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Bank expectations and prudential outcomes

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Abstract

We study bank expectations using a unique and rich data set derived from regulatory returns. The data covers key bank-level variables, including profitability, capital, and loan impairments. We find that banks tend to be optimistic, expecting higher returns, higher capital ratios and fewer impairments than are subsequently realised. However, there is substantial variation in forecasting performance across banks, and banks with better quality governance and management tend to also have smaller forecast errors. We go on to examine the relationship between forecast performance and bank outcomes, finding that forecast errors are associated with greater prudential risk, even after controlling for bank and time fixed effects. Importantly, forecast errors have an asymmetric effect on bank outcomes – errors of optimism drive our findings. We find that forecast errors are also associated with lending – banks that have higher errors tend to have significantly lower subsequent loan growth.

Key words: Banks, forecasts, prudential risk.

JEL classification: L2, M2, G21.

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1 Introduction

Banks, like all firms, are forward looking. Together, they make decisions about the allocation of credit to the real economy based on how they expect the future to unfold. While the literature on firm expectations has grown markedly in recent years (e.g. Altig et al., 2020; Bloom et al., 2021), we know surprisingly little about expectations of financial sector firms. In this paper, we document a new dataset on bank expectations and examine variation in bank forecasting performance. To do so, we construct a unique and rich dataset of forecasted regulatory returns. The data, which covers the universe of regulated banks and building societies in the UK from mid-2008 to the present, includes forecasts of key financial variables from 6 to 24 months into the future. We focus our attention on forecasts of key bottom-line items – net profit, Common Equity Tier 1 capital (CET1) and loan impairments, but the data allows us to also examine forecasting performance for other, more granular variables, such as income and expense line items.

We have three main findings. First, while banks tend to be optimistic about their future profitability, capital and impairments, there is wide variation in forecasting performance, with some banks tending towards pessimism (e.g. exceed profit forecasts). Moreover, in the post-Covid era banks have been pessimistic on average whereas prior they tended to be optimistic. Second, managerial and governance attributes are important factors explaining forecast performance. Banks with a higher proportion of females on executive and board committees perform substantially better. Similarly, committees with higher average tenure tend to have better forecasting ability, pointing to the role of management and oversight quality. Third, we find that banks that are better forecasters also tend subsequently to have better outcomes, both in terms of financial performance and risk of insolvency. This effect is asymmetrical, driven by errors of optimism – banks that expect more profit and capital, or fewer impaired loans, than is realised tend to have poorer outcomes. These results hold even after controlling for time and firm fixed effects and are robust to alternative measures of forecast errors and empirical specifications.

This paper contributes to a nascent body of work which explores the determinants and consequences of firm forecasting performance. These studies can be categorised depending on whether the forecasts are for macroeconomic or firm-level variables. In the former category, Tanaka et al. (2020) examine the performance of large Japanese firms in forecasting GDP growth 12 months ahead. The authors find that better forecasting performance leads to better firm-level business outcomes, and that errors are symmetrical in their effect – both positive (optimistic) and negative (pessimistic) forecasting errors lead to worse outcomes. Dovern et al. (2020) and Koga and Kato (2017) study the effects of macro growth expectations on firm behaviour, for German and Japanese firms respectively. These papers find evidence for behavioural biases in expectation formation (driven by over-extrapolation of recent local business conditions) and find that firm investment decisions are positively related to their growth expectations.[2] The impact of inflation expectations on firm economic decisions was explored by Coibion et al. (2019). The authors found causal effects of higher inflation expectations, leading to increased demand for credit, higher prices, and reduced employment and capital.

Closer to our own exercise and focused on forecasts of firm-level variables, Bloom et al. (2020) evaluate the forecasting performance of US manufacturing firms for their own sales, employment and investment growth over the next 12 months. They find that firms that have better management practices tend to have better forecasts. Bachmann and Elstner (2015) also look at the determinants of expectations errors for a sample of manufacturing firms (from West Germany) – they find that larger and exporting firms tend to be more accurate. A more recent paper by Bloom et al. (2021) analyses data from the ONS Management and Expectation Survey, documenting associations between forecast performance (both macro and firm-level) and managerial quality and finding that better managed firms and firms that are not family owned and run are better at forecasting. By looking at how managerial attributes – i.e. tenure, age, and gender – affects forecasting performance, our paper builds on this work while also connecting to a separate body of work looking at how board and management body characteristics (e.g. gender diversity) affect governance and performance outcomes (for example, Adams and Ferreira, 2009; Arnaboldi et al., 2021; Bennouri et al., 2018; Faccio et al., 2016).

We also document a tendency for banks to be optimistic about their future profitability. This builds on work from the psychological and behavioural sciences that demonstrates that managers (and people more generally) tend to be optimistic due to overconfidence in their abilities (Kahneman and Lovallo, 1993). For example, Ben-David et al. (2013) report that overconfident (or ‘overprecise’) managers tend to invest more and take on more debt (see also Malmendier and Tate (2005) and Malmendier and Tate (2008)). Hackbarth (2008) shows how optimistic management forecasts are associated with higher level of corporate debt because managers

[2] See also the work of Ma et al. (2020), who study managerial forecast errors for a set of Italian firms and quantify the aggregate level impact of forecast biases.

overestimate their firm's ability to meet liabilities. On the other hand, using a survey of US firm expectations Barrero (2022) finds that managers are generally not overly optimistic.

The current work analyses a unique source of forecasting data. Whereas other studies rely on surveys to elicit forecasts (e.g., Altig et al., 2020; Cassar and Gibson, 2008), resulting in often very large non-response and attrition rates, we have access to regulatory returns that are mandated by law. We therefore have complete coverage of the UK banking sector, including both listed and unlisted banks. The potential implications of providing low quality or inaccurate returns, e.g. large regulatory fines[3], means that the data is likely to be of reasonable quality and approved at the highest levels within institutions.[4]

Our study also contributes to a nascent literature on bank expectations (Falato and Xiao, 2022; Ma et al., 2021). Most previous studies on firm expectations, such as that of Tanaka et al. (2020) and Coibion et al. (2019), explicitly omit financial sector firms due to the differences that exist between financial and non-financial firms. But given the importance of the banking sector for supporting economic activity and growth through lending, the analysis here presents important new understanding of the implications of expectations. While we focus attention on the implications of bank micro-level expectations on firm-level outcomes, the research on bank expectations largely looks at the implication of macro-level forecasts. For example, Ma et al. (2021) examines the implications of bank forecasts of US metropolitan area economic conditions on lending decisions. We build on this study here by looking at how micro-expectations affect bank lending volumes.

The rest of this paper is organised as follows: in Section 2 we describe the data. Section 4 examines variation in bank forecast performance. Section 4 explores the determinants of forecast performance. Section 5 provides the empirical results for the relationship between forecast performance and bank outcomes. Lastly, Section 6 concludes with a discussion of the limitations and suggestions for further research.

[3] For example, in 2019 Citigroup UK was fined £44mn by the Bank of England for failings in their regulatory reporting governance and controls. Fines have also been levied against Standard Chartered Bank and Metro Bank for regulatory reporting issues.

[4] Since the introduction of the Senior Managers and Certifications Regime in 2016, the CFO is considered the 'responsible person' for accurate completion of regulatory returns.

