and the real estate 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. Moreover, due to attribution bias overprecise investors have a tendency to systematically overestimate asset prices (Daniel et al., 1998). 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 Northern American analysts and Hayunga and Lung (2011) for the US real estate market. However, all of these papers rely on indirect proxies to construct their measure of overprecision.

Following the logic outlined above, we expect overprecise respondents to be less accurate in their predictions and to be err more in the positive direction, i.e., to be overly optimistic. To test the first prediction we use the absolute distance of one year ahead predictions of the German Stock Index (DAX), Germany's blue-chip stock market index, from the realized value (*err_dax*).[17] We test the second prediction using the standardized difference between the one year ahead prediction and the realized value so that a positive value denotes an overestimation of the stock market realization (*opt_dax*). Analogously, we expect overprecise respondents to systematically make prediction errors regarding the development of the real estate market. To test this prediction, we use the absolute error

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.

[16] 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).

[17] Note that the observations from the 2018 waves are almost all within the period before March 2019 and are thus unaffected by the stock market decline caused by the Corona-crisis in March 2020.

made in the one-year ahead prediction of the German housing and rental prices (*err_rent* and *err_buy* respectively).[18]

The results in Table 2 show that our measure of overprecision is highly correlated with forecast errors in asset prices. A one standard deviation increase in overprecision is associated with an increase in the absolute forecast error of 1.15 percentage points and a .09 standard deviation increase in the overestimation of the one-year-ahead stock market forecast. Moreover, the results show that a one standard deviation increase in overprecision leads to an increase in the absolute forecast error of rental and housing prices, whereby the latter is less strong. 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 forecast and rental prices, as well as ranking high (between 2 and 9) in the R^2 rank approach.

Next, we test the theoretical prediction of Odean (1998) that overprecision is associated with underdiversified portfolios. Intuitively, overprecise investors overweigh their private information, thereby trading too frequently while being concentrated on too few favorable assets. Goetzmann and Kumar (2008) provide empirical evidence supporting this prediction for traders in the US and Merkle (2017) 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 zero and standard deviation of one that captures the degree to which a respondent diversifies her hypothetical portfolio among stocks, real estate, government bonds, savings, and gold (*std_divers*).[19]

Our results confirm the theoretical prediction that overprecision is associated with underdiversification. The point estimate in Column (1) in Table 2 shows that a one standard error increase in overprecision leads to a .13 standard deviation decrease in our diversification measure. That means that their optimal portfolio is skewed towards a certain asset category. Moreover, overprecision is among the LASSO estimation variables and ranked third in the R^2 rank approach.

[18]We calculate the one-year ahead forecast from the two-year ahead prediction of the respondents assuming linearity. We include a dummy variable that indicates house ownership and 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.6 in the appendix. The qualitative results remain unaffected by this change, with the sample size decreasing.

[19]For a detailed description of the measure refer to Table B.3 in the appendix.

Political Views and Voting Behavior

In the context of 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 visit 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 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 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 *std_lr*. Using the answer to this same question, we also construct *std_extreme*, which measures from 0 to 5 how far away from the political center respondents see themselves. Finally, to study whether overprecise respondents are more likely to vote, we use a dummy that equals one if a respondent indicated to be 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 suggest that overprecision is correlated with ideological extremeness. Overprecision is among the variables chosen by the LASSO estimation and ranking 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 neither correlated to political ideology nor 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, as it seems, overprecision increases the likelihood of voting absenteeism rather than increasing the likelihood of voting: with a one standard deviation increase in overprecision resulting 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, one should be cautious when comparing the voting behavior of overprecise respondents in the US and Europe. 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 (e.g., Miller and Conover, 2015). As opposed, in Germany, more extreme respondents gravitate to fringe parties (e.g., Die Linke, AfD, NPD)[20] with smaller chances of winning elections, so the incentives to vote are very different than for those in the dataset of Ortoleva and Snowberg (2015b).[21] Hence, the theoretical assumptions underlying the predictions of Ortoleva and Snowberg (2015b) regarding voter turnout and overprecision are a good description of voting behavior in the two-party system of the US, but are not appropriate for the more disperse German system.

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 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,

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

[21] 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 resulted after the 2019 Thuringian election shows how strongly such *cordon* is enforced.

but do not detect any effect of gender on overprecision. Both the relationship with the respondents' behavior and with the socio-demographic determinants are robust to a series of modifications, giving further credence to our approach.

