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How good are banks' forecasts?

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Non-technical summary

Research Question

Accurate planning is a crucial part of operations for all enterprises, not least in banking. We investigate the planning of small and medium-sized German banks that they provided in various waves of a quantitative survey. We deal especially with three questions: i) How good is the planning? ii) Is there a relationship between the forecast quality and the performance of a bank? iii) What can we learn from the banks' forecast with respect to the interest level?

Contribution

As data set, we use the low-interest-rate environment survey (LIRES), which the Deutsche Bundesbank and the Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin) carry out every other year among the small and medium-sized German banks. This survey is compulsory and the banks have to provide their planning and simulated data (for the following five years) for various interest rate scenarios. We employ four waves of this survey (the ones of the years 2015, 2017, 2019 and 2022) and combine this data with actual realisations. An analysis like this of German banks has not been made available to the public.

Results

We find that the banks‘ forecasts are relevant; this hold true especially of the net interest income in the first year of the forecast. Moreover, banks with an above average forecast quality in the current wave tend to have an above average forecast quality in the previous wave. In addition, we find that the forecasts are biased and not rational. When the macro-environment drastically changes after the banks have made their forecasts (as happened in the last wave of the year 2022), the explanatory power of the forecasts goes down. The relationship between forecast quality and bank performance is weak. As to the forecast of the interest level, it seems as if the banks were surprised by the interest environment change.

Nichttechnische Zusammenfassung

Fragestellung

Genaues Planen ist ein wichtiger Teil des Geschäfts aller Unternehmen, auch der Banken. Wir untersuchen die Planungen der kleinen und mittelgroßen Banken in Deutschland, die sie im Rahmen einer quantitativen Umfrage in mehreren Zyklen machten. Besonders drei Fragen stehen im Vordergrund: 1) Wie gut sind die Planungen? 2) Gibt es einen Zusammenhang zwischen der Planungsgüte und dem Erfolg einer Bank? 3) Was können wir aus den Vorhersagen der Banken in Bezug auf das Zinsniveau ableiten?

Beitrag

Als Datengrundlage nehmen wir eine Umfrage, die die Deutsche Bundesbank zusammen mit der Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin) alle zwei Jahre verpflichtend unter den kleinen und mittelgroßen Banken in Deutschland durchführt (im Rahmen der Niedrigzinsumfeld-Umfrage bzw. des LSI-Stresstests). Darin müssen die Banken ihre Plandaten und simulierte Daten in verschiedenen Zinsszenarien für ihre Gewinn- und Verlustrechnung (und andere Größen) für die nächsten fünf Jahre melden. Wir verwenden die vier Zyklen der Jahre 2015, 2017, 2019 und 2022 und verknüpfen diesen Datensatz der Vorhersagen mit den tatsächlichen Realisationen – eine Analyse dieser Art wurde im deutschen Bankensektor noch nicht der Öffentlichkeit zugänglich gemacht.

Ergebnisse

Es zeigt sich, dass die Prognosen der Banken aussagekräftig sind; das gilt besonders für den Zinsüberschuss im ersten Jahr der Prognose. Darüber hinaus zählen Banken häufig in einem Zyklus zu den Banken mit überdurchschnittlicher Prognosegüte, wenn sie bei dem vorhergehenden Zyklus überdurchschnittlich gute Prognosen ablieferten. Jedoch sind die Prognosen verzerrt und nicht rational. Wenn sich das Marktumfeld nach der Prognoseerstellung drastisch ändert (so geschehen im letzten Zyklus 2022), dann schwindet die Aussagekraft der Prognosen der Banken erheblich. Der Zusammenhang zwischen Prognosegüte und Erfolg ist nur sehr schwach ausgeprägt. In den Zinsprognosen sehen wir, dass die Banken von der Zinswende 2022 überrascht worden zu sein scheinen.

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Abstract

We analyse the financial forecasts small and medium-sized German banks provided in several waves of a quantitative survey, called LIRES, and compare them with the results the banks actually realized. Based on this unique data set, we find that the predictions are relevant, especially concerning the net interest income for the next year, and persistent, but neither unbiased nor rational. We also find slight evidence for a positive relationship between planning and performance, i.e. banks whose predictions are more accurate tend to have a higher return on assets. Looking at the forecasts made just before the end of the low-interest rate environment, we observe that the explanatory power of predictions went down.

Keywords: Forecasts, Banks, Quantitative Survey (LIRES)

JEL classification: G21

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1 Introduction

Accurate planning is a crucial part of operations for all enterprises, not least in banking. Banks' internal planning for the next years incorporates expectations on the macroeconomic environment, e.g. on interest rates or economic developments, and planned strategic actions, e.g. the run-off of certain business areas (Armstrong (1983)). It leverages upon internal regular accounting procedures and reports (Cassar and Gibson (2008)) and might also take into account risk-based information to improve the forecast accuracy (Ittner and Michels (2017)). However, it is unclear whether a good forecasting capability is related to a good performance by the bank in general, a question that relates to the planning-performance controversy (Pearce, Freeman, and Robinson (1987)). A good forecast may indicate that the bank's managers know and can reliably plan their business, allocate resources efficiently and are successful in implementing strategic measures. Furthermore, if forecasts are publicly available, they might be considered more informative and reliable to investors and analysts and thus have a positive impact on the market's view of the bank.[1] One could thus conclude that a bank which is able to produce reliable forecasts should be more profitable and successful. By contrast, one could hypothesize that very profitable banks do not need to engage in much planning as it is not needed and only costly, which could lead to a negative correlation between planning accuracy and profitability. Furthermore, it might be that planning does not influence profitability at all, e.g. if management plans are not implemented by staff. Finally, one can ask how reliable banks' forecasts are in general and whether they give a good indication of banks' future performance.[2]

Strategic planning in firms (not only banks) and its effect on financial performance have been studied for several decades; however, the results are mixed. For the US, several studies find a slightly negative relationship between profitability and planning capacity (Whitehead and Gup (1985), Gup and Whitehead (1989)). In a meta-analysis, Boyd (1991) finds only a moderate correlation between planning and performance measures, while a related study concludes that there is a slightly positive relationship (Capon, Farley, and Hulbert (1994)). However, other studies claim to have found a positive relationship, e.g. Miller and Cardinal (1994) perform a meta-analysis and find a generally positive relationship between planning and performance. Another study also finds a positive relationship and even a reciprocal reinforcement between strategic planning and financial performance at banks (Hopkins and Hopkins (1997)). In a study on the Nigerian banking sector to examine whether strategic management actions have a positive influence on profitability (see Jimoh (2003)), the author finds that banks using strategic planning seem to have a higher profitability and a better asset quality. Another study focuses on the effects of internal control on Nigerian banks' performance (see Hussaini and Muhammed (2018)) and also finds positive effects.

[1]The information provided by the publication of strategic planning and its influence on markets has been studied by Stephen P. Baginski, Saverio Bozzolan, Antonio Marra, and Pietro Mazzola (2017), where the authors find that (voluntary) publication of strategic planning may be a relevant tool with respect to market perception.

[2]E.g. it could be discussed whether banks have an incentive to provide good forecasts or whether there might be a tendency to overstate or understate their results. This is not the focus of our paper, but we will touch upon this below. Furthermore, the effect of behavioral biases on forecasts is also a matter of research, see e.g. Mark Davis and Sébastien Lleo (2020).

The literature mentioned above deals with the question of whether it makes a comparative difference whether and how sophisticated firms/banks plan. In this context, planning quality is usually assessed based on statements made by banks in surveys (e.g. on the number of staff involved in planning). Few studies compare banks' actual forecasts to their realization and thus quantify and challenge forecasting accuracy itself. One such study (see Kao and Liu (2004)) leverages upon the fact that Taiwanese banks are required to publish one-year financial forecasts. This data is used to calculate an efficiency score for the predictive power of banks and to compare predicted variables with actual financial statements. They find that the banks' financial forecasts can be used to predict the performance of the respective bank. One recent study (see Suss and Hughes (2023)) analyses the UK banking sector from 2008 onwards and finds that banks tend to be (too) optimistic about their future performance and that expectations tended to be more optimistic before the Covid crisis. Furthermore the authors find a positive relationship between good forecasts and good performance.

A further related and recent strand of literature deals with banks' expectations on macroeconomic conditions and how they translate into business decisions. Falato and Xiao (2022) show that banks' forecasts are biased and forecast errors autocorrelated and that especially large banks do not seem to incorporate information efficiently into their business decisions. Ma, Paligrorova, and Peydro (2021) discuss the large dispersion of banks' forecasts of economic conditions and show that lenders expectations have an impact on credit supply: Pessimistic banks display a lower loan growth and are associated with higher interest rates for certain banks.