2 Data

2.1 Sources

The bank forecast data comes from regulatory returns submitted to the Financial Services Authority (FSA; 2008-2013) and the Bank of England's Prudential Regulation Authority (PRA; 2014-present). We have merged together a number of returns: i) FSA014 (Q3 2008 to Q4 2017) for net profit and impairment forecasts, ii) PRA101-103 (2014 to present) for detailed capital forecasts, and iii) PRA104-107 (Q1 2018 to present) for the latest income and impairment forecasts. These regulatory returns mirror the accounting-based returns which banks submit to report realised positions and are thus well-defined and understood by reporting institutions.[5]

The reporting frequency for income and impairment forecasts is every half-year. Banks were only required to provide one forecast per reporting date for FSA014 (for the end of the current or next financial year, i.e. 6 or 12 months ahead), whereas for PRA104-107 banks are required to provide two forecasts (for the end of the current and next financial year, i.e. either 6 and 18, or 12 and 24 month forecasts are made each reporting period depending on the bank's financial year quarter). This means that there are two forecasts for each bank's financial end-year for the FSA returns (the 6 month is a revision of the initial 12 month forecast), and up to four forecasts for each end-year position for the PRA returns.[6]

Capital forecasts are reported more frequently depending on the size of the bank – larger banks report forecasts every month versus every half-year for smaller banks and every year for the smallest banks. Forecast horizons also differ in the capital returns – rather than at half-year intervals, a forecast is made for each quarter up to 8 quarters out, as well as for the year-end following the 8th quarter out (i.e. up to a max prediction of 12 quarters out). We make the capital and financial forecasts consistent in terms of horizon, focusing only on the capital forecasts made for 6, 12, 18 and 24 months in the future.

We match the forecast data to the corresponding regulatory returns containing realised positions. This comes from two sources: first, up until 2013 the Historical Banking Regulatory

[5] The FSA014 template and reporting instructions can be found here and PRA101-107 templates and instructions can be found here.
[6] Across all returns, we round reporting dates to nearest end quarter of the calendar year to harmonise reporting quarters across banks.

Database (de-Ramon et al., 2017), and second from 2013 onwards the relevant reporting templates contained in FINREP and COREP.[7]

As all these returns are compulsory, our dataset includes forecasts for the universe of banks operating in the UK, covering a range of firm sizes, complexities, business models, and legal structures.[8] Our sample includes building societies, domestic UK banks that are both listed and unlisted, and subsidiaries of overseas banks. Altogether we have quarterly data for a total of 210 banks from Q3 2008 to mid 2022 (N = 4,539). 66.4% of banks in our sample are unlisted, and 25.5% of banks in our sample are building societies – see Table A.1 for descriptive statistics.

2.2 Measuring forecast errors

We take the percentage error (PE) – the difference between forecast and actual as a percentage of a bank's total assets – as our primary measure of forecasting performance, calculated as:

$$PE = \frac{(\hat{Y} - Y)}{Assets} * 100$$

Where $\hat{Y}$ is the forecasted value, Y is the actual value, and $Assets$ is total assets at the end of the period. The PE is unitless and has direction, allowing us to distinguish between positive and negative errors. Moreover, scaling by total assets ensures errors are meaningful in magnitude for any given bank. For example, a small and large bank might both expect to have a profit of £10mn for a given period. Exceeding this amount by £10mn would be relatively more material for the smaller bank even if an un-scaled error measure is equivalent. In robustness checks, we examine an alternative measure of forecast errors which does not rely on scaling by assets – the arc distance measure, defined as:

$$\frac{(\hat{Y} - Y)}{1/2(|\hat{Y}| + |Y|)}$$

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[7] FINREP and COREP are the reporting frameworks that apply to regulated deposit takers developed by the European Banking Authority (EBA) to implement Basel standards. Since January 2022, the UK COREP and FINREP versions have been aligned to the EBA Taxonomy 3.0.

[8] The wording in the reporting guidance differs between capital and financial forecast returns. The former "should be aligned with the firm's internal corporate capital plans" whereas the latter "should be made on a reasonable endeavours basis." This likely reflects the different origin of these returns rather than any practical difference in regulator expectations around completion – capital forecast returns are unique to the UK regulatory landscape, whereas the other returns were initiated at the European-level.

We deal with data quality issues as follows: first, we manually correct obvious multiplication or division errors, e.g. where returned values were divided by a factor of 1,000 (the most common data entry error) relative to previous returns. Second, we winsorise values above the 99th percentile and below the 1st percentile to remove very large and implausible figures.

Our focus is on the PE of three key variables: net profit, CET1 capital (i.e. common equity tier 1 capital), and impairments. Positive values are errors of optimism with respect to net profit – banks expect higher profits (or less negative profits) than is realised. The reverse is true for negative PE values for net profit, which indicates errors of pessimism. Likewise, positive forecast errors for CET1 capital indicate optimism – banks expect to have higher levels of capital than is subsequently realised. However, the direction is reverse for impairments – positive PE values indicate banks are pessimistic, expecting higher impairments than is realised.

3 Variation in forecast performance

To analyse the variation in forecasting performance, we first plot the mean percentage error (MPE) across banks for each year. Panel A of Figure 1 provides the MPE per year across all forecast horizons. Panel B breaks this down by horizon. Across the different variables, we can see a tendency for banks to be optimistic – the MPE is generally positive for CET1 and profit across all years, and negative for impairments. There are some interesting counterpoints to this general tendency, however. Notably, the MPE for profit turned negative in 2022. Panel B indicates banks were also on average pessimistic about their profit in 2021 when forecasts were made after the onset of the pandemic (i.e. 6- and 12-month predictions, the MPE is still positive for the 18- and 24-month horizon forecasts).

Figure 1: Forecast errors by year

Note: The figures show the unweighted mean percentage error across banks for each calendar year.

Unsurprisingly, 2020 saw the largest MPE across all horizons as bank forecasted profits were affected by the pandemic. The MPE when bank forecasts and realisation are both before the declaration of the Covid pandemic by the World Health Organization in March 2020 is 0.161. When forecasts are made pre-Covid but realisation of the forecasts post-Covid, the MPE is 0.495. And finally, when both forecasts and realisation are post-Covid, the banking sector MPE is -0.048. The figure corresponds with intuition – the unexpected impact of Covid on profits inflated MPE upwards, whereas banks that have made forecasts post Covid have been pessimistic, perhaps because the economy was supported by fiscal policy and rebounded better than initially expected.