Overall, our work contributes to a literature that tries to understand overconfidence, "the most significant of the cognitive biases" (Kahneman, 2013), and how it affects our lives. Because overconfidence can result in reckless behavior and lead to extreme political views of the world, our results and methodology should be of interest not only to economists and political scientists, but also to psychologists, financial researchers, policymakers, and educators.

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A Extra Figures

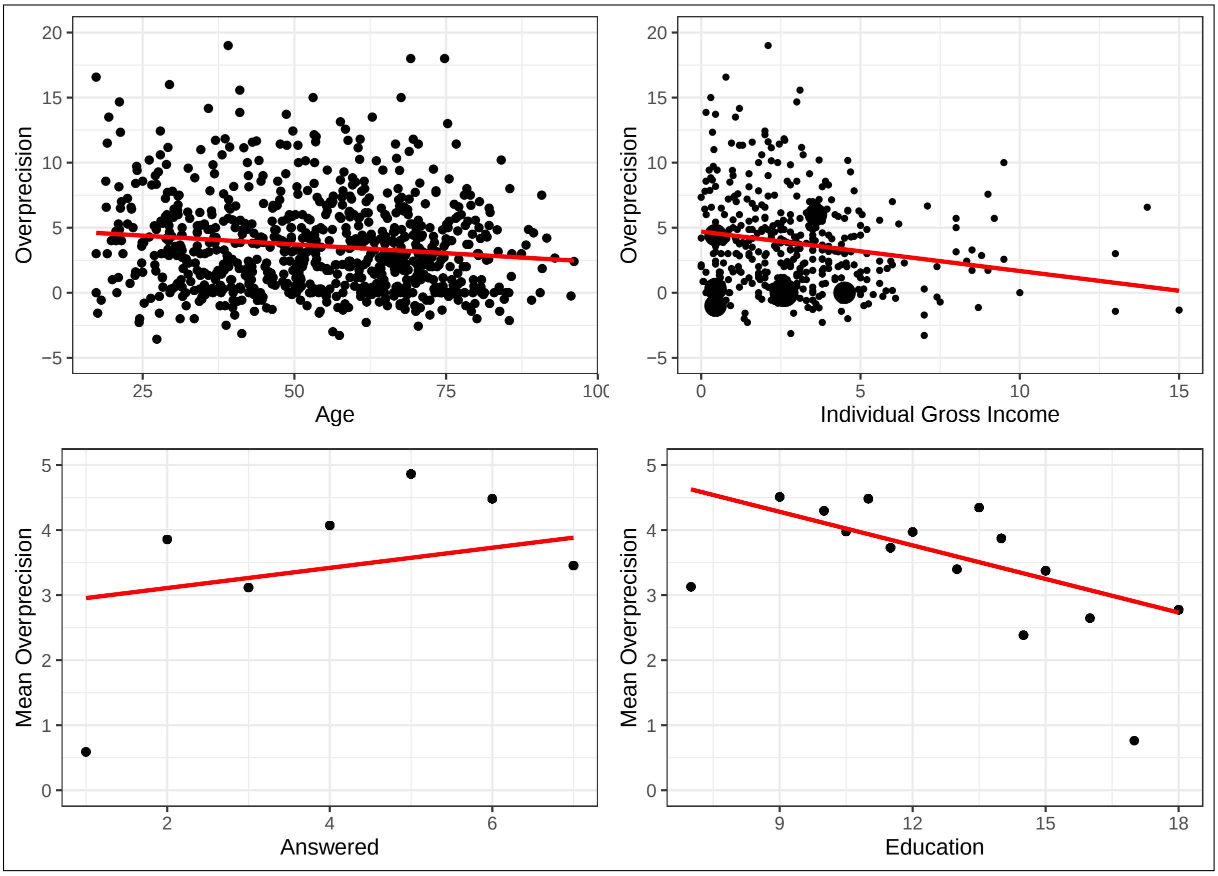


Figure A.1: Correlation of Overprecision. In the vertical axis of each panel we plot the overprecision (upper row) and mean overprecision across all groups which we plot in the horizontal axis (lower row). In all four cases the red line is the fitted linear regression. We dropped one individual outlier in all cases to make the graphs more readable.