Published analysis of German or other European banks' capacities to provide accurate forecasts regarding their profit and loss statement, their balance sheet composition or macroeconomic variables (e.g. interest rates) is rare, presumably one major reason being data limitation. While it is necessary and common in risk management to assess the validity of forecasts of applied risk models, there is no broad analysis of the accuracy of banks' planning data in general.

We try to reduce this gap and use a unique data set built from four waves of the low-interest rate environment survey (abbreviated LIRES), which contains German banks' planning and forecasting data for five projection years, respectively, and regular reporting data on actual bank figures. We can therefore compare the forecasts submitted by banks with actual realizations and can do this not only in the cross-section, but also (due to the multiple waves) in a time series. Our analysis thus gives a unique view onto small and medium-sized German banks' internal capacities to perform accurate planning of their figures and the relation to performance. Furthermore, banks provide expectations of interest rates and we analyse these forecasts as well, where we can shed light onto banks' interest rate expectations during the low-interest rate environment.

The data contained in the low-interest rate surveys (LIRES) was already used in Busch, Drescher, and Memmel (2017), Heckmann-Draisbach and Moertel (2020), Dräger, Heckmann-Draisbach, and Memmel (2021), Busch, Littke, Memmel, and Niederauer (2022) and Memmel and Heckmann-Draisbach (2023). A more detailed description of the data is given in Section 2. Since 2020, banks are, in Germany, required to regularly report information on their planning data to supervisors, which may enable and induce further analysis in this direction in the future.

A conceptual framework for the evaluation of forecasting capacities is introduced and discussed in Büttner and Horn (1993). We use similar approaches when analysing the accuracy of forecasts provided by banks.

We extend the existing literature as follows: To our knowledge, in part due to lack of data, there is no study that quantitatively challenges predictions by individual banks in Europe and compares them to actual data at the granularity we do in our analysis. That is, we have predictions on a single-bank basis for up to five years for various measures, such as their total assets, contributions to their profit and loss statement, but also predictions on interest rate levels. We find that the forecasts for the following year, especially for the net interest income, are relevant and persistent, but biased and not rational. As to forecasts just before the end of the low-interest rate environment, we observe that relevance went down and that the dispersion in the cross-section of banks increased for some variables.

Our paper is organized as follows: In Section 2, we describe the data we use. In the Sections 3 and 4, we introduce our research questions and present the corresponding results for forecast quality and persistence, and expectation on interest rates, respectively. We discuss the findings in Section 5. Section 6 concludes.

2 Data

2.1 General

We use four waves of the low-interest rate environment survey (LIRES) conducted jointly by the Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin) and the Deutsche Bundesbank among all German small and medium-sized banks every other year. This survey, for which participation is compulsory for banks, was conducted in 2015, 2017, 2019 and 2022 and contains broadly similar information in each wave: Banks report starting points and their planning data for their profit and loss accounts and balance sheets over the next five years, their projections for different interest rate scenarios, and some additional information, for instance the expected interest level. The number of participants ranged from 1,459 (in 2015) to 1,299 (in 2022), which corresponds to a coverage of around 90 % of the German banking sector in terms of number of banks.[3] We also use reporting data to compare the actual (realized) data to the projections provided by banks (see Figure 1 for a schematic visualization of the data structure). In our analysis, we focus mainly on the first projection year, first, because forecasts for the near future should be more reliable than for longer horizons (see the Tables 10 to 13 in Appendix A.6), but also as this allows us to compare the 2022 wave with reporting data.

To ensure that the data is not perturbed by mergers, we exclude banks from the analysis which participated in a merger during a given year.

We analyze relative changes in the bank-specific variables, i.e. they are standardized with the respective historical value in the year before the planning horizon (in Figure 1 dark gray). For instance the forecasts for changes in total asset in the wave 2017 are

[3] More precisely, for the years 2017 to 2022, it covers between 89% and 91% of the German credit institutions representing between 38% and 45% of total assets. This difference (to 100%) is due to the fact that large banks (significant institutions) under the Single Supervisory Mechanism (SSM) are excluded.

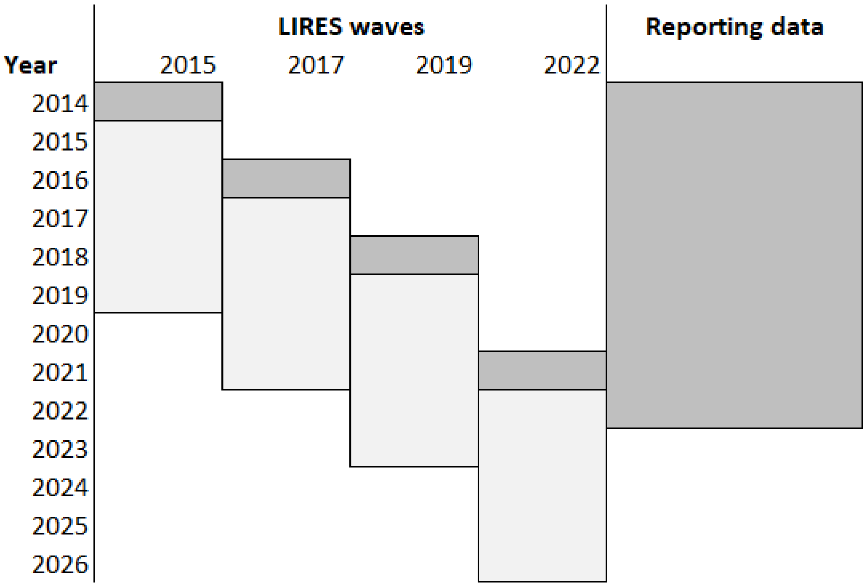

Figure 1: Visualization of data structure: In the various waves of the low-interest rate environment survey (LIRES), banks provide historical (actual) starting points (dark gray) and projections (light gray). The data set is merged with actual reporting data.

standardized with the bank's historical total assets of 2016 (see the Appendix A.5). For the interest rate forecast, we do not consider relative, but absolute changes.

We apply a mild outlier correction by removing the lowest and highest percentile for each variable of the data.

2.2 Summary statistics

In Table 1, we show summary statistics concerning the mean and the standard deviation of the one-year forecasts. In our analysis, we choose five variables: the balance sheet size (total assets, TA), three variables of the profit and loss account (P&L), namely the net interest income (NII), the net fee and commission income (NFCI) and the administrative expenses (Costs) as well as the expected change over 1 year in the 10-year interest rate for the macro-environment. The three variables of the profit and loss account (NII, NFCI and Costs) cover nearly entirely what the banks earn and what they pay, i.e. the net interest income (NII) and the fee and commission income make up 65% and 30% of the operating income and the administrative expenses (Costs) equal 73% of the operating income (see Deutsche Bundesbank (2022)). We see in Table 1 that during the low-interest rate environment banks planned on average with a shrinking net interest income (mean for NII is negative), but an increase in the net fee and commission income (mean for NFCI is positive), which is in all waves higher than the planned average increase in total assets (TA). For the administrative expenses (Costs), banks planned in all waves that they would increase less than their total assets. For interest rates, we observe that banks expected an increase in interest rates in all waves and that the average absolute expected change was highest in 2019 which could be attributed to the uncertainty about monetary policy at that time. The high standard variation across all waves shows that banks'

Table 1: Summary statistics

		Wave	2015	2017	2019	2022
TA	Mean	% rel. change	1.14	1.57	2.06	2.27
	SD	% rel. change	2.69	3.10	2.88	3.42
	Nobs		1363	1315	1269	1200
NII	Mean	% rel. change	-0.93	-3.47	-2.61	-1.08
	SD	% rel. change	6.94	7.28	6.17	6.85
	Nobs		1373	1315	1259	1199
NFCI	Mean	% rel. change	1.51	5.11	2.47	2.78
	SD	% rel. change	7.98	9.33	8.55	9.51
	Nobs		1380	1304	1258	1196
Costs	Mean	% rel. change	1.94	0.92	1.87	2.11
	SD	% rel. change	4.24	4.60	4.68	4.56
	Nobs		1356	1309	1264	1197
$\triangle R^e$	Mean	bp abs. change	8.93[a]	8.90	13.12	5.44
	SD	bp abs. change	29.74[a]	19.42	21.25	20.21
	Nobs		1253	1371	1324	1257

This table shows the mean, the standard deviation ("SD") and the number of observations ("Nobs") of the standardized forecasts (standardization as in Appendix A.5, one-year forecasts). "TA", "NII", "NFCI", "Costs" and $\triangle R^e$ stand for total assets, net interest income, net fee and commission income, administrative costs and change in the interest rate (10y), respectively. "bp", "rel." and "abs." and stand for basis points, relative (see Equation (18)) and absolute (see Equation (20)). [a]For the wave 2015, no values for the historical interest rates were reported, so the historical values have been estimated by transferring the best-fitting benchmark (either German government bonds or a form of asset-backed securities, "Pfandbriefe") from the wave 2017 to the wave 2015 using the same shift per bank.

expectations varied largely between the expectation of a further decline or an increase in interest rates. For some forecast variables, namely NFCI and total assets, we observe that the cross-sectional variation of the forecasts is highest in the last wave.