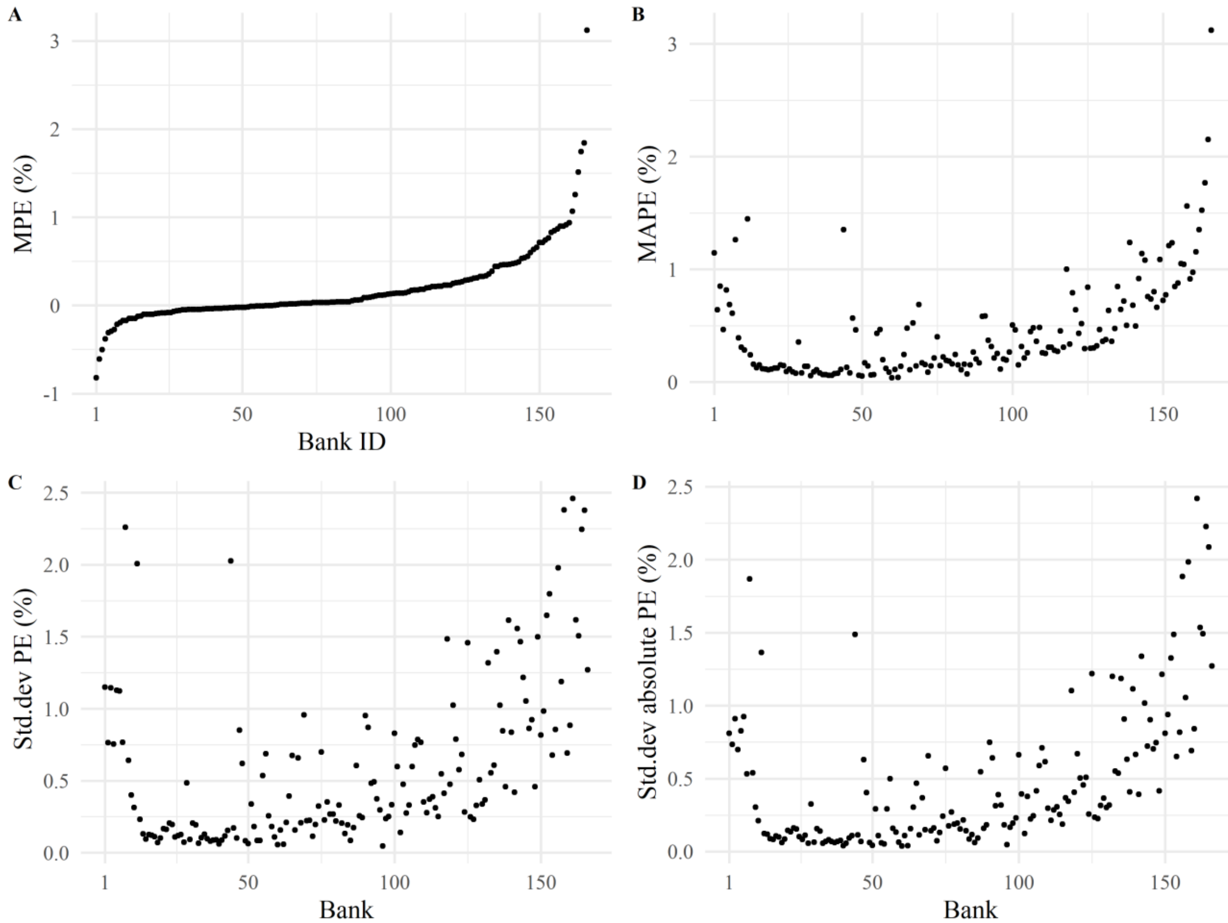
There are two other years where the average profit error is negative: 2014 and 2017. The former year was a small economic recession in the UK, and the latter was in the wake of the Brexit referendum vote. Together this suggests that bank expectations tend to be pro-cyclical – when the economic situation is good banks are overoptimistic and vice versa. This is most prominent when looking at profit forecasts, although there is some evidence of this also for impairments, where in recent years banks have tended to be overly pessimistic as opposed to optimistic.

While our main focus is on net profit, CET1 capital and impairments, our dataset provides forecasts for more detailed variables, allowing for even more extensive analysis of bank expectations. For example, from 2018 (the introduction of PRA104-107) banks are required to provide forecasts of income and expense line items, allowing us to compare expectations of overall revenue and expenses, as well as individual income and expense line items. We can therefore seek to understand the main sources of net profitability forecast errors by bank or groups of banks. Figure A.1 in the Annex provides a decomposition of net profitability across years. This demonstrates that, while banks are typically optimistic with regards income items and overall revenue, at the same time they tend to be pessimistic about expenses.

Next, we collapse the time dimension and calculate the MPE and mean absolute percentage error (MAPE) for each bank, as well as the standard deviation for the PE and absolute PE. Figure 2 shows these measures for our profit variable (for brevity, we include the equivalent figures for CET1 and impairments in the Annex). This demonstrates substantial variation in performance across banks – while most banks are on average optimistic, some are generally pessimistic (33.8% of banks have a negative profit MPE over our time period). Panel A and Panel B of Figure 2 also clearly show that some banks tend to perform better than others, with MPE and MAPE values close to zero. Panel C and D show that better performing banks also tend to have lower standard deviations, suggesting that they are also more consistent – the correlation between the MAPE and standard deviation of the absolute PE (i.e. the variables in Panel B and D) is 0.609. We find similar patterns for CET1 and impairments – see Figures A.2 and A.3.

We also ask whether errors are correlated across variables – i.e. do banks tend to perform similarly in forecasting profit, CET1 and impairments? To answer this question, we look at the simple correlations for the MPE and MAPE figures when we collapse over time (Table 1). We find that the signs on the correlation coefficients are as expected – profit and CET1 PE are positively correlated, whereas impairment PE is negatively correlated with the other variables. While there are moderate to large correlation coefficients between profit and CET1, and between profit and impairments, the correlation coefficient between impairments and CET1 is small.

Figure 2: Forecast performance by bank – net profit



Note: The figure shows forecast performance and uncertainty by bank. The x-axis is arranged by MPE in each panel. At least 10 observations per bank per forecasted variable.

Table 1: Correlation of MPE and MAPE by bank across variables

	MPE profit	MPE impairments	MPE CET1
MPE profit			
MPE impairments	-0.303		
MPE CET1	0.153	-0.044	
	MAPE profit	**MAPE impairments**	**MAPE CET1**
MAPE profit			
MAPE impairments	0.459		
MAPE CET1	0.532	0.067	

4 Determinants of forecasting performance

We have thus far documented a wide variation in bank expectations. What explains why some banks are better than others at forecasting? In this section we examine the characteristics of banks and their senior leadership team that affect forecast performance. We merge the forecast data with information on tenure, age, and gender of bank executives and directors. The data comes from applications to serve in Controlled (2008 to Q1 2016) or Senior Management (Q1 2016 to present) functions, which all executives and directors must submit for regulatory approval[9] – see Suss et al. (2021a) for further details. We take two sets of variables from this data. First, we compute the average tenure in role (quarters), average age, and proportion female for the pool of key bank decision-makers, which taken to be all executive committee and board members. Second, we take the tenure in role, age, and gender of the Chief Executive Officer (CEO).

We also include variables known to be important for forecast performance. In particular, we include bank size (log of total assets), ownership structure (whether a bank is a UK unlisted bank, listed bank, building society, or subsidiary of an international bank), and business volatility (proxied by taking the standard deviation of ROA over the previous 8 quarters). Descriptive statistics for all variables are available in Table A.1 in the Annex.

[9] With the exception of some directors – ‘notified NEDs’ (non-executive directors who do not serve as Chair of a board sub-committee) – are no longer required to obtain regulatory approval following the introduction of the Senior Managers Regime in March 2016

Table 2 provides the regression results where the dependent variable is the absolute value of net profit PE. For the sake of brevity, results for CET1 and impairments are included in the Annex (Tables A.2 and A.3 respectively). All models include time fixed effects and robust standard errors clustered at the bank-level, and each right-hand side continuous variable (aside from the forecast horizon) is mean-centered and scaled by one standard deviation.

For the group-level managerial variables, we find that coefficients on the average tenure and proportion female variables are negative and statistically significant, whereas average age is not. This suggests that senior teams which are longer tenured and more gender diverse are expected to be more accurate. The coefficients on these variables are large – a one standard deviation increase in average tenure of a bank's board and executive members is associated with an expected reduction in PE by 0.07 (Column 9). For gender diversity, the equivalent figure is 0.03. In comparison, the average profit PE is 0.18 (Table A.1).