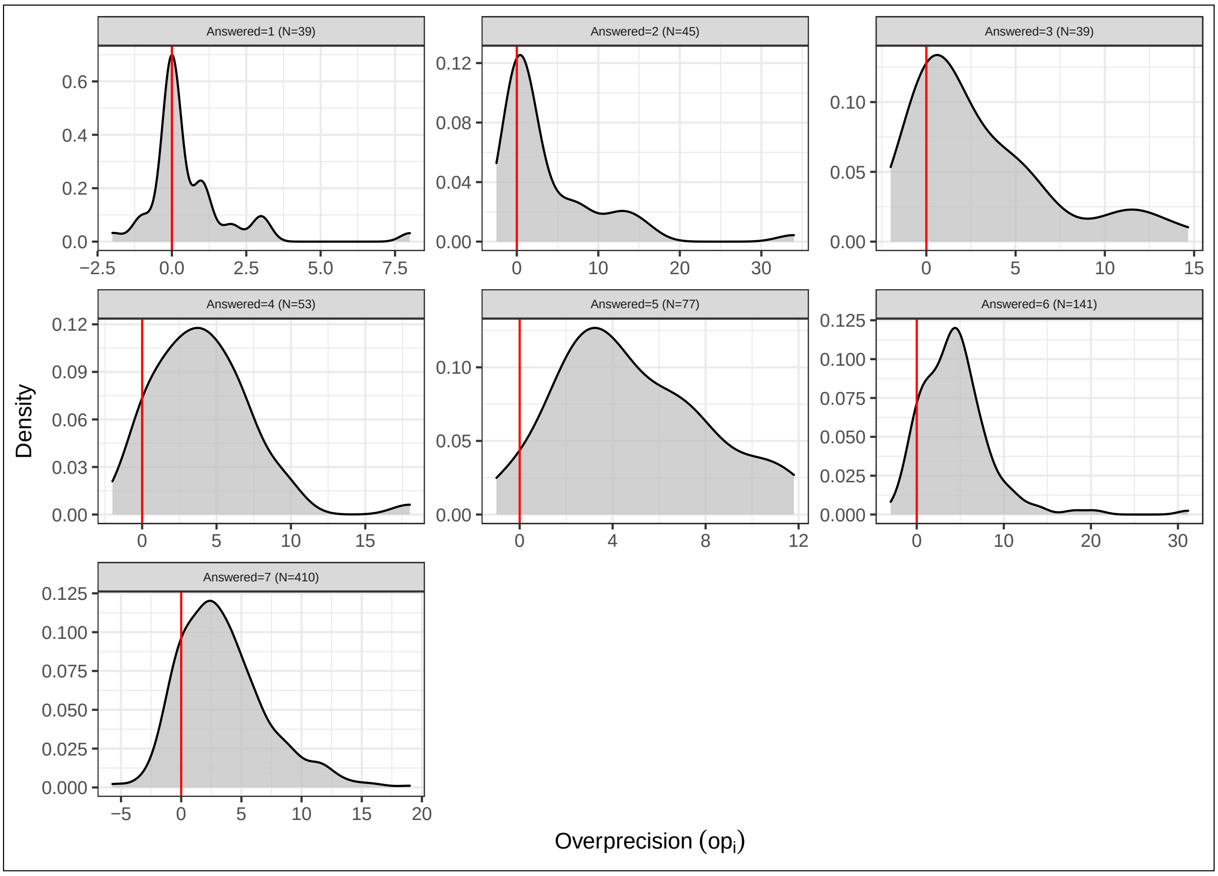


Figure A.2: Density of Overprecision (op_i) for each of the subsets of questions answered. We plot from left to right the densities of op_i for those respondents who answered from the minimum number of answers (1) to the maximum number of answers (7). In the title we report the number of respondents for each density. Notice that the scale of the Y-axis changes across panels.