3 Forecast quality and persistence

3.1 General

Are banks capable of providing forecasts that are better than naive? We try to challenge banks' projections with a baseline forecast which consists of providing constant projections or a constant growth rate. We use the following notation: the variable $x_{t,i,h}$ is forecast by bank $i = 1, ..., N$ for the horizon $h = 1, ..., H$ (in years) and for the waves $t = 2015, 2017, 2019$ and 2022, where the banks use the forecast $\eta_{t,i,h}$ (for the standardization see Appendix A.5). To test whether the forecast contains any information about the future, we run the following regression:[4]

$$x_{t,i,h} = \alpha_i + \lambda_t + \beta \cdot \eta_{t,i,h} + \delta_{t,i,h} \tag{1}$$

where α_i and λ_t are bank and wave fixed effects. As explained below, we put a particular focus on the first projection year and check whether the one-year forecast $\eta_{t,i,1}$ is related to the corresponding realization $x_{t,i,1}$.[5] In our analysis, we check empirically whether the forecasts are biased[6] by regressing the forecast error $error_{t,i,h}$ on a constant and see whether the estimated coefficient is different from zero, where we define the error of the forecast as:

$$error_{t,i,h} = x_{t,i,h} - \eta_{t,i,h} \tag{2}$$

If we only stipulate that the forecast is relevant (i.e. that it provides some information about the future realized values), we check whether the slope β is positive. By contrast, if the forecasts are naive, then we expect the slope β to be zero. The R^2 of the regression (1) states how much of the variation of the future realization is explained by the forecast.

As a further research question we analyse the persistence of the forecast accuracy: Here, we analyse whether a bank with a small absolute forecast error in the previous survey wave still has a small absolute forecast error in the following wave. Finally, we check whether the forecast errors of one bank are correlated across waves (and thus time). If the forecasts are rational, we would expect that the correlation is zero. Our methods are also summarized and further explained in Appendix A.2.

[4] Often, we deal solely with the cross-section of banks in a certain wave. In this case, Equation (1) is used without fixed effects (i.e. no fixed effects for the banks and for the wave are included).

[5] In Appendix A.6, we show that the explanatory power R^2 is far higher for one-year forecasts (i.e. if the horizon is $h = 1$) than for longer horizons. We also discuss the different projection horizons below.

[6] Note that it could be discussed whether forecasts should in general be expected to be unbiased, see e.g. Ehrbeck and Waldmann (1996).

3.2 Implications of quality of forecasting

As a next question, we ask: What are the implications if banks make a good forecast and does forecasting capability correlate with performance? As discussed in Section 1, the literature is inconclusive on whether a positive relationship between planning and performance exists. Here, we argue in favor of such a relationship as detailed in the following: In general, one could assume that a bank which makes good forecasts has a sound understanding of its own business, can reliably plan resources and seems to be able to implement strategic decisions, which would imply that this bank is more profitable. In addition, it could be that banks that provide good forecasts are perceived as more reliable and thus may receive better funding conditions. On the contrary, a bank that regularly under- or overestimates its business development will not be able to reliably plan resources and will suffer frictions. Furthermore, if a bank continuously overestimates its results, it may lose the confidence of investors and clients and suffer reputational risks. On the other hand, a bank that repeatedly underestimates its own performance may also be perceived as not reliable or not ambitious enough, e.g. by investors or customers. Thus, we think that there may be an intrinsic motivation for banks to provide reliable forecasts.

The reasoning outlined above is formalized as follows:We assume that a bank provides a service whose price is p and its marginal costs are c.[7] At the beginning of the planning horizon, the bank decides how much of this service it supplies, denoted by x. However, the bank faces a demand of D for the service at a price p which the bank takes as given. If demand D is lower than the supply x, the bank can satisfy only this demand, but has to bear the full costs for the entire supply. If the demand is higher than expected, the bank can still only supply x. Accordingly, the turn-over depends on the demand whereas the costs depend on the supply and we get for the earnings π:

$$\pi = p \cdot min(D, x) - c \cdot x \tag{3}$$

The bank does not know the exact demand D and we assume a normal distribution, where the (inverse of the) precision of the forecast is measured by σ_D:

$$D \sim N\left(\mu_D, \sigma_D^2\right) \tag{4}$$

Using the Equations (3) and (10) of the Appendix A.1, we obtain for the expected earnings

$$E(\pi) = p \cdot (\mu_D - \sigma_D \cdot f(\beta)) - c \cdot x \tag{5}$$

with $\beta = (x - \mu_D)/\sigma_D$, $f(\beta) = \phi(\beta) - (1 - \Phi(\beta)) \cdot \beta$ and $\phi(\cdot)$ (and $\Phi(\cdot)$) are the (cumulative) density functions of the normal distribution. In Appendix A.3, we show that the expected earnings increase if the forecasts improve (smaller σ_D), i.e. we measure the forecast quality with σ_D where small values mean a high forecast quality. This gives rise to the two following empirical implementations:[8]

[7] An example might be the issuance of housing loan contracts, for which the bank needs to plan how many employees and infrastructure such as office space etc. are needed for acquisition of new business, consultations with customers, preparation of contracts, and further administrative activities. Another example might be services for which a certain infrastructure is needed and has to be prepared for, e.g. transfer of money.

[8] Here, and as discussed below, we are dealing only with forecast of the next year, i.e. $h = 1$. To

$$RoA_{t,i} = \alpha_i + \lambda_t + \beta \cdot |error_{t,i,1}| + \varepsilon_{t,i} \quad (6)$$

where α_i and λ_t are bank and wave fixed effects and $RoA_{t,i}$ is bank i's return on assets as a performance measure, and its average over time (waves):

$$\overline{RoA_i} = \alpha + \beta \cdot MAE_i + \varepsilon_i \quad (7)$$

with $\overline{RoA_i} = 1/T \cdot \sum_{t=1}^{T} RoA_{t,i}$ and $MAE_i = 1/T \sum_{t=1}^{T} |error_{t,i,1}|$. In Equation (7), the coefficient α gives the average return on assets (RoA) for a bank that produces perfect forecasts.

3.3 Results

We turn to the one-year prognosis of the standardized total assets (TA) and of selected items of the profit and loss account (P&L), namely the net interest income (NII), the net fee and commission income (NFCI) and the administrative expenses (Costs). In Table 2, we summarize the results of the one-year forecasts for the total assets and the three positions of the profit and loss account. Looking at the first row of Table 2 ("Biased") related to the prognosis errors (see Equation (2)), we find that their mean is different from zero and it is systematically positive. That means, e.g. regarding total assets, it seems as if the banks systematically underestimate their balance sheet growth as the intercepts of a regression of the forecast error on a constant are always (i.e. for every wave) positive (see Table 8). According to the results, the forecasts of the total assets and the P&L items for the next year are thus biased.

They are relevant, because the coefficients of determination, the $R^2(within)$s, are clearly positive and substantially contribute to the explaining the future positions. In the last wave, the forecast quality shrank, especially for the net interest income. It seems as though the banks did not expect the pronounced rise in interest rates when they made their predictions. In general, the forecasts were slightly more dispersed in the last wave, as can be seen by the higher standard deviation in Table 1 for some variables. In addition, the forecasts do not seem to be rational as the current forecast error can be (at least in parts) explained by the previous forecast error (significant positive correlation across waves, see row "Serial correlation of the forecast error" in Table 2). This could be interpreted such that banks that provide overly optimistic forecasts once (e.g. they earn a lower net interest income (NII) than they predicted) are more likely to provide overly optimistic forecasts again.

Moreover, we observe that the absolute forecast error, a measure of the goodness of fit, is correlated with the previous absolute forecast error (see row "Serial correlation of the absolute forecast error" in Table 2). This suggests that good forecasters remain good forecasters.[9]

By way of example, we show in Table 3, how persistent the forecasts are for the total

facilitate the notation, we omit the index for the forecast horizon.

[9]In Tables 2, 3 and 15, we look at the serial correlation of the absolute forecast error with respect to the directly preceding wave. In the appendix (Table 16), we also look at serial correlations over several waves. For TA (total assets) and NFCI (net fee and commission income), the serial correlation of the absolute forecast error is even significant for a distance of three waves.