The coefficient on CEO tenure is significant in Column 6 and 8, however once we control for group level variables it ceases to be significantly different from zero. The coefficient on CEO age is consistently insignificant. As for the other variables in the model, as expected the length of horizon is positively associated with forecast errors. Size is also positively associated with forecast errors. The type of bank is also important, with building societies (the omitted category) seeing substantial reductions in errors relative to other bank types, likely due to the nature of their business (primarily domestic mortgage lending, with limited complexity in business lines or strategy). Building societies are expected to have a PE which is roughly 0.28, 0.32, and 0.38 lower than domestic banks, international subsidiaries and listed banks respectively (Column 9). Lastly, in line with findings by Bloom et al. (2021), banks with more volatile businesses tend to have higher PE values.

Table 2: Determinants of profit forecast errors

	Dependent variable:								
	|PE profit|								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tenure board + exec average (quarters)	-0.075***			-0.100***					-0.065**
	(0.023)			(0.026)					(0.032)
Age board + exec average (years)		0.009		0.037*					0.020
		(0.018)		(0.020)					(0.024)
Female proportion board + exec			-0.030**	-0.029*					-0.033**
			(0.014)	(0.015)					(0.015)
Tenure CEO (quarters)					-0.039***			-0.044***	-0.026
					(0.013)			(0.016)	(0.018)
Age CEO (years)						0.003		0.021	0.016
						(0.014)		(0.017)	(0.020)
Female CEO							-0.041	-0.049	-0.010
							(0.061)	(0.061)	(0.061)
Horizon (months)	0.017***	0.017***	0.017***	0.017***	0.017***	0.016***	0.017***	0.016***	0.017***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Ln(Assets)	-0.056***	-0.045***	-0.044***	-0.049***	-0.050***	-0.047***	-0.049***	-0.049***	-0.049***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)
Domestic banks	0.310***	0.310***	0.302***	0.285***	0.299***	0.314***	0.319***	0.295***	0.282***
	(0.046)	(0.046)	(0.046)	(0.047)	(0.046)	(0.047)	(0.047)	(0.049)	(0.049)
International subsidiary	0.339***	0.338***	0.320***	0.294***	0.341***	0.345***	0.384***	0.351***	0.316***
	(0.046)	(0.049)	(0.048)	(0.050)	(0.046)	(0.047)	(0.051)	(0.048)	(0.052)
Listed	0.408***	0.405***	0.389***	0.371***	0.397***	0.416***	0.420***	0.399***	0.375***
	(0.037)	(0.038)	(0.039)	(0.038)	(0.037)	(0.037)	(0.038)	(0.037)	(0.038)
Bank age (years)	-0.039***	-0.046***	-0.044***	-0.039***	-0.043***	-0.042***	-0.040***	-0.040***	-0.035***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Business volatility	0.253***	0.262***	0.260***	0.254***	0.249***	0.252***	0.255***	0.251***	0.247***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)	(0.034)
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of banks	154	154	154	154	153	153	151	151	151
N	3335	3335	3335	3335	3289	3276	3224	3211	3211
R2	0.19	0.188	0.188	0.192	0.186	0.183	0.186	0.186	0.188

Note: *p<0.1; **p<0.05; ***p<0.01

The table displays regression results for the determinants of absolute profit forecast errors, defined as the difference between forecast and actual as a percentage of total assets.

Clustered standard errors (bank-level) are in parentheses. All continuous right-hand side variables (aside from the forecast horizon) are mean-centred and scaled by 1 standard deviation.

The results in Table 2 suggest that the quality of management and oversight, proxied by average tenure and gender diversity of the executive committee and board of directors (e.g. Adams and Ferreira, 2009; Vafeas, 2003), affects bank forecasting performance. This is in line with the findings of Bloom et al. (2021), who show that managerial quality is associated with forecast accuracy for a sample of non-financial firms. To further investigate this point, we make use of supervisory assessments of bank management and governance. All financial institutions regulated by the PRA are subjectively assessed by supervisors on a number of dimensions. One of these dimensions is management and governance (M&G). This score ranges from 1-10, with 10 being the highest risk level.[10]

Table 3 shows the regression results for each of our key outcome variables when the supervisory M&G score it the outcome measure. Each column includes controls, time fixed effects and robust standard errors clustered at the bank level. Moreover, we standardise the M&G score such that coefficients can be interpreted in terms of expected increases in $|PE|$ for a one standard deviation increase in the M&G score. We find that the M&G score is associated with forecasting errors for each outcome measure, with coefficients ranging from 0.072 to -0.014 for CET1 capital and impairments respectively.

[10] The scoring of firms changed from a 1-10 scale to a 1-4 scale for regulated banks in a staggered timeline beginning in 2021. We make use of the known date when the scoring system was switched over by bank to exclude data after the switch.

Table 3: Relationship between forecast errors and M&G

	Dependent variable:		
	|PE profit|	|PE CET1|	|PE impairments|
	(1)	(2)	(3)
M&G score	0.057**	0.044**	0.091***
	(0.027)	(0.019)	(0.031)
Controls	Y	Y	Y
Time fixed effects	Y	Y	Y
Number of banks	130	150	141
N	1896	2003	1364
R2	0.198	0.16	0.176

Note: *p<0.1; **p<0.05; ***p<0.01
Clustered standard errors (bank-level) are in parentheses.
All continuous right-hand side variables (aside from the forecast horizon) are mean-centred and scaled by 1 standard deviation.

5 Forecast performance and bank outcomes

5.1 Outcome measures

In this section we look at how forecast performance relates to important bank outcomes, namely financial performance and prudential risk. First, for financial performance we take a bank's return on assets (net profit divided by average assets). Second, for risk of insolvency, we take two different indicators: a subjective risk score applied to each bank by PRA supervisors – known as the PIF score (for Proactive Intervention Framework)[11], and the ratio of non-performing loans (i.e. loans which are in arrears for 90+ days) and common equity tier one capital (NPL). The PIF score is a discrete number that ranges from 1 (low risk of insolvency) to 4 (very high risk of insolvency) and is reviewed by supervisors once every 6 months.

We have data on ROA and NPL for the entire time period, but for the PIF score we are confined to the period from 2014 onwards (when the PRA was created). The PIF score is arguably

[11] See details of the PRA's risk scoring framework here.

a more holistic risk indicator than NPL, encompassing subjective assessments of financial and non-financial risks, whereas NPL is focused on one specific source of risk of insolvency (credit risk) and is less suitable for banks with business models that are less focused on lending, e.g. banks with large custodian, asset management, or trading operations. Indeed, because our sample contains banks with a wide array of business models, there are 26 banks, largely subsidiaries of international firms, that do not have any non-performing loans during the period. We drop these banks when looking at NPL as an outcome measure in the empirical analysis below. Descriptive statistics for the outcome measures are included in Table A.1.

Given the large percentage of banks in our sample that are unlisted (66.4%) we do not include an indicator of risk derived from market information in the main analysis. We do, however, also examine the relationship forecast errors and two market risk measures: equity price volatility and tail risk (Ellul and Yerramilli, 2013), for the subset of listed banks in the Annex as part of robustness checks.

5.2 Results

We first collapse the time dimension and examine whether the bank-level mean absolute percentage error (MAPE) is associated with the averaged outcome measures. Given the changes in mean forecast performance highlighted in Figure 1 of Section 3, we restrict the sample to the period pre-Covid – i.e. both forecast and realisation are pre-March 2020 (we relax this to include the full sample in robustness checks and find qualitatively similar results). We include as controls the full set of variables introduced in Section 4 on the determinants of forecast performance and add to that the standard deviation of the absolute percentage error (SDAPE; introduced in Figure 3). Table 4 provides OLS regression results, focusing on forecast errors of net profit, with all continuous variables mean-centered and standardised by one standard deviation.