B Extra Tables

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?	1983
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.1: Original questions in English language 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?	1983
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: Original questions in German language from the 2018 SOEP-IS

Variable	Definition
A Prediction error:	
err_dax	Absolute distance between one year-ahead prediction of the DAX realization and the actual realization over the horizon. Data from the first trading day of each month was used depending on the month of the interview. The data does not contain the Corona crash.
opt_dax	Difference between one year-ahead prediction of the DAX realization and the actual realization over the horizon. Positive values indicate an overestimation of the returns. Data from the first trading day of each month was used depending on the month of the interview. The data does not contain the Corona crash.
err_rent	Absolute distance between one year-ahead prediction of rental prices in Germany and the actual realization over the horizon. One year-ahead predictions were linearly derived from two year-ahead predictions. Quarterly data according to the month of the interview was used.
err_buy	Absolute distance between one year-ahead prediction of house prices in Germany and the actual realization over the horizon. One year-ahead predictions were linearly derived from two year-ahead predictions. Quarterly data according to the month of the interview was used.
B Diversification:	
std_divers	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.

Variable	Definition
C Ideological Positioning:	
std_extreme	Absolute distance to the center of an ideology scale from 0 (left) to 10 (right). Standardized to have mean 0 and standard deviation 1.
std_lr	Location on an ideology scale from 0 (left) to 10 (right). Standardized to have mean 0 and standard deviation 1.
D Voting Behavior:	
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.
east1989	=1 if living in East Germany in 1989.
std_risk	Location on risk scale from 0 (risk avers) to 10 (risk loving). Standardized to have mean 0 and standard deviation 1.
pgbilzt	Years of education.
pglabgro	Monthly gross labor income in thousands. Missings are coded with a zero.
mispglabgro	=1 if missing pglabgro.
finlit	Share of correct answers to 6 questions related to financial knowledge.
owner	=1 if living in own property.
owner_rent	=1 if earning money from renting out property.
assets	=1 if owning financial assets.
std_narcis	Average narcissiscm measure over 6 items on scale from 1 to 6. Standardized to have mean 0 and standard deviation 1.
std_impuls	Location on impulsivity scale from 0 (not impulsive) to 10 (fully impulsive). Standardized to have mean 0 and standard deviation 1.
std_patient	Location on the patience scale from 0 (not patient) to 10 (fully patient). Standardized to have mean 0 and standard deviation 1.
empl	=1 if employed.
unempl	=1 if unemployed.

Variable	Definition
nonwork	=1 if non-working.
matedu	=1 if on maternity, educational or military leave.
retire	=1 if retired.
answered	Number of questions answered for overprecision.
pol_int	Political interest on a scale from 1 (high) to 4 (low). Reversed and standardized to have mean 0 and standard deviation 1.

Table B.3: Overview and definition of the variables used in the analysis.

	(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	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
east (1989)	0.186	(0.014)	0.198	(0.004)	0.012	0.404	24,591
years education	12.704	(0.098)	17.276	(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.4: Representativeness of the SOEP-IS sub-sample. This table shows the descriptives of selected personal characteristics of the respondents for 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) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) R^2	(7) N
A Prediction error:							
err_dax	1.321**	0.014	0.081	2/43	yes/20	0.15	537
opt_dax	0.094***	0.010	0.068	3/43	yes/20	0.41	537
err_rent	0.335*	0.056	0.159	5/43	yes/2	0.01	624
err_buy	0.140	0.342	0.567	14/43	no/1	0.01	602
B Portfolio Diversification:							
std_divers	-0.117***	0.002	0.016	4/43	yes/15	0.13	719
C Ideological Positioning:							
std_extreme	0.081**	0.048	0.179	7/44	yes/14	0.06	716
std_lr	-0.021	0.594	0.594	23/44	no/17	0.10	716
D Voting Behavior:							
non_voter	0.029**	0.015	0.073	3/44	yes/20	0.14	706

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5: This table shows the estimation results of Section 4 including the Big Five personality traits. 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 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 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 4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)).

	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) LASSO R^2	(7) N
A Prediction error:							
err_dax	1.011**	0.043	0.197	5/41	yes/22	0.18	573
opt_dax	0.096***	0.007	0.048	3/41	yes/11	0.40	573
err_rent	0.323*	0.075	0.209	7/41	yes/18	0.08	660
err_buy	0.158	0.279	0.480	9/41	no/0	0.00	634
B Portfolio Diversification:							
std_divers	-0.126***	0.001	0.008	4/41	yes/19	0.14	762
C Ideological Positioning:							
std_extreme	0.084*	0.053	0.196	6/42	yes/14	0.04	705
std_lr	-0.001	0.980	0.980	20/42	no/15	0.08	705
D Voting behavior:							
non_voter	0.030**	0.016	0.092	3/42	yes/17	0.12	693

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.6: This table shows the estimation results of Section 4 including assets and home-ownership as controls. 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 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 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 4.1 along with the R^2 of the estimated model (Column (6)).