Table 2: One-year forecasts of the total assets, the net interest income, fee and commission income and the administrative costs

Forecast variable	**TA**	**NII**	**NFCI**	**Costs**
Biased	Yes (+)	Yes (+)	Yes (+)	Yes (+)
$R^2(within)$ of regression (1)	4.90	42.22	13.89	20.03
R^2 2015	12.24	31.78	6.20	17.01
R^2 2017	12.88	30.18	10.02	10.30
R^2 2019	12.66	21.99	6.71	14.66
R^2 2022	5.25	4.97	7.06	6.62
Serial correlation of the forecast error	Yes	Yes	Yes	Yes
Serial correlation of the absolute forecast error	Yes	Yes	Yes	Yes

This table shows the one-year forecast quality and persistence of forecasts (standardized as explained in Section A.5) for total assets ("TA") and three positions of the profit and loss account, namely the net interest income ("NII"), the net fee and commission income ("NFCI") and the administrative expenses ("Costs"). The serial correlation analysis is done with non-parametric tests in contingency tables (see Appendix A.2). The regressions correspond to Equation (1) and contain bank fixed effects and wave dummies. With "Biased", we mean that when regressing the forecast error (see Equation (2)) on a constant (equivalent to taking the mean), the result is systematically different from zero.

Table 3: Total assets: Frequencies of absolute forecast error

		Current wave	
		low	*high*
Previous wave	*low*	**882**	783
	high	807	**915**
Nobs		3387	
Statistic		12.64***	
p-value		0.0%	

This table shows the frequencies of the absolute forecast error (one-year horizon) for total assets that are above ("high") or below ("low") the median from wave to wave. For the previous waves 2015, 2017 and 2019, the current waves are 2017, 2019 and 2022, respectively. *** means significant at the 1% level. The highest frequencies are highlighted in bold to facilitate reading.

assets.[10] We do this by tabulating the number of banks with an absolute forecast error above/below the median in the previous wave and comparing this to the current wave. We see that banks with a small absolute forecast error concerning the total assets tend to have a small absolute forecast error in the next wave (with a significance at 1% level).[11] The same is true of large absolute forecast errors, thus indicating that good forecasters tend to stay good forecasters over time.

We run regression (6) and obtain mixed results, especially when we include bank fixed effects and wave fixed effects (see Table 9 in the appendix). The coefficient of the absolute forecast error for total assets and costs is significantly negative, meaning that an imprecise forecast (high absolute forecast error) is correlated to a low economic success (low return on assets). This could be interpreted as a slight confirmation of a positive relationship between planning and performance. However, we obtain the opposite result at lower significance for NII and no significance (and a coefficient of approximately 0) for NFCI.

To obtain results that do not depend on regressions, we run non-parametric tests. For each wave, and the total assets and each of the three P&L components, we perform a sample split and analyse whether a bank's RoA counts among the higher or lower half of observations, and the same is done for the respective absolute forecast error. The number of observations belonging to the four resulting categories across all waves are displayed in Table 4.

We see that a lower than the median absolute forecast error (column "low") is more often associated with a higher than the median return on assets (row RoA "high"), apart from the net fee and commission income (NFCI). However, in this test, we observe significant effects only for costs and (in an economic implausible direction) NFCI.

For the time-series average in Equation (7), we do not obtain any significant results for total assets (TA) and administrative expenses (Costs). For the net interest income (NII), we obtain significantly negative results, i.e. banks with a small absolute forecast

[10]For the P&L components net interest income (NII), net fee and commission income (NFCI) and administrative expenses (Costs), see Table 15 in the appendix. In Table 3, we see a share of more than 53% (instead of 50%) of cases in which the absolute forecast error for total assets (TA) remains in the same category (either "low- low" or "high- high"). For NFCI, the share is highest with more than 57%.

[11]We define "low" and "high" relative to the median, i.e. "low" refers to observations below the median.

Table 4: Return on assets and absolute forecast error

		Absolute forecast error							
		TA		**NII**		**NFCI**		**Costs**	
		low	*high*	*low*	*high*	*low*	*high*	*low*	*high*
RoA	*low*	1258	**1290**	1259	**1289**	**1349**	1196	1204	**1334**
	high	**1290**	1256	**1289**	1258	1196	**1346**	**1332**	1204
Nobs		5094		5095		5087		5074	
Statistic		0.86		0.73		18.05***		13.12***	
p-value		35.5%		39.3%		0.0%		0.0%	

This table shows the results of contingency tables where a bank's RoA and the respective forecast errors are tabled. "TA", "NII", "NFCI" and "Costs" stand for total assets, net interest income, net fee and commission income, and administrative costs, respectively. * and *** mean significant at the 10% and 1% level, respectively. The highest frequencies are highlighted in bold to facilitate reading.

error have higher earnings which would be in line with the hypothesis that performance and planning are positively correlated. However, for the net fee and commission income (NFCI), the absolute forecast error and the earnings are highly significantly positively correlated, which is not in line with economic thinking. The results (not shown in detail) of this complimentary analysis are thus mixed.

3.4 Robustness checks

We perform several robustness checks to challenge our results.

If we use the return on equity (RoE) as a measure of performance instead of the return on assets (RoA), the results remain qualitatively the same. Furthermore, as mentioned above, our analysis of interest rates focuses on a projection horizon of one year, but we also checked other horizons and found no contradicting results.

In addition, while our standardization procedure focuses on relative changes in certain metrics (e.g. relative change in net interest income), we also conducted additional analyses where we considered the forecasts of the measures themselves, standardized by total assets. Naturally, the predictive power of these metrics is much higher than for relative changes, i.e. banks seem to be able to reliably forecast the level of their income/expense items (relative to total assets). When regressing the actual net interest income on the predicted net interest income, the coefficient of determination is above 90%. When regressing RoA on the forecast error in this measure, we also find a negative relationship for some waves and projection years, and an insignificant relationship for the other constellations. This confirms the slight evidence for a positive planning-performance relationship.

To check the procedure we use to account for merging activities, we also tested different definitions of which banks should be excluded in which years, but this did not influence the results.

It may be that a macro-factor has undue influence on the comparison between forecast and realisation, especially when making solely use of the cross-section of banks in one point in time. To mitigate this problem, we make use of all four waves, i.e. adding a time dimension (see the panel regression (1)), and analyse groups of banks clustered by size (the results are shown in Table 14). When comparing the results across different size classes, we see that the results remain broadly qualitatively the same, and although there are unsystematic deviations, there is no trend across sizes.

4 Expectations on interest rates

4.1 General

While the survey does not ask banks to provide comprehensive forecasts on variables like the gross domestic product (GDP), it does ask them to provide estimations (or rather expectations) for the (spot) interest rates of maturity 1Y, 5Y, 10Y for each of the next five years. Here, we deal with several questions related to these projections: Do banks provide consistent projections across different maturities and projection years? How well do these forecasts match actual interest rate developments? And did banks' expectations change over time? To have a profound view on the future interest rate levels is important for banks because the interest level has a strong impact on a bank's net interest income (see Claessens, Coleman, and Donnelly (2018)) and the net interest income erodes the longer an environment with low interest levels lasts (see Busch et al. (2022)).

In addition to these questions, we relate the banks' expectations on interest rates to their exposure to interest rate risk. We do this for two reasons. First, the earnings from the premium of the interest rate risk constitute a significant part of the banks' net interest income.[12] Second, a forecast of a change in the interest rate levels should be primarily reflected in a bank's interest rate risk exposure. For instance, if a bank forecasts a rise in the interest rate level it should reduce its exposure to interest rate risk; otherwise the bank exposes itself to a risk which it believes that it materialises.

Each LIRES wave includes an interest rate scenario, where an end of the low-interest rate environment is assumed, namely a rise in the interest level by 200 bp, and banks have to report their figures under this scenario. Dräger et al. (2021), who analyse the LIRES wave of 2017, find that the impairment of securities impacts the banks' earnings much more than changes in net interest income, at least in the first year after the rise in the interest level.

We are especially interested in the impairment (valuation yield) of securities (mostly bonds) belonging to the liquidity reserve. For banks reporting according to the HGB standard[13], these securities are subject to the what is known as *strenges Niederstwertprinzip*[14], which states that the securities have to be written down if the market value is lower than the book value.[15]

We look at an idealized low-interest rate environment, where the interest level falls by $\triangle_{begin} < 0$, remains at this low level for the period T_{LIRE} and then increases by $\triangle_{end} > 0$. In Appendix A.4, we show in Figure 3 the time structure of such a low-interest rate environment and the market value of a passive trading strategy at the end of the

[12] Up to one third of the net interest income of German banks is due to interest rate risk (see Memmel and Heckmann-Draisbach (2023) for an overview).

[13] *Handelsgegesetzbuch*, the German Commercial Code, which most of the banks taking part in LIRES use as reporting standard.

[14] Strict lower of cost or market principle.