As expected, we find a negative relationship between the profit forecast MAPE and ROA – banks that are on average worse forecasters tend to also have lower ROA. The effect is substantive – a one standard deviation increase in the MAPE is associated with an expected decrease in ROA by 0.313 of a standard deviation, controlling for all other variables (Column 2 of Table 4).

Turning to the risk measures, the coefficients on the PIF score are positive and significant, suggesting that banks that have higher MAPE also have higher average PIF scores. The coefficient on the PIF score is large – a one standard deviation increase in MAPE is associated with an expected increase in the PIF score by 0.459 of a standard deviation, controlling for all other variables. Moreover, the R^2 value for the unrestricted model (Column 3) is also large – 14.4% of the variation in the PIF score can be explained by cross-bank variation in MAPE. For NPL, the coefficient is significant and positive in the unrestricted model (Column 5), but when introducing the control variables the coefficient becomes indistinguishable from zero (Column 6).

Table 4: Relationship between profit forecast errors and bank outcomes, bank-level averages

	Dependent variable:					
	ROA		PIF		NPL	
	(1)	(2)	(3)	(4)	(5)	(6)
MAPE	-0.281***	-0.313**	0.391***	0.459***	0.168**	0.177
	(0.070)	(0.128)	(0.072)	(0.161)	(0.073)	(0.124)
Std.dev abs(PE)		0.036		-0.022		0.049
		(0.120)		(0.151)		(0.118)
Ln(Assets)		0.120		0.400***		0.442***
		(0.087)		(0.103)		(0.092)
Domestic bank		0.253		0.168		-0.495*
		(0.257)		(0.325)		(0.259)
International subsidiary		0.230		0.223		-0.914***
		(0.256)		(0.327)		(0.285)
Listed		0.258		-0.049		-0.650***
		(0.238)		(0.290)		(0.239)
Bank age (years)		-0.042		-0.142		-0.010
		(0.081)		(0.099)		(0.087)
Business volatility		0.019		0.129		0.154*
		(0.083)		(0.097)		(0.086)
Tenure board + exec average (quarters)		0.169		0.009		-0.096
		(0.118)		(0.109)		(0.130)
Age board + exec average (years)		-0.153		0.251**		0.236**
		(0.093)		(0.105)		(0.099)
Female proportion board + exec		-0.021		-0.158		-0.081
		(0.084)		(0.100)		(0.083)
Tenure CEO (quarters)		0.010		-0.065		-0.028
		(0.107)		(0.108)		(0.120)
Age CEO (years)		0.048		0.039		0.035
		(0.092)		(0.105)		(0.099)
Female CEO		0.011**		0.001		-0.006
		(0.005)		(0.005)		(0.006)
Observations	196	141	179	133	163	123
R^2	0.077	0.167	0.144	0.436	0.032	0.287

Note: *p<0.1; **p<0.05; ***p<0.01
All continuous variables are mean-centred and scaled by 1 standard deviation.

Next, we exploit the panel nature of the data. In the main analysis, we lag all explanatory variables by one quarter (one year in robustness checks) such that our outcome measures are at time t and forecasts (which vary in terms of horizon) are realised at time $t-1$. As with the averaged regression, we exclude all data post-Covid given the big effect the pandemic has had on forecast errors (in robustness checks we include the full sample). We include time (date at which forecast is made) and bank fixed effects, and cluster standard errors at the bank-level. While including bank fixed effects entails looking at within bank variation only, this approach allows us to rule out factors which are constant within bank over time that might be correlated with forecast performance and also the outcome measures of interest, for example organisational culture, which has been shown to be an important factor affecting prudential risk (Suss et al., 2021b) and could conceivably affect forecast performance.

Table 5 provides the headline regression results for the panel data. The main variable of interest is the absolute value of profit PE (as above, we also provide results for other forecasted variables in the Annex). The results show that greater forecasting errors are associated with worse outcomes, even after controlling for both time and bank fixed effects.

For ROA, a one standard deviation increase in abs(PE) is associated with an expected decrease in ROA of 15.4% of a standard deviation in the next quarter. For NPL, the expected effect is to increase the risk ratio by 8.3% of a standard deviation in the next quarter. When not including bank fixed effects, the effect sizes are 18.8% and 8.9% of a standard deviation respectively, and the corresponding coefficient is 10.6% for the PIF score.

Table 5: Relationship between profit forecast errors and bank outcomes, panel data

	Dependent variable:								
	ROA			PIF			NPL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
| PE profit |	-0.180***	-0.188***	-0.154***	0.164***	0.106***	0.065***	0.016	0.089***	0.083***
	(0.040)	(0.047)	(0.030)	(0.027)	(0.027)	(0.021)	(0.022)	(0.033)	(0.027)
Horizon (months)	0.053	0.052*	0.032*	-0.048	-0.019	-0.023	-0.015	-0.036	-0.009
	(0.033)	(0.031)	(0.018)	(0.039)	(0.042)	(0.018)	(0.043)	(0.047)	(0.038)
Ln(Assets)		0.120***	0.815***		0.221***	-0.122		0.405***	-0.160
		(0.034)	(0.150)		(0.045)	(0.138)		(0.041)	(0.178)
Domestic bank		0.150*			0.318***			-0.081	
		(0.081)			(0.087)			(0.087)	
International subsidiary		0.225***			0.576***			-0.480***	
		(0.049)			(0.095)			(0.087)	
Listed		0.200***			0.194**			-0.181**	
		(0.053)			(0.083)			(0.079)	
Bank age (years)		-0.040***	-0.145*		-0.197***	-0.272**		-0.008	-0.803***
		(0.013)	(0.079)		(0.027)	(0.132)		(0.026)	(0.132)
Business volatility		0.087*	0.016		0.120***	0.048**		0.033	-0.008
		(0.051)	(0.028)		(0.028)	(0.020)		(0.029)	(0.029)
Tenure board + exec average (quarters)		0.233***	0.063*		0.003	-0.024		-0.235***	0.015
		(0.048)	(0.032)		(0.043)	(0.036)		(0.054)	(0.044)
Age board + exec average (years)		-0.083***	0.019		0.171***	0.128***		0.148***	0.070**
		(0.031)	(0.028)		(0.024)	(0.028)		(0.030)	(0.031)
Female proportion board + exec		0.030	0.047***		-0.065***	0.045*		-0.029	0.071**
		(0.021)	(0.017)		(0.025)	(0.027)		(0.020)	(0.030)
Tenure CEO (quarters)		0.063***	0.062***		-0.020	-0.011		-0.014	-0.034
		(0.021)	(0.015)		(0.028)	(0.022)		(0.029)	(0.026)
Age CEO (years)		-0.027	-0.051**		-0.015	-0.037		0.049**	-0.009
		(0.022)	(0.021)		(0.025)	(0.023)		(0.024)	(0.029)
Female CEO		-0.007	-0.031**		0.029	-0.024		-0.032*	-0.066***
		(0.021)	(0.012)		(0.024)	(0.016)		(0.016)	(0.025)
Number banks	186	139	139	177	130	130	156	120	120
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank fixed effects	N	N	Y	N	N	Y	N	N	Y
N	3173	2301	2303	1978	1374	1374	2226	1537	1539
R2	0.044	0.092	0.686	0.06	0.321	0.805	0.018	0.178	0.624

Note: *p<0.1; **p<0.05; ***p<0.01

All right-hand side variables are lagged 1 quarter. All continuous variables are mean-centred and scaled by 1 standard deviation (aside from the forecast horizon). Standard errors are clustered at the bank-level.