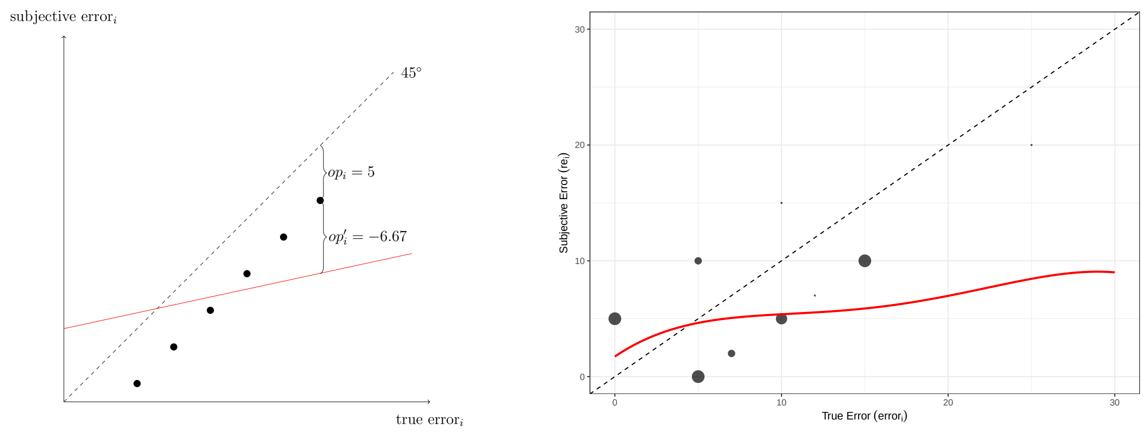
C Alternative Measures of Overprecision

To test the robustness of our overprecision measure, in Section C.1 we discuss five alternative measures of overprecision. In Section C.2 we use these alternative measures to test the robustness of our results from Section 3 regarding the socio-demographic characteristics and Section C.3 the robustness of the predictions in Section 4.2.

C.1 Alternative Measures

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 absolute subjective error. (for an illustrative example see Figure C.1). Thus, for every measure of op'_i, the residual 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.



(a) Illustration

(b) Data

Figure C.1: Misspecification of participants. This figure shows 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 3. In panel (a), the dots represent observations for respondents for whom, in the example, the Subjective Error Method yields $op_i = error_i - se_i = 3$ 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 3 and -3 respectively. The red line indicates the fitted line of the *residual* approach using a fourth order polynomial.

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 realized error (see Figure C.2).

Assume that, similar to the example in Figure 1, the true error is normally distributed with mean 0 and variance σ^2 (blue 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 (red 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 differ, e.g., by having different confidence intervals in mind, the ranking as computed with the absolute measure might