[15] By contrast, if the market value exceeds the book value, the book value only increases as long as the book value does not exceed the *Anschaffungskosten* (historical costs).

low-interest rate environment, where this strategy consists in investing in par-yield bonds with maturity M in a revolving manner and taking out the coupon payments of these bonds. Accordingly the valuation yield V (Bewertungsergebnis) for this trading strategy is (just after the interest level has increased again by $\triangle_{end}$):

$$V(T_{LIRE}) = \begin{cases} -\triangle_{begin} \cdot \frac{(M-T_{LIRE})^2}{2M} - \triangle_{end} \cdot \frac{M}{2} & 0 \leq T_{LIRE} \leq M \\ -\triangle_{end} \cdot \frac{M}{2} & M < T_{LIRE} \end{cases} \tag{8}$$

These theoretical values are shown in Figure 2 as a solid line which we will discuss in more detail below. The curve shows a decline over time, but no sudden fall because the revolving investment into the then current par-yield bond leads to an interest income that corresponds to the moving average of the past interest levels. It also leads to huge hidden reserves at the beginning of the low-interest rate environment. The longer the low-interest rate environment lasts, the more the hidden reserves vanish as the interest income of this trading strategy is higher than the current interest level, i.e. the hidden reserves boost the interest income.

Turning to the LIRES data, at bank level, we run the following regression:

$$V_{t,i} = \alpha_i + \beta_1 \cdot D_{2015} + \beta_2 \cdot D_{2017} + \beta_3 \cdot D_{2019} + \beta_4 \cdot D_{2022} + \gamma \cdot \triangle R^e_{t,i} + \varepsilon_{t,i} \tag{9}$$

where $\triangle R^e_{t,i}$ is the expected change in the interest level (relative to the actual level at the beginning of the respective forecast horizon) expected by bank i in wave t and $V_{t,i}$ is the valuation yield of bank i in wave t. We perform the regressions where we use as dependent variable the level of the valuation yield $V_{t,i}$ or the change of the economic value of equity of a bank under a +200 bp shock $IRR_{t,i}$.We also perform the same analysis in differences ($\triangle V_{t,i}$ and $\triangle IRR_{t,i}$). All variables are standardised with total assets. In the regressions (1) and (6), we also include fixed effects of each survey wave. In contrast to the regression above (Equation (9)), these fixed effects are intended to capture the macroeconomic or regulatory environment. In regression (9), the fixed effects ($D_{2015}, ..., D_{2022}$) are designed to capture the low-interest rate environment and the impact it has on the bonds' valuation yield when it finally ends. According to Equation (8), the valuation yield is the deeper in negative territory, the longer the low-interest rate environment lasts.

4.2 Results

Regarding the interest rate forecasts for three different maturities and for five projection years, we find that the interest rate forecasts are highly correlated across maturities and projection horizons. For instance, when we compare interest rate forecasts over different maturities and projection years to the respective medians, we find that a bank whose projections for a certain maturity (projection year) is higher than median is very likely to produce a higher than median projection for the other maturities (projection years). The correlation is significant and above 0.26 for different maturities (over all waves and projection years) and also significant and above 0.33 for different projection years (over all maturities and waves, selected combinations are shown in Table 5). This is also why we mainly focus on the first year and a maturity of 10 years.

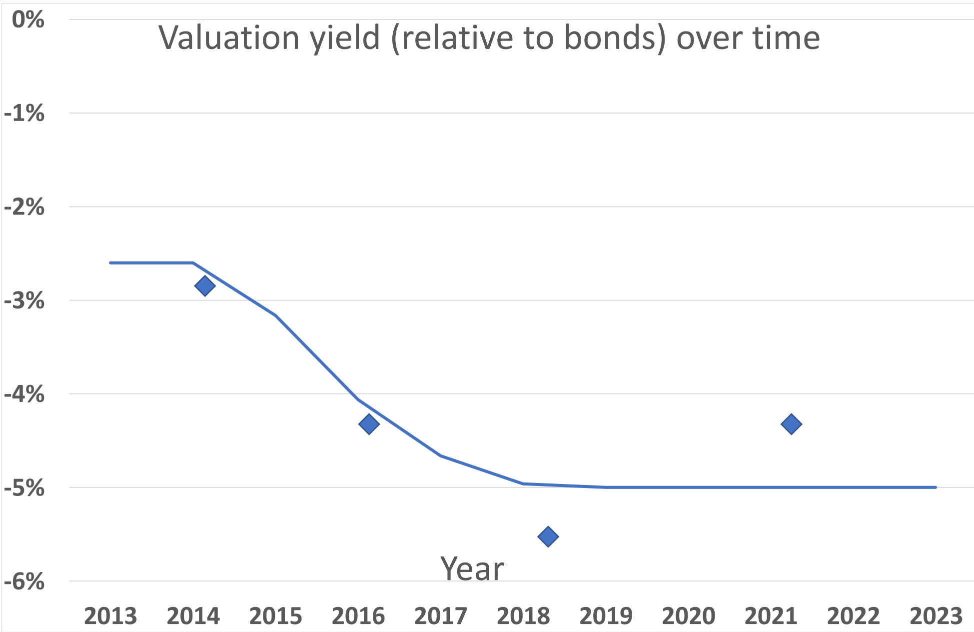

Figure 2: This figure shows the theoretical valuation yield according to Equation (8) as solid line and the valuation yield in the four waves of LIRES (dots). The parameters of Figure 3 and $M = 4$ apply.

Table 5: Persistence of interest rate projections across projection years and maturities

	Projection horizon	1 vs. 5		1	5
	Maturity	1y	10y	1y vs. 10y	
Wave	2015	0.33***	0.63***	0.43***	0.71***
	2017	0.63***	0.79***	0.61***	0.78***
	2019	0.91***	0.84***	0.78***	0.83***
	2022	0.90***	0.74***	0.59***	0.79***

This table shows the correlations of a dummy variable indicating that a bank's interest rate projections are above the cross-sectional median, where a sample split is performed for each maturity, projection year and wave. The correlation is calculated for each wave (row) and two maturities (1y and 10y) across the projection horizon (1y vs. 5y) (second and third column) and for two projection horizons (1y and 5y) across the maturities (1y vs. 10y) (fourth and fifth column).

Table 6: Correlation of interest rate projections across waves

Maturity	1y			10y		
Wave	2015	2017	2019	2015	2017	2019
2017	0.19***	1		0.23***	1	
2019	0.08***	0.32***	1	0.26***	0.42***	1
2022	-0.01	0.18***	0.46***	0.10***	0.19***	0.31***

This table shows the correlations of a dummy variable indicating that a bank's interest rate projections are above the cross-sectional median , where a sample split is performed for each maturity, projection year and wave. The correlation is calculated for maturities 1y and 10y and a projection horizon of 1 year, across waves.

More interestingly, when looking at Table 6 and comparing projections across different waves, we find that banks projecting above the median in 2015 are fairly likely to project above the median in 2017 and 2019, however with decreasing correlation, and the relation drops and turns (for a maturity of 1y) insignificant when directly comparing 2015 and 2022. This indicates again (as with the bank-specific variables) that over-/underestimations seem to be persistent over time.

Furthermore, turning to the question how well the forecasts match actual interest rate developments, we observe that the forecasts for the 10-year interest rate are biased in each wave (results not shown). This might have been expected for the 2022 wave, where markets and banks faced a huge increase in the interest level especially in the second half of the year, but planning was presumably carried out at the end of 2021 or at the beginning of 2022 and therefore banks underestimated the interest rate development. However, it is notable that in the previous years, banks expected a larger increase in interest rates than in 2022 (see row $\triangle R^e$/ Mean in Table 1), thus overestimating the actual development.

Turning now to banks' exposure to interest rate risk, in Figure 2, we show the theoretical valuation yield (solid line) and the valuation yield in the four waves (dots). We see that in the first two waves the theoretical valuation yields are more or less in line with the empirical ones (i.e. the dots are close to the line), while in the third year, the empirical yield is more negative than the theoretical value. However, the valuation yield of the wave 2022 seems much smaller (in terms of its absolute value) than theoretically predicted. Table 7 shows the results of Equation (9), where a bank's valuation yield on securities and its expectation of the change in the interest level are related. We see that the fixed effects for the different waves are highly significant, apart from the change in the interest rate risk ($\triangle IRR$). The dummy concerning the interest level expectation is only significant in the regression for the change in the valuation yield (regression (2)).

5 Discussion

Overall, banks are quite good at providing forecasts of relevant figures, namely of the three most important components of the P&L statement and total assets. While forecasts of the level of different income components seem very reliable (see section 3.4), the forecasting of relative changes is more demanding and seems to suffer greater uncertainty.