We run the exact same regressions for PE CET1 and PE impairments – see Table A.4 and Table A.5 in the Annex. As with PE profit, we find an association between absolute forecast errors and prudential risk, even when controlling for bank and time fixed effects. For CET1 forecasts, a one standard deviation increase in absolute errors is associated with an expected 2.6% and 4.8% of a standard deviation increase in PIF and NPL respectively. The equivalent figures are 6.2% and 6.8% for absolute impairments forecast errors.

How sensitive are these results to the empirical choices we make? We run a number of robustness checks to verify our results. First, we examine results when we use an alternative measure of forecast errors. Rather than PE, we instead take the arc distance measure, defined above in Section 2.2. The correlation coefficient between the two error measure is 0.593. Using the arc distance, we find a similar pattern of results as in Table 5 – the coefficient on the forecast error variable is significant and in the same direction (albeit in some cases slightly weaker) for all specifications, including when controlling for both bank and time fixed effects. Table A.6 in the Annex provides these results.

Next, we lag our explanatory variables for 4 quarters (as opposed to 1 quarter in Table 5). This is to account for the possibility that the channels running from forecast errors to outcomes operate with a longer lag. Here, once more we have similar results except now the coefficient on absolute forecast errors is significant when our outcome variable is the PIF score – see Table A.7. We also look at the relationship between forecast performance and a market-based measure of risk, stock price volatility (defined as the standard deviation of a bank's stock price over the last year). This amounts to a subsample analysis due to the fact that 66.4% of banks in our sample are not public. Nevertheless we find a similar pattern of results – banks that have larger forecasting tend to have higher stock price volatility and tail risk, albeit when controlling for bank fixed effects the coefficient is insignificant for equity volatility. See Table A.8 in the Annex for these results. Finally, in our main analysis we restricted the sample to the pre-Covid era given the structural break in mean forecast performance after the onset of the pandemic. This restriction does not affect our results: when including the full sample we do not see any difference in the regression results – see Table A.9.

5.3 Asymmetric forecast errors

We now ask whether there is a distinction between positive and negative errors. In particular, should we expect the impact of errors to be symmetrical, such that both positive errors and negative errors contribute equally to the overall relationship for a given forecasted variable?

To investigate this, we run the same panel regressions as Table 5, albeit the error measure is now separated into two variables: one which is equal to the PE when errors are positive and zero otherwise, and the second which is equal to the absolute PE when errors are negative and zero otherwise. Table 6 presents these findings for profit forecasts, and the Annex we include the results for CET1 and impairment forecasts.

We find that positive profit forecasting errors (i.e. optimistic errors) are driving the associations between forecast errors and outcomes – the coefficients on the positive error variable is in the same direction and of similar, but generally larger, magnitude as those observed in Table 5. In particular, for models with all control variables, time and bank fixed effects included, the coefficients on the positive error variable are -0.182, 0.079, 0.074 for ROA, PIF and NPL respectively.

On the other hand, the coefficient on the negative error variable is generally insignificant from zero. Looking at Columns 3 of Table 6, we see that a one standard deviation increase in absolute negative errors is associated with a decline in ROA by 2.9% of a standard deviation, although this coefficient is not statistically different from zero. This provides some reassurance that the relationship between overall absolute errors and ROA documented in Table 5 is not due to a mechanical relationship between profit errors and ROA.

Table 6: Asymmetric relationship of profit forecast errors and bank outcomes

	Dependent variable:								
	ROA			PIF			NPL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Positive errors	-0.266***	-0.244***	-0.182***	0.201***	0.128***	0.079***	0.021	0.076***	0.074***
	(0.041)	(0.043)	(0.033)	(0.033)	(0.031)	(0.023)	(0.021)	(0.029)	(0.024)
Negative errors	0.088	0.036	-0.029	0.028	0.012	0.006	-0.010	0.103**	0.066*
	(0.054)	(0.073)	(0.031)	(0.023)	(0.028)	(0.019)	(0.034)	(0.051)	(0.038)
Horizon (months)	0.070**	0.065**	0.037**	-0.051	-0.021	-0.024	-0.016	-0.032	-0.006
	(0.034)	(0.032)	(0.018)	(0.038)	(0.040)	(0.017)	(0.043)	(0.047)	(0.038)
Ln(Assets)		0.137***	0.841***		0.211***	-0.120		0.413***	-0.156
		(0.036)	(0.153)		(0.043)	(0.134)		(0.041)	(0.177)
Building society		0.127			0.320***			-0.099	
		(0.081)			(0.087)			(0.088)	
International subsidiary		0.237***			0.572***			-0.470***	
		(0.048)			(0.095)			(0.086)	
Listed		0.186***			0.197**			-0.190**	
		(0.052)			(0.083)			(0.079)	
Bank age (years)		-0.044***	-0.146*		-0.192***	-0.269**		-0.011	-0.808***
		(0.013)	(0.078)		(0.027)	(0.130)		(0.026)	(0.131)
Business volatility		0.069	0.010		0.141***	0.058***		0.022	-0.016
		(0.056)	(0.031)		(0.030)	(0.022)		(0.026)	(0.027)
Tenure board + exec average (quarters)		0.221***	0.063**		0.002	-0.029		-0.234***	0.015
		(0.046)	(0.031)		(0.045)	(0.038)		(0.054)	(0.043)
Age board + exec average (years)		-0.080**	0.018		0.182***	0.138***		0.144***	0.069**
		(0.031)	(0.029)		(0.027)	(0.031)		(0.030)	(0.031)
Female proportion board + exec		0.030	0.047***		-0.066***	0.043		-0.030	0.071**
		(0.022)	(0.017)		(0.025)	(0.027)		(0.020)	(0.030)
Tenure CEO (quarters)		0.053***	0.056***		-0.019	-0.010		-0.020	-0.037
		(0.019)	(0.014)		(0.031)	(0.023)		(0.029)	(0.026)
Age CEO (years)		-0.026	-0.050**		-0.013	-0.035		0.049**	-0.008
		(0.022)	(0.021)		(0.026)	(0.024)		(0.024)	(0.029)
Female CEO		-0.009	-0.034**		0.030	-0.028		-0.031*	-0.066***
		(0.023)	(0.014)		(0.026)	(0.017)		(0.016)	(0.025)
Number banks	186	139	139	177	130	130	156	120	120
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank fixed effects	N	N	Y	N	N	Y	N	N	Y
N	3173	2301	2303	1978	1374	1374	2226	1537	1539
R2	0.078	0.109	0.688	0.063	0.323	0.805	0.019	0.182	0.625

Note: *p<0.1; **p<0.05; ***p<0.01
All continuous variables are mean-centred and scaled by 1 standard deviation.
All right-hand side variables are lagged 1 quarter.
Standard errors are clustered at the bank-level.

We find a similar pattern of asymmetry between negative and positive errors for our other forecasted variables of interest. Table A.10 in the Annex provides the results for CET1 forecasts.

As with profit forecasts, the relationship between errors and prudential outcomes is driven by positive errors – banks that are overly optimistic about future capital levels are subsequently riskier, both when measured by the PIF score and NPL (coefficients of 0.03 and 0.054 when controlling for all variables, bank and time fixed effects). Moreover, as with profit forecasts, there is no statistically significant relationship between errors of pessimism (negative errors) and prudential outcomes. However, while the coefficient on the aggregate error term for ROA was statistically insignificant (Column 3 of Table A.4), we now find a significant, albeit small in magnitude, relationship between negative CET1 forecast errors and ROA, controlling for all other variables (β = 0.019; Column 3 of Table A.10).