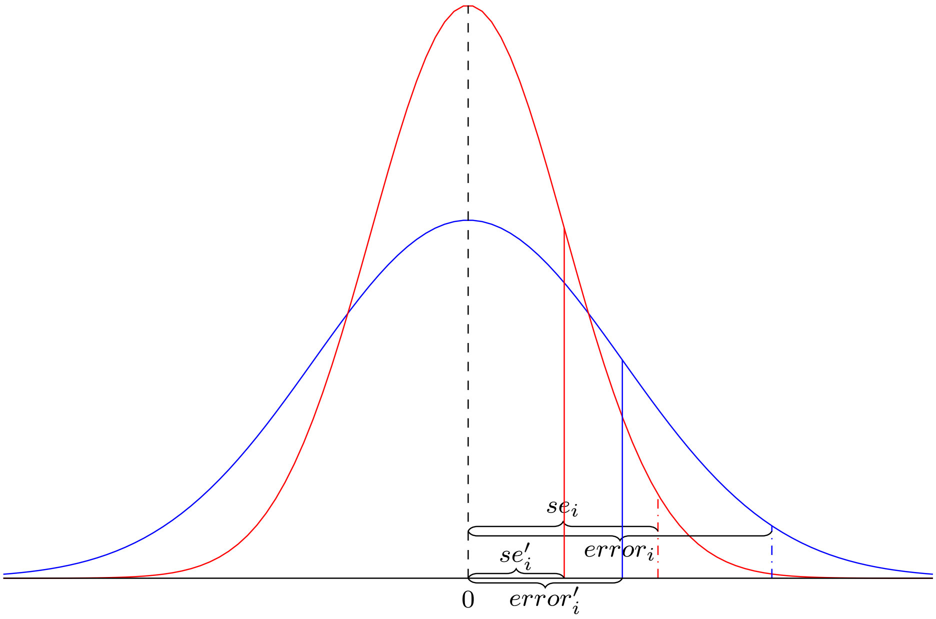


Figure C.2: Two distributions of the error. The blue curve shows the true distribution of the error with a standard deviation of 2 (precision of .25). The red curve shows the perceived distribution by an overprecise respondent with a standard deviation of 1.25 (precision of .64). The solid and dashed 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.

not be consistent anymore whilst the sign of the deviation still being correct. Taking the example in Figure C.2, 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.[22] Given the high correlation between both approaches, using the absolute measure

[22]Note that the relationship between the absolute and the relative measure is non-linear. Therefore,

is preferable as it avoids having to drop the observations of respondents whose subjective error is zero.

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.

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 C.3 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 2.1, 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.

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.

we report the Spearman correlation coefficient only.