Our starting point is to assume that banks have rational expectations and report their planning figure as they think and expect them to be realized. However, it may

Table 7: Valuation yield, interest rate risk and expectation on interest rates

Dependent variables	V	$\triangle V$	IRR	$\triangle IRR$
d2015	-38.74***		-208.54***	
	(1.20)		(2.05)	
d2017	-60.88***	-25.18***	-196.62***	1.26
	(0.82)	(1.55)	(1.30)	(1.65)
d2019	-76.10***	-17.28***	-187.13***	8.21***
	(0.94)	(1.44)	(1.43)	(1.92)
d2022	-59.97***	14.82***	-148.05***	35.04***
	(0.94)	(1.33)	(1.54)	(1.66)
$d(\triangle R^e > 0)$	1.70	4.89*	0.11	-2.45
	(1.29)	(2.52)	(2.15)	(3.13)
Nobs	5031	3621	5008	3768
Bank FE	Yes	Yes	Yes	Yes

This table shows the results of regression (9). * and *** mean significant at the 10%, and 1% level, respectively. Robust standard errors in brackets. $d(\triangle R^e > 0)$ is a dummy variable, indicating whether the forecast of the 10-year interest rate is larger than the then current interest rate. The dependent variables are the valuation yield of the liquidity reserve V, its difference to the previous wave $\triangle V$, the change in economic value of equity through a +200bp shock IRR or the difference of this quantity to the previous wave $\triangle IRR$. All variables are standardized with total assets of the respective bank. "FE" stands for fixed effects.

be that this assumption is not in line with internal processes and optimisation of the banks. Perhaps, banks might have an incentive to exceed their own forecasts or may follow prediction patterns (see e.g. Ehrbeck and Waldmann (1996)). This may explain why we find (though highly relevant) forecasts that are biased.

We see that the standard deviation of changes is high in 2022, especially for total assets. We hypothesize that this could be related to uncertain macroeconomic conditions as e.g. the evolution of the Covid-19 pandemic was not clear. A similar observation can be made for interest rate forecasts in 2019 where the markets were inconclusive about the further evolution of central bank rates and where we observe a high standard deviation for the expectations in interest rate changes.

Furthermore we observe that the quality of banks' projections seems to have a persisting element, i.e. some banks tend to make more reliable forecasts (across waves) than others. This might indicate that some banks are better at planning and/or reliably predicting future developments, which could indicate that there is an intrinsic motivation for banks to provide accurate forecasts. Or to put it another way, it is not random whether a bank provides accurate forecasts, there is, in fact, a systematic element. This is also in line with recent findings by Suss and Hughes (2023) on UK banks.

Coming to the planning-performance paradigm, we find only slight evidence for a higher performance of banks which predict their individual changes more precisely. This holds true to some extent (as partially not statistically significant) for total assets and is statistically significant for administrative costs. However, for the projections of net fee and commission income (NFCI), in the non-parametric tests, we find the opposite relationship. Here, also not least in view of the huge standard deviation of NFCI, one interpretation would be that many banks were too uncertain about future NFCI and that some banks managed to outperform their plans.

Taken together, our results indicate that macroeconomic uncertainty can make it difficult for banks to plan ahead and might have negative effects on banks.

Looking at expected interest rates and comparing the different waves of the LIRES, it seems as if the banks have more and more refrained forecasting an increase in the interest level over time. The forecasts of the short-term interest rate show that banks that were, in 2015, predicting a fast end of the low-interest rate environment do not tend to maintain this (presumably optimistic) forecast in 2022. Furthermore, we find slight evidence that banks that forecast (and thus expect) comparably higher interest rates (above median) seem to be less exposed to interest rate risk, as they report lower losses under a +200 bp shock scenario. We interpret this as follows: With increasing duration of the low-interest rate environment, many banks have stopped expecting a rise in interest rates and accommodated their business model accordingly. They planned with decreasing net interest income (NII), but hoped for (and partially achieved) an increase in their NFCI. However, other banks still held on to the expectation that interest rates would rise at some point. They hedged against rising interest rates and reported higher expected interest rates, knowing full well that these would not impact them much. These findings indicate that expectations on interest rates and the macroeconomic environment matter for banks' business decisions.

6 Conclusion

In our study, we analysed banks' planning data reported in the four last waves (2015, 2017, 2019 and 2022) of the LIRES, a quantitative survey among small and medium-sized German banks, where banks have to forecast their financial statements and report expectations on interest rates. From this unique data set, we find that the banks' one-year forecasts are relevant, especially concerning their main income source, namely the net interest income. In addition, we observe that banks' forecasts display partially systematic over- or underestimations which might be a subject for future research. Furthermore, we contribute to the planning-performance discussion as we find mixed results, but overall an indication slightly in favor of a positive relationship between planning and performance.

Concerning expectations on interest rates, we observe that the end of the low-interest rate environment was apparently not forecast by the banks. However, the cross-section of banks contained some clues, e.g the general reduction in the valuation yield of securities or the increase in the cross-sectional variation of the forecasts for some variables. We see indications that banks had adapted to the low-interest rate environment and adjusted their expectations on their income components accordingly.

To conclude, we provide a unique view on German banks' planning capacity, the relationship between planning accuracy and performance, and banks' interest rate expectations during the low-interest rate environment.

A Appendix

A.1 Useful formula

Let the scalar y be normally distributed with $E(y) = \mu$ and $var(y) = \sigma^2$ and b a non-random value. Then the expected value of the minimum function is

$$E\left(min(y, b)\right) = \mu - \sigma \cdot f(\beta) \tag{10}$$

with $\beta = (b - \mu)/\sigma$ and $f(\beta) = \phi(\beta) - (1 - \Phi(\beta)) \cdot \beta$, where $\phi(\cdot)$ and $\Phi(\cdot)$ are the density and the cumulative density functions of the normal distribution, respectively.

A.2 Methods: regression and non-parametric tests

In this section, we present more details on our methods. Basically, we regress the realized value x_i of bank i on the corresponding forecast η_i:

$$x_i = \alpha + \beta \cdot \eta_i + \varepsilon_i \tag{11}$$

and we define the forecast error as:

$$error_i = x_i - \eta_i \tag{12}$$

Unbiasedness: If the forecast η is unbiased, the forecast error *error* is on average zero.[16] In our analysis, we check this by regressing the forecast error on a constant and test whether the constant is zero.

Relevance: If the slope β in Equation (11) is different from zero (i.e. larger than zero), the forecast η is relevant for the future realisations of x. The coefficient of determination R^2 of Equation (11) shows how relevant the forecast is (0%: no relevance at all; 100% the forecast η explains all the variations of x)

Rationality: A forecast is rational if it includes all available information at the time when the forecast is established. One implication is that present forecast errors are uncorrelated with past ones, i.e. no serial correlation of the forecast error.[17] We check possible correlations by so-called contingency tables. To carry out this non-parametric test, we divide the forecast error of Equation (12) into to two groups: the first group contains the forecast errors below the median ("low"), the second group the errors above the median ("high"). The same is done with the previous forecast errors. If the previous and present forecast errors are uncorrelated, we expect one fourth of the banks to have a low forecast error in the past and in the present.

Persistence We call a forecast to be persistent, if good forecasters remain good forecasters, where we denote good forecasters as forecasters whose absolute forecast errors are below the median. We carry out the corresponding tests with the contingency tables in the same way as the correlation tests under rationality.

[16] If the intercept α is equal to zero and the slope β equals one in Equation (11), the forecast is unbiased. However, there are other combinations of the intercept and the slope that yield unbiased forecasts.

[17] However, a forecast need not be rational if past and present forecast errors are uncorrelated, this is only a necessary condition, not a sufficient one.

A.3 Optimizing

Starting from Equation (5) with the expected earnings and differentiating with respect to the inverse of the precision, σ_D:

$$\frac{\partial E(\pi)}{\partial \sigma_D} = -p \cdot f(\beta^*) - p \cdot \sigma_D \cdot f'(\beta^*) \cdot \frac{\partial \beta^*}{\partial \sigma_D} - c \cdot \frac{\partial x^*}{\partial \sigma_D} \tag{13}$$

with $f(\beta) = \phi(\beta) - (1 - \Phi(\beta)) \cdot \beta$ and $f'(\beta) = -(1 - \Phi(\beta))$, where $\phi(\cdot)$ and $\Phi(\cdot)$ are the density and the cumulative density functions of the normal distribution, respectively. β^* and x^* mean the corresponding variables at their optimum, i.e. when setting the derivative of the expected profit with respect to the quantity x to zero. From this optimisation, we obtain as first order condition:

$$\frac{c}{p} = (1 - \Phi(\beta^*)) \,. \tag{14}$$

Applying $\beta = (x - \mu_D)/\sigma_D$ to β^*, we get

$$\frac{\partial \beta^*}{\partial \sigma_D} = -\frac{1}{\sigma_D} \cdot \beta^* + \frac{1}{\sigma_D} \cdot \frac{\partial x^*}{\partial \sigma_D}. \tag{15}$$

Combining the Equations (13), (14) and (15), we obtain

$$\frac{\partial E(\pi)}{\partial \sigma_D} = -p \cdot \phi(\beta^*). \tag{16}$$

The derivative in Equation (16) is always negative and only depends on c and p.