Looking at impairments (Table A.11), it is negative errors which are driving the results that we report in Table A.5. In other words, just as with profit and CET1 it is over-optimism with respect to impairments (i.e. expecting smaller impairments than what is realised) which is associated with subsequently higher prudential riskiness. The coefficients for PIF and NPL when controlling for all variables (Column 6 and 9 of Table A.11) are 0.071 and 0.076 respectively. Consistent with the results reported in Table A.5, we find no relationship between positive or negative impairment errors and ROA.

5.4 Loan growth

Next, we ask whether forecasting performance affects important bank business decisions. In particular, we focus on lending – the primary activity of banks, and examine whether forecast errors are associated with changes in lending at the firm-level. For changes in lending, we take yearly loan growth (%), inclusive of all types of loans.

Table 7 provides the regression results for each of our main explanatory variables with all controls (including bank and time fixed effects) included. We find that forecast errors have a significant impact on loan growth, across all our forecasted variables of interest. The impact of forecasting performance on lending is also economically large: a one standard deviation increase in the absolute profit PE is associated with an expected 5.38 percentage point decrease in lending year-on-year. The equivalent figures are 8.92 and 6.27 for CET1 and impairment forecasts respectively. When decomposing absolute errors into positive and negative errors, we once more see that it is optimistic errors which are driving the association for CET1 and impairment forecasts – see Table 8. However, for profit forecast errors, both positive and negative errors are associated with reduced loan growth. In other words, banks that expect higher capital and lower impairments than is realised tend to reduce lending, whereas banks that expect higher or lower profit than is realised reduce lending. The coefficient on the negative profit error variable is over three times larger than that of positive errors, suggesting that expectations of reduced profitability affect lending even when this turns out to be wrong. This chimes with findings by Enders et al. (2022), who show that incorrect expectations by German manufacturing firms affects production and price setting.

Table 7: Relationship between forecast errors and loan growth, absolute forecast errors

	Dependent variable:		
	Loan growth		
	Profit	CET1	Impairments
	(1)	(2)	(3)
| PE |	-5.381***	-8.920***	-6.274***
	(1.439)	(2.431)	(1.635)
Control variables included	Y	Y	Y
Time fixed effects	Y	Y	Y
Firm fixed effects	Y	Y	Y
Number of banks	138	132	137
N	2475	1622	2159
R2	0.195	0.544	0.262

Note: *p<0.1; **p<0.05; ***p<0.01

Regression results for the effect of forecast performance on bank loan growth (year on year percent).

The percentage error measure is mean-centred and scaled by one standard deviation. Clustered standard errors (bank-level) are in parentheses.

Table 8: Relationship between forecast errors and loan growth, panel data

	Dependent variable:		
		Loan growth	
	Profit	CET1	Impairments
	(1)	(2)	(3)
Positive errors	-5.879***	-9.209***	-1.767
	(1.899)	(2.475)	(1.281)
Negative errors	-16.079***	1.155	-6.247***
	(4.606)	(2.050)	(1.628)
Control variables included	Y	Y	Y
Time fixed effects	Y	Y	Y
Firm fixed effects	Y	Y	Y
Number of banks	138	132	137
N	2475	1622	2159
R2	0.198	0.546	0.262

Note: *p<0.1; **p<0.05; ***p<0.01

Regression results for the effect of forecast performance on bank loan growth (year on year percent).

The percentage error measure is mean-centred and scaled by one standard deviation. Clustered standard errors (bank-level) are in parentheses.

6 Discussion and conclusion

In this paper, we use a newly constructed dataset based on detailed regulatory returns to analyse bank expectations. We document a number of findings. First, banks tend to be optimistic. This holds for forecasts of different key variables: net profit, CET1 capital, and loan impairments, and is in line with a body of work on individual and managerial optimism biases (e.g. Ben-David et al., 2013) However, while the tendency is towards optimism, we show that there is a wide variation in performance across banks – a substantial proportion of firms are characterised by pessimism, while others can simply be seen as accurate forecasters. Moreover, we find that on average banks become more pessimistic during periods of economic difficulty or uncertainty, exemplified by the Covid pandemic. We then investigate the predictors of forecast performance, finding that important board and executive characteristics, namely tenure and gender diversity, are associated with reduced forecast errors. We also show a more direct association between forecast errors and quality of a bank's management and governance as rated by regulators, echoing findings by Bloom et al. (2021).

Importantly, we show that forecast errors are robustly associated with bank prudential outcomes, even after controlling for time and bank fixed effects. Banks that have higher forecast errors tend also to be higher risk in future periods. This relationship is driven by errors of optimism across our forecast variables of interest – it is banks that wrongly expect higher profits, higher capital levels, and lower loan impairments in future that are subsequently higher risk. Errors of pessimism, on the other hand, are not associated with bank prudential outcomes. Finally, we also show that forecast errors affect subsequent bank lending growth. Banks that have higher forecast errors also tend to have lower lending growth. This is in line with findings by Ma et al. (2021), who also show that forecast errors affect loan growth, albeit their study uses bank macro forecasts.

How would bank expectations affect firm-level prudential outcomes? While we do not have empirical data to address this question, there are a number of possible channels through which forecasting might affect bank outcomes: i) strategic – poor forecasting can lead to mis-allocated investments and strategic churn, ii) liability costs – poor forecasting performance can affect the cost of short term liabilities, and iii) employee morale – poor forecasting may diminish employee morale and coordination.

First, forecast errors suggest that a series of investment and strategic decisions were not, in hindsight, optimal. For example, a bank might have hired a certain number of additional employees, invested in new business lines, or opened new branches, all in expectation of a certain level of future profitability. Tanaka et al. (2020) support this view via a theoretical model showing that firm forecasting errors affect business outcomes based on mis-allocated investments.[12]

Not only are the mis-allocated investments sunk to a certain extent, putting downward pressure on overall performance and increasing riskiness, but also there are likely to be additional costs. In particular, if expectations around key items, such as profitability and capital, are not realised in a substantial sense, i.e. the forecasting error is large, strategic re-direction and retrenchment may become necessary, e.g. in response to pressure from shareholders or private

[12] However, the model in Tanaka et al. (2020) predicts symmetrical effect of errors – i.e. errors of optimism are as damaging as errors of pessimism, and the authors test the model's predictions for a set of Japanese manufacturing firms, finding evidence of a roughly symmetrical effect for forecasting performance and financial outcomes. We find asymmetric effects, perhaps due to the different types of firms examined.

owners. A bank that is relatively poor at forecasting thus might experience greater strategic churn, as the business strategy will need to be more frequently revised and updated relative to firms that are better at forecasting. This in and of itself may lead to relatively worse performance and higher riskiness as the transformation costs are unlikely to be trivial. For example, certain executives might be replaced as a result of a loss of confidence from shareholders/owners, which contributes to senior staff churn. Note that the costs of this element is likely to be asymmetric – while strategic re-direction might be required in cases where banks are overly pessimistic (e.g. opportunities were left un-seized), the consequences of being optimistic are likely to be more costly, as it is under-performance relative to expectations which is likely to result in more drastic personnel and strategy overhauls.