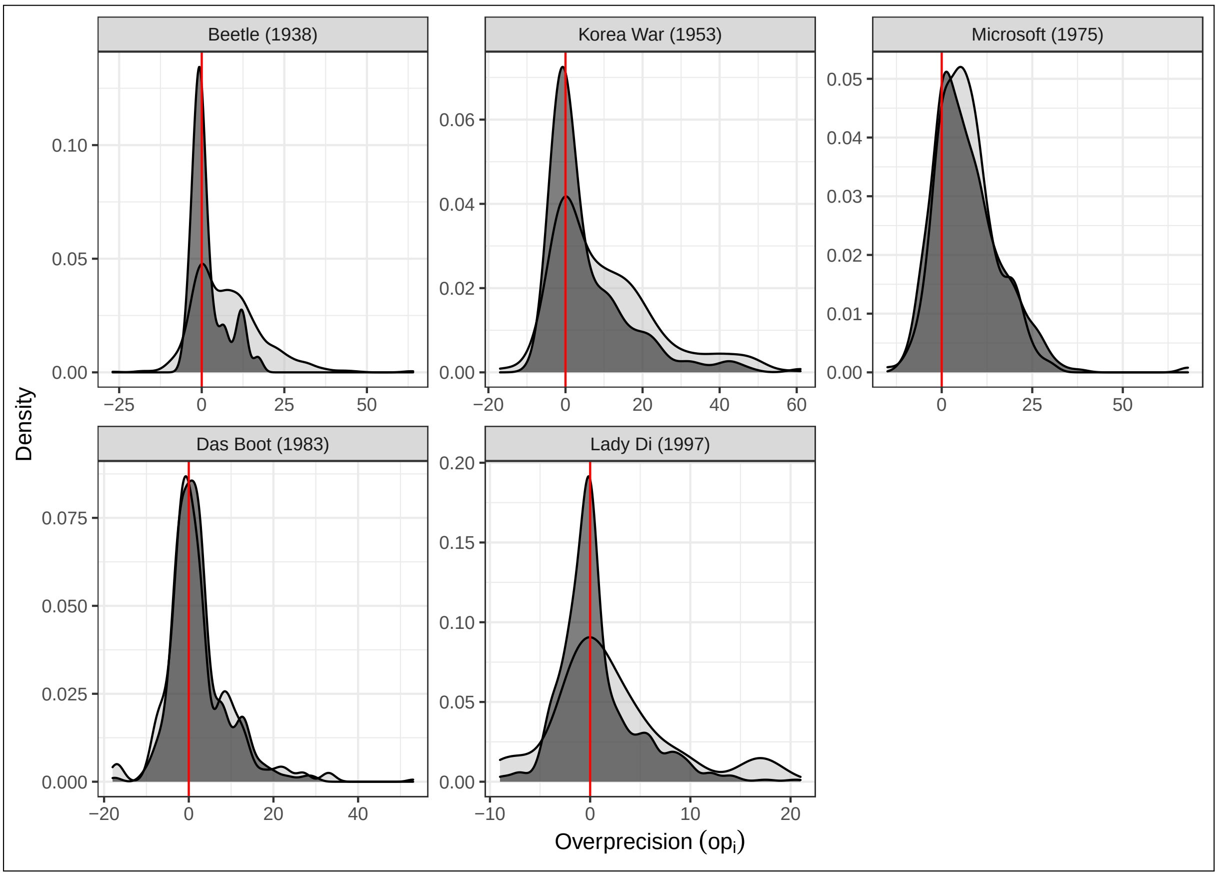


Figure C.3: Density of Overprecision (op_{ij}) and Age. From left (less recent) to right (more recent) We plot the density of the measured overprecision ($op_{i,j}$) for each question j. In darker color, we plot the density of all respondents born at the year of the event or before. In lighter color, 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. 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.

C.2 Robustness of Descriptive Results

In Table C.1 we replicate Table 1 using each of the measures described in Section C.1 (Columns (2) to (6)) and our baseline measure sop_i in Column (1).

Column (2) of Table C.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.

Column (3) replicates the baseline estimations using the *relative* approach (op_i''), while Column (4) shows the results for the *standardized* measure (op_i'''). The results in both columns 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 (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) 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 insignificant.

Given the results in in Table C.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 C.3 where we test the predictive power of all robustness measures.

	Baseline (1)	Residual (2)	Relative (3)	Standardized (4)	Age robust (5)	Centered (6)
age	-0.007**	0.006**	0.002	-0.002	0.018***	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
gender	0.082	-0.204***	0.056	0.067	0.023	0.150**
	(0.072)	(0.071)	(0.080)	(0.073)	(0.071)	(0.072)
pgbilzt	-0.044***	-0.002	-0.015	-0.020	-0.015	-0.044***
	(0.014)	(0.014)	(0.016)	(0.014)	(0.014)	(0.014)
answered	0.070***	-0.107***	0.016	-0.042**	0.065***	-0.023
	(0.021)	(0.020)	(0.026)	(0.021)	(0.021)	(0.021)
pglabgro	-0.051**	0.002	-0.035	-0.051**	-0.041*	-0.045*
	(0.023)	(0.023)	(0.025)	(0.023)	(0.023)	(0.023)
mislabgro	-0.083	0.134	-0.139	-0.187	-0.193	-0.075
	(0.208)	(0.204)	(0.237)	(0.210)	(0.204)	(0.207)
_cons	0.502	0.361	0.085	0.822**	-0.620*	0.964**
	(0.377)	(0.370)	(0.426)	(0.381)	(0.371)	(0.376)
N	805	805	702	805	801	805
adj. R^2	0.083	0.117	0.028	0.060	0.123	0.088
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Employment Status Dummy	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.1: Determinants of overprecision using alternative measures of overprecision. For comparison, in Column (1) we run an OLS with the baseline measure. In Column (2) - (6), we run an OLS using the *residual* measure, the *relative* measure, the *standardized* measure, the *age-robust* measure, and the *centered* measure respectively. All include dummies for the labor force status (employed, unemployed, retired, maternity leave, non-working), and whether the respondent was a GDR citizen before 1989. We also control for the federal state (*Bundesland*) where the respondent lives and the time at which he/she responded to the questionnaire.

C.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 C.2 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 C.1.

Table C.3 shows the results from the predictions using the *relative* measure of overprecision instead. The advantage is that it makes the measure more comparable across

	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) R^2	(7) N
A Prediction error:							
err_dax	0.014	0.977	0.977	17/38	no/15	0.14	578
opt_dax	-0.014	0.681	0.997	10/38	no/11	0.39	578
err_rent	-0.048	0.781	0.998	19/38	no/12	0.06	670
err_buy	-0.161	0.244	0.893	3/38	no/0	0.00	644
B Portfolio Diversification:							
std_divers	-0.028	0.450	0.972	13/38	no/14	0.12	774
C Ideological Positioning:							
std_extreme	-0.044	0.274	0.894	8/39	no/9	0.04	716
std_lr	-0.009	0.811	0.964	17/39	no/11	0.07	716
D Voting Behavior:							
non_voter	-0.003	0.807	0.993	18/39	no/17	0.13	706

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.2: This table shows the estimation results of Section 4 using the *residual* aggregation method of Ortoleva and Snowberg (2015a). 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 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 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 4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)).