A.4 Present value and the duration of a low-interest rate environment

We assume that a low-interest rate environment starts in $t = t_0$ with a parallel shift of the flat term structure by $\triangle_{begin} < 0$ and ends in $t = 0$ with a parallel shift by $\triangle_{end} > 0$, so that the low interest environment lasts for the period $T_{Lire} = -t_0$ (see Figure 3).

Moreover, we look at a trading strategy that consists in investing in risk-free par-yield bonds with maturity $M$and in taking out the coupon payments of these bonds as recurring payments of this investment strategy. Using the approximation of a small interest level, we obtain (see Busch et al. (2022), Equation (15)) for the present value PV of the trading strategy in $t = 0$, i.e. just after the low-interest rate environment has finally ended and the interest level has risen by $\triangle_{end}$ again, standardized per euro of investment:[18]

$$PV(T_{Lire}) = \begin{cases} 1 - \triangle_{begin} \cdot \frac{(M - T_{Lire})^2}{2M} - \triangle_{end} \cdot \frac{M}{2} & 0 \le T_{Lire} \le M \\ 1 - \triangle_{end} \cdot \frac{M}{2} & M < T_{Lire} \end{cases} \tag{17}$$

The longer the low-interest rate environment lasts, the lower the present value of the trading strategy and the stronger the effect of the rise in the interest level because the

[18] Under the additional assumption $\triangle_{begin} = -\triangle_{end}$, i.e. the downward shift in the beginning is equal (in absolute values) to the upward shift at the end, we obtain for the case $0 \le T_{Lire} \le M$: $PV(T_{Lire}) = 1 - \triangle_{begin} \cdot \left(T_{Lire} - T_{Lire}^2/(2M)\right)$

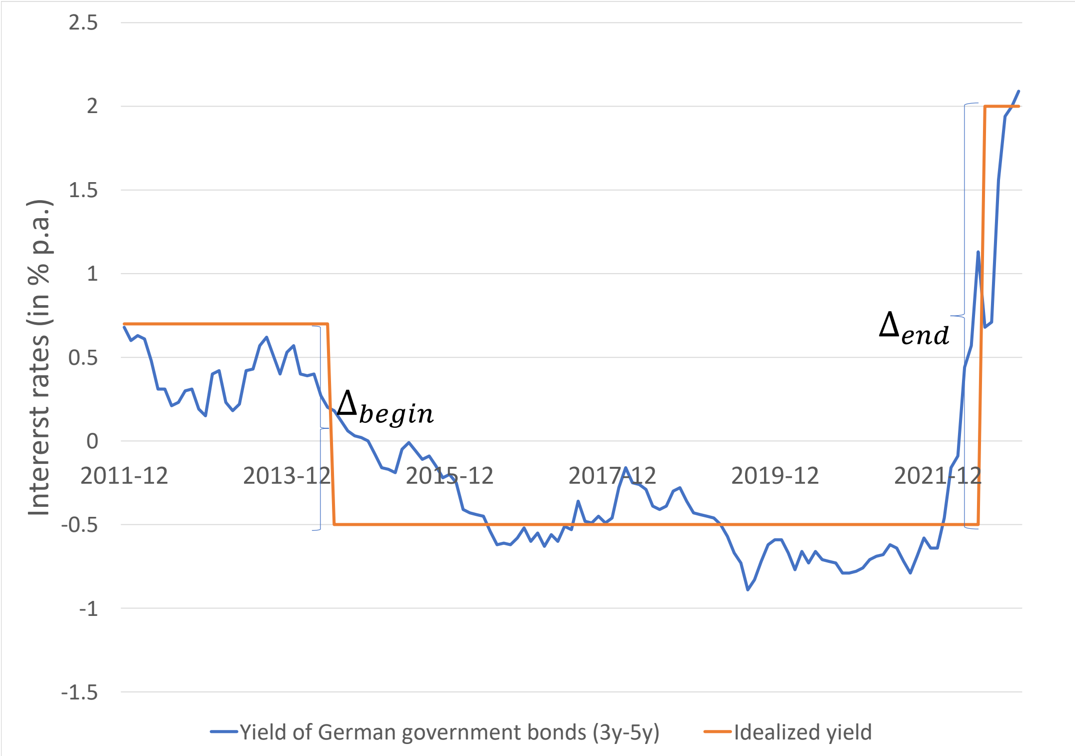

Figure 3: This figure shows the yield of German government bonds with a maturity of 3 to 5 years and the yield of an idealized low-interest environment, lasting from June 2014 to July 2022 with $\triangle_{begin} = -120bp$ and $\triangle_{end} = 250bp$.

Table 8: Total assets: forecasts and realizations

Wave	2015	2017	2019	2022
Intercept	0.0293***	0.0340***	0.0415***	0.0364***
	(0.0011)	(0.0021)	(0.0021)	(0.0031)
Slope	0.5322***	0.6205***	0.6562***	0.5505***
	(0.0591)	(0.1161)	(0.1058)	(0.0993)
$R^2 (in\,\%)$	12.24	12.88	12.66	5.25

This table shows the results of regression (1) (please observe Footnote 4) for the total assets, realizations and forecasts (for each wave). *** means significant at the 1% level. Robust standard errors in brackets.

trading strategy transfers parts of the initial present value gains into an increase in the interest income.

A.5 Standardization of the forecasts

Let X_h be the variable to be forecast with $h = 1, ..., H$ as the forecast horizon and let X_0 be the variable of the regular reporting in the base period. We standardize the variables (apart from the interest rates):

$$x_h := \frac{X_h - X_0}{X_0} = \prod_{i=1}^{h} (1 + \varepsilon_i) - 1 \tag{18}$$

with $\varepsilon_i = (X_i - X_{i-1})/X_{i-1}$ for $i = 1, ..., h$. When taking the logarithm, which yields quite similar values, we obtain:

$$x_h^{ln} := ln\, X_h - ln\, X_0 = \sum_{i=1}^{h} \varepsilon_i^{ln} \tag{19}$$

with $\varepsilon_i^{ln} = ln\, X_i - ln\, X_{i-1}$.

For the interest rate forecast, we do not look at relative, but absolute changes:

$$x_h := X_h - X_0 = \sum_{i=1}^{h} \delta_i \tag{20}$$

with $\delta_i = X_i - X_{i-1}$.

A.6 Further tables

In Table 8, we report the results of regression (1) for total assets for each wave. For each wave (and for the entire sample), we observe highly significant slope coefficients β. However, the slopes are smaller than one and the intercepts are clearly different from zero. In the wave of 2022, the explanatory power of the one-year forecast of the total assets (at 5.25%) is especially small. In 2021, when the forecast was made, the change in the interest environment might already have been foreseeable, however, there was presumably a high uncertainty. The high standard deviations in Table 1 for this wave may be seen as an additional indication that this was the case. The forecasts are relevant as the slope

Table 9: Return on assets and absolute forecast error

Forecast variable	TA	NII	NFCI	Costs
Absolute forecast error	-0.00169**	0.00070*	0.00000	-0.00153**
	(0.00074)	(0.00039)	(0.00035)	(0.00065)
Bank FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes

This table shows the results of regression (6), i.e. the bank's RoA is always the dependent variable. "TA", "NII", "NFCI" and "Costs" stand for total assets, net interest income, net fee and commission income, and administrative costs, respectively. * and ** mean significant at the 10% and 5% level, respectively. Robust standard errors in brackets. "FE" stands for fixed effects.

coefficients for each wave (and for the entire sample[19]) are clearly positive. Similar results can be obtained for NII, NFCI and Costs, where we always observe highly significant positive slopes and where we observe that the explanatory power given by R^2 is smallest in the 2022 wave.

In Table 9, we show the quantitative results when regressing the return on assets (RoA) on the absolute forecast errors of the different variables, i.e. Equation (6). The results are mixed: We observe a negative significant relationship for total assets and costs, meaning that a higher forecast error in these variables results in a smaller return on assets, which would support the hypothesis of a positive relationship between planning capacity and performance. On the other hand, the relationship is insignificant for NFCI and we observe the opposite sign for NII.

For total assets, we try to estimate the economic impact of our results. The coefficient indicates that return on assets declines by -0.00169 for 1 unit of the absolute forecast error. The standard deviation of the absolute forecast error is approximately 15%, which leads to a reduction of approximately -0.025%. A typical return on asset for small and medium-sized German banks could be inferred to be around 0.4% for the period considered, thus the impact for banks that are one standard deviation apart is around 6% of return on assets.

In the Tables 10, 11, 12 and 13, we report the coefficients of determination (R^2) of regression (1), where we standardize the forecasts and the actual values according to Equation (18).

In Table 14, we analyse groups of banks clustered by size (see section 3.4). Table 15 shows results for a similar analysis as Table 3, but for the P&L components net interest income (NII), net fee and commission income (NFCI) and administrative expenses (Costs). Finally, in Table 16, we show the autocorrelation across multiple waves.