Second, forecast performance might have important implications for banks due to the distinct nature of their balance sheet. In particular, banks lend for the long term, e.g. mortgages, but are funded largely through short term and liquid sources, e.g. debt or demand deposits. In other words, there is a temporal mismatch between a typical bank's assets and liabilities. Institutions which have forecast higher profitability than is realised might therefore see their existing funding base become more expensive as those providing short term funding require larger risk premia, and vice versa – banks which exceed expectations might be looked on as safer than expected, thereby gaining through less costly short-term borrowing. If the error is sufficiently large and positive (i.e. optimistic), this might even require additional funding to be raised to plug the shortfall, and this can be additionally costly, e.g. raising fresh capital.

Third, poor forecasting performance might also contribute to worse outcomes by affecting employee morale. In particular, repeatedly under-performing against targets might sap employee confidence in management and sense of shared purpose, thereby potentially reducing productivity and increasing staff turnover. On the other hand, exceeding expectations might boost morale and suggest to employees that remuneration will increase.

While we set out some possible mechanisms that explain our findings here, an empirical exploration of possible mechanism is warranted. In particular, setting out the importance of these channels (and other possible channels), as well as how they might reinforce one another, would be valuable. For example, empirical analysis might be able to verify whether consistently poor forecasting performance leads to reduced morale, perhaps by looking at staff turnover or employee surveys. Empirical researchers armed with relevant data might be able to substantiate or disprove the findings here on the relationship between micro-level forecast errors and prudential outcomes.

Of course we do not claim that our empirical results confirm a causal relationship between forecast performance and bank outcomes, merely that our findings provide evidence that this is the case. For example, we cannot control for an idiosyncratic exogenous shock that throw bank forecasts off and increase risk simultaneously, and there may be omitted variables which vary across banks and over time which affect both forecast performance and outcomes. Future work might seek to exploit quasi-experimental data to bolster the evidence presented here.

The forecast data used here might also be of value when looked at in aggregate. For example, further research might seek to assess what the system-level implications of optimistic or pessimistic aggregate forecasts might be, as other studies have done for non-financial firms (Ma et al., 2020; Tanaka et al., 2020; Enders et al., 2022). While this question is outside of the scope of this work, it is clearly important – if the banking sector on the whole looks to the future with rose-tinted glasses or vice versa, what might that mean for the efficient allocation of capital to the real economy?

Overall, the evidence presented in this paper suggests a previously undocumented source of bank prudential risk in the form of bank forecast errors. Our findings are important from a regulatory perspective as well as for other stakeholders – supervisors, shareholders, and directors, among other interested parties, should seek to interrogate bank forecasting operations or to track forecasting performance to understand whether expectations are consistently off the mark and in order to avert the potentially negative consequences.

Annex

Table A.1: Descriptive statistics

Statistic	N	Median	Mean	St. Dev.
PE profit	4,539	0.010	0.177	0.900
PE CET1	4,034	0.052	0.668	4.514
PE impairments	3,754	0.000	-0.071	0.437
Ln(Assets)	8,088	7.243	7.943	2.755
Domestic bank	8,959	0.000	0.153	0.360
Building society	8,959	0.000	0.238	0.426
International subsidiary	8,959	0.000	0.164	0.370
Listed	8,959	0.000	0.446	0.497
Bank age (years)	8,230	29.000	45.923	43.377
Business volatility	6,704	0.091	0.214	0.369
Tenure board + exec average (quarters)	7,923	9.958	10.781	6.337
Age board + exec average (years)	7,904	54.512	54.778	3.635
Female board + exec (%)	7,923	16.092	17.031	12.613
Tenure CEO (quarters)	7,712	9.000	11.223	9.479
Age CEO (years)	7,582	54.000	53.565	5.823
Female CEO	7,539	0.000	0.076	0.264
ROA (%)	7,469	0.238	0.227	0.909
NPL CET1 (%)	5,815	12.767	24.050	33.078

Figure A.1: MPE by year for income and expense sub-components

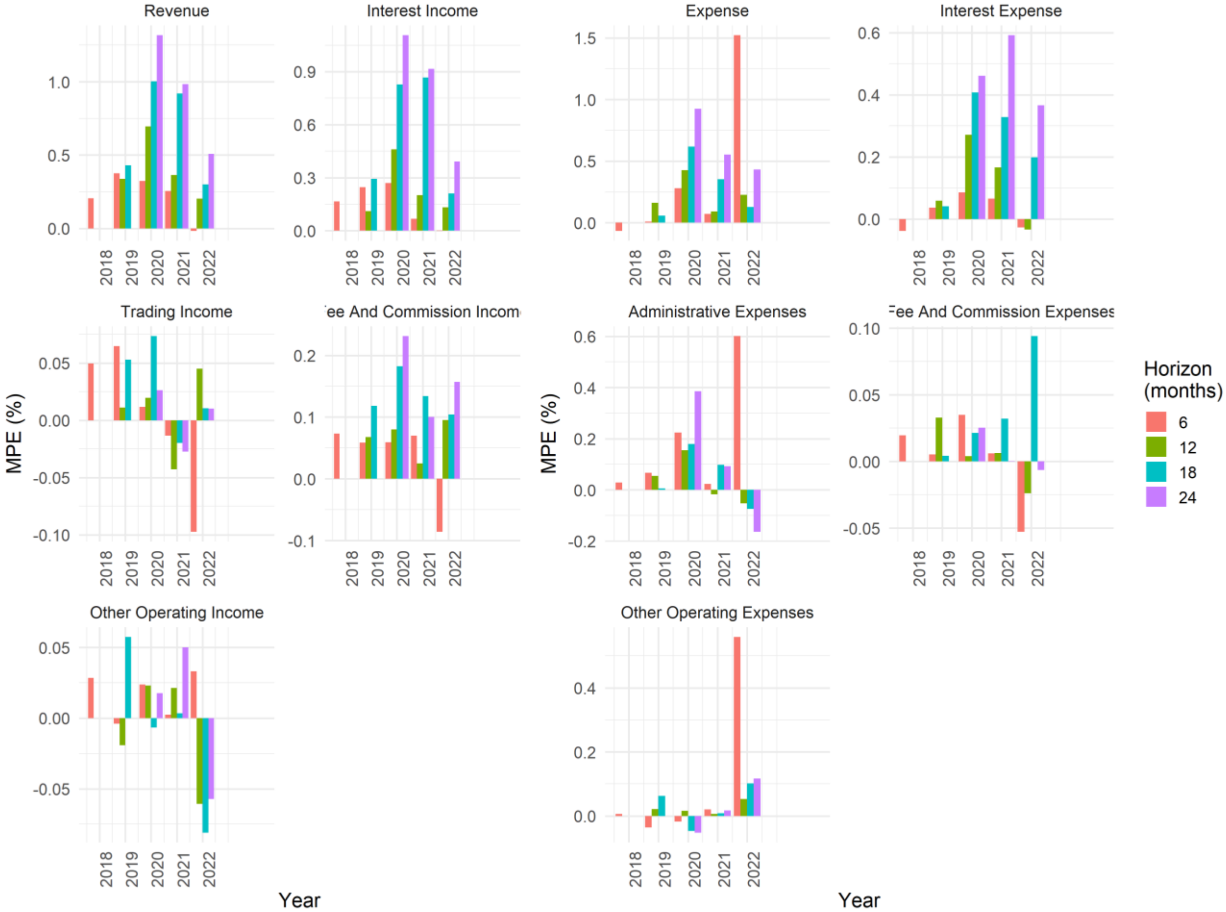


Figure A.2: Forecast performance by bank – impairments