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, remain qualitatively similar.

Table C.4 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 C.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

	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) R^2	(7) N
A Prediction error:							
err_dax	1.072**	0.040	0.217	4/38	yes/20	0.17	530
opt_dax	0.112***	0.002	0.016	2/38	yes/12	0.38	530
err_rent	0.316*	0.091	0.317	2/38	yes/16	0.10	608
err_buy	-0.159	0.290	0.642	7/38	no/0	0.00	644
B Portfolio Diversification:							
std_divers	-0.068*	0.078	0.334	24/38	yes/13	0.11	681
C Ideological Positioning:							
std_extreme	0.116***	0.005	0.034	2/39	yes/12	0.05	624
std_lr	-0.035	0.394	0.633	19/39	no/7	0.05	716
D Voting Behavior:							
non_voter	0.003	0.796	0.796	3/39	no/17	0.13	706

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.3: This table shows the estimation results of Section 4 using the *relative* overprecision measure. 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 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 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 4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)).

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 C.6 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.

	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) R^2	(7) N
A Prediction error:							
err_dax	0.782	0.112	0.378	8/38	yes/15	0.15	578
opt_dax	0.129***	0.000	0.000	2/38	yes/9	0.40	578
err_rent	0.253	0.137	0.357	2/38	yes/13	0.07	670
err_buy	0.124	0.369	0.602	15/38	no/0	0.00	644
B Portfolio Diversification:							
std_divers	-0.102***	0.005	0.034	3/38	yes/19	0.13	774
C Ideological Positioning:							
std_extreme	0.093**	0.020	0.114	3/39	yes/12	0.05	716
std_lr	-0.020	0.610	0.610	17/39	no/11	0.07	716
D Voting Behavior:							
non_voter	0.026**	0.025	0.119	4/39	yes/19	0.14	706

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.4: This table shows the estimation results of Section 4 using the *standardized* overprecision measure. 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 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 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 4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Point	Unadj.	SH	R^2	LASSO		
	estimate	p-value	p-value	rank	included	R^2	N
A Prediction error:							
err_dax	-0.071	0.885	0.885	40/38	no/15	0.14	578
opt_dax	0.114***	0.001	0.008	2/38	yes/10	0.39	576
err_rent	0.132	0.434	0.819	7/38	yes/14	0.07	668
err_buy	-0.065	0.631	0.864	8/38	no/0	0.00	644
B Portfolio Diversification:							
std_divers	-0.051	0.170	0.525	6/38	yes/15	0.12	770
C Ideological Positioning:							
std_extreme	0.067*	0.090	0.432	5/39	no/9	0.04	713
std_lr	-0.063	0.107	0.432	6/39	yes/12	0.07	713
D Voting Behavior:							
non_voter	0.023**	0.039	0.243	4/39	yes/19	0.14	702

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.5: This table shows the estimation results of Section 4 using the *age-robust* overprecision measure. 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 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 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 4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)).

	(1) Point estimate	(2) Unadj. p-value	(3) SH p-value	(4) R^2 rank	(5) LASSO included	(6) R^2	(7) N
A Prediction error:							
err_dax	1.004**	0.047	0.175	2/38	yes/21	0.17	578
opt_dax	0.098***	0.005	0.034	2/38	yes/11	0.39	578
err_rent	0.327**	0.066	0.185	2/38	yes/16	0.08	670
err_buy	0.136	0.341	0.566	12/38	no/0	0.00	644
B Portfolio Diversification:							
std_divers	-0.123***	0.001	0.008	3/38	yes/24	0.14	774
C Ideological Positioning:							
std_extreme	0.085**	0.047	0.175	5/39	yes/14	0.06	716
std_lr	0.000	0.997	0.997	17/39	no/13	0.08	716
D Voting Behavior:							
non_voter	0.026**	0.033	0.182	4/39	yes/17	0.13	706

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table C.6: This table shows the estimation results of Section 4 using the *centered* overprecision measure. 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 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 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 4.1 along with the number of control variables chosen by LASSO and the R^2 of the estimated model (Column (6)).