References

Armstrong, J. S. (1983). Strategic planning and forecasting fundamentals. In K. Albert (Ed.), *The strategic management handbook*.

[19]The $R^2(within)$ for the entire sample is 4.90% and the slope is 0.341 .

Table 10: Total assets and coefficient of determination

Year \ Horizon	**1**	**2**	**3**	**4**	**5**
2015	12.24	15.22	7.95	5.85	6.48
2017	12.88	7.89	7.08	5.27	4.10
2019	12.66	4.72	2.92	3.84	
2022	5.25				

This table shows (for each wave) the coefficient of determination (R^2 in %) of regression (1) for the forecast of the total assets (TA), in dependence of the forecast horizon.

Table 11: NII and coefficient of determination

Year \ Horizon	**1**	**2**	**3**	**4**	**5**
2015	31.78	18.96	9.45	11.44	8.79
2017	30.18	17.40	15.33	13.92	12.82
2019	21.99	7.29	10.17	7.67	
2022	4.97				

This table shows (for each wave) the coefficient of determination (R^2 in %) of regression (1) for the forecast of the net interest income (NII), in dependence of the forecast horizon.

Table 12: NFCI and coefficient of determination

Year \ Horizon	**1**	**2**	**3**	**4**	**5**
2015	6.20	5.42	5.98	0.39	0.21
2017	10.02	3.36	3.77	3.06	6.59
2019	6.71	3.38	2.13	5.05	
2022	7.06				

This table shows (for each wave) the coefficient of determination (R^2 in %) of regression (1) for the forecast of the net fee and commission income (NFCI), in dependence of the forecast horizon.

Table 13: Costs and coefficient of determination

Year \ Horizon	**1**	**2**	**3**	**4**	**5**
2015	17.01	7.28	5.97	4.01	5.14
2017	10.30	7.68	6.20	5.03	5.52
2019	14.66	6.64	3.71	4.30	
2022	6.62				

This table shows (for each wave) the coefficient of determination (R^2 in %) of regression (1) for the forecast of administrative expenses (Costs), in dependence of the forecast horizon.

Table 14: Size class

Variable	TA		NII		NFCI		Costs	
size cl.	**Slope**	R^2	**Slope**	R^2	**Slope**	R^2	**Slope**	R^2
first	0.3460	3.79	0.7896	44.84	0.5676	20.74	0.5902	16.72
second	0.1450	1.99	0.7545	42.69	0.5789	16.77	0.6276	25.87
third	0.2837	4.23	0.7226	37.82	0.5977	24.35	0.6226	24.22
fourth	0.5470	10.22	0.7145	49.41	0.2821	4.61	0.4846	22.21
fifth	0.3343	7.47	0.7716	47.85	0.4599	13.68	0.5122	16.62
all	0.3413	4.90	0.7408	42.22	0.4894	13.89	0.5764	20.03

This table shows the slope and the coefficient of determination (R^2 in %) of regression (1) for different size classes (total assets as of 2014 as criterion for the size classes).

Table 15: Frequencies of absolute forecast error for NII, NFCI and Costs

		Current wave					
		NII		NFCI		Costs	
		low	*high*	*low*	*high*	*low*	*high*
Previous wave	*low*	**954**	736	**977**	720	**891**	772
	high	727	**973**	710	**965**	746	**930**
Nobs		3390		3372		3339	
Statistic		63.49***		77.74***		27.46***	
p-Value		0.00%		0.00%		0.00%	

This table shows the absolute forecast error (one-year horizon) for the relevant P&L positions that are above ("high") or below ("low") the median from wave to wave. "NII", "NFCI" and "Costs" stand for net interest income, net fee and commission income, and administrative costs, respectively. For the previous waves 2015, 2017 and 2019, the current waves are 2017, 2019 and 2022, respectively. *** means significant at the 1% level. The highest frequencies are highlighted in bold to facilitate reading.

Table 16: Absolute forecast error: p-values of an autocorrelation test

Distance (in waves)	TA	NII	NFCI	Costs
1	0.0%	0.0%	0.0%	0.0%
2	0.7%	8.8%	0.0%	3.7%
3	2.7%	25.4%	0.0%	59.7%

This table shows the p-values of a non-parametric test with the null hypothesis that the absolute forecast errors are serially uncorrelated, where the first column gives the time span between the forecast errors. "TA", "NII", "NFCI" and "Costs" stand for total assets, net interest income, net fee and commission income, and administrative costs, respectively.

Boyd, B. K. (1991). Strategic planning and financial performance - a meta-analytic review. *Journal of Management Studies 28*, 353–374.

Busch, R., C. Drescher, and C. Memmel (2017). Bank stress testing under different balance sheet assumptions. Discussion Paper 07/2017, Deutsche Bundesbank.

Busch, R., H. C. N. Littke, C. Memmel, and S. Niederauer (2022). German banks' behavior in the low interest rate environment. *Financial Markets and Portfolio Management 36(3)*, 267–296.

Büttner, T. and G. A. Horn (1993). Wie gut sind Prognosen? Eine Überprüfung der Vorhersagen der Gemeinschaftsdiagnose und des DIW am Beispiel des BSP. DIW Discussion Papers 73, DIW, Berlin, Kiel, Hamburg.

Capon, N., J. U. Farley, and J. M. Hulbert (1994). Strategic planning and financial performance: more evidence. *Journal of Management Studies 31*(1), 105–110.

Cassar, G. and B. Gibson (2008). Budgets, internal reports, and manager forecast accuracy*. *Contemporary Accounting Research 25*(3), 707–738.

Claessens, S., N. Coleman, and M. Donnelly (2018). "Low-For-Long" interest rates and banks' interest margins and profitability: Cross-country evidence. *Journal of Financial Intermediation 35*, 1–16.

Deutsche Bundesbank (2022). Monthly Report. 09/2022.

Dräger, V., L. Heckmann-Draisbach, and C. Memmel (2021). Interest and credit risk management in German banks: Evidence from a quantitative survey. *German Economic Review 22(1)*, 163–95.

Ehrbeck, T. and R. Waldmann (1996). Why are professional forecasters biased? Agency versus behavioral explanations. *The Quarterly Journal of Economics 111*(1), 21–40.

Falato, A. and J. Xiao (2022). Expectations and credit slumps. Technical Report, Federal Reserve Board of Governors, University of Notre Dame.

Gup, B. E. and D. D. Whitehead (1989). Strategic planning in banks – does it pay? *Long Range Planning 22*(1), 124–130.

Heckmann-Draisbach, L. and J. Moertel (2020). Hampered interest rate pass-through - a supply side story? Discussion Paper 59/2020, Deutsche Bundesbank.

Hopkins, W. E. and S. A. Hopkins (1997). Strategic planning - financial performance relationships in banks: a causal examination. *Strategic Management Journal 18*(8), 635–652.

Hussaini, U. and U. Muhammed (2018). The effect of internal control on performance of commercial banks in Nigeria. *International Journal of Management Research and Review 8*, 13–32.

Ittner, C. D. and J. Michels (2017). Risk-based forecasting and planning and management earnings forecasts. *Review of Accounting Studies 22*(3), 1005–1047.

Jimoh, A. (2003). Strategic management and the performance of the Nigerian banking industry. *African Review of Money Finance and Banking*, 119–138.

Kao, C. and S.-T. Liu (2004). Predicting bank performance with financial forecasts: A case of Taiwan commercial banks. *Journal of Banking and Finance 28*(10), 2353–2368.

Ma, Y., T. Paligrorova, and J.-L. Peydro (2021). Expectations and bank lending. University of Chicago, Unpublished Working Paper.

Mark Davis and Sébastien Lleo (2020). Debiased expert forecasts in continuous-time asset allocation. *Journal of Banking & Finance 113*, 105759.

Memmel, C. and L. Heckmann-Draisbach (2023). Banks' net interest margin and changes in the term structure. Discussion Paper 11/2023, Deutsche Bundesbank.

Miller, C. C. and L. B. Cardinal (1994). Strategic planning and firm performance: A synthesis of more than two decades of research. *Academy of Management Journal 37*(6), 1649–1665.

Pearce, J. A., E. B. Freeman, and R. B. Robinson (1987). The tenuous link between formal strategic planning and financial performance. *The Academy of Management Review 12*(4), 658–675.

Stephen P. Baginski, Saverio Bozzolan, Antonio Marra, and Pietro Mazzola (2017). Strategy, valuation, and forecast accuracy: Evidence from Italian strategic plan disclosures. *European Accounting Review 26*(2), 341–378.

Suss, J. and A. Hughes (2023). Bank expectations and prudential outcomes. *Bank of England Staff Working Paper* (1035), 1–45.

Whitehead, D. and B. Gup (1985). Bank and thrift probability: Does strategic planninc really pay? *Economic Review Federal Reserve Bank of Atlanta 70*, 14–25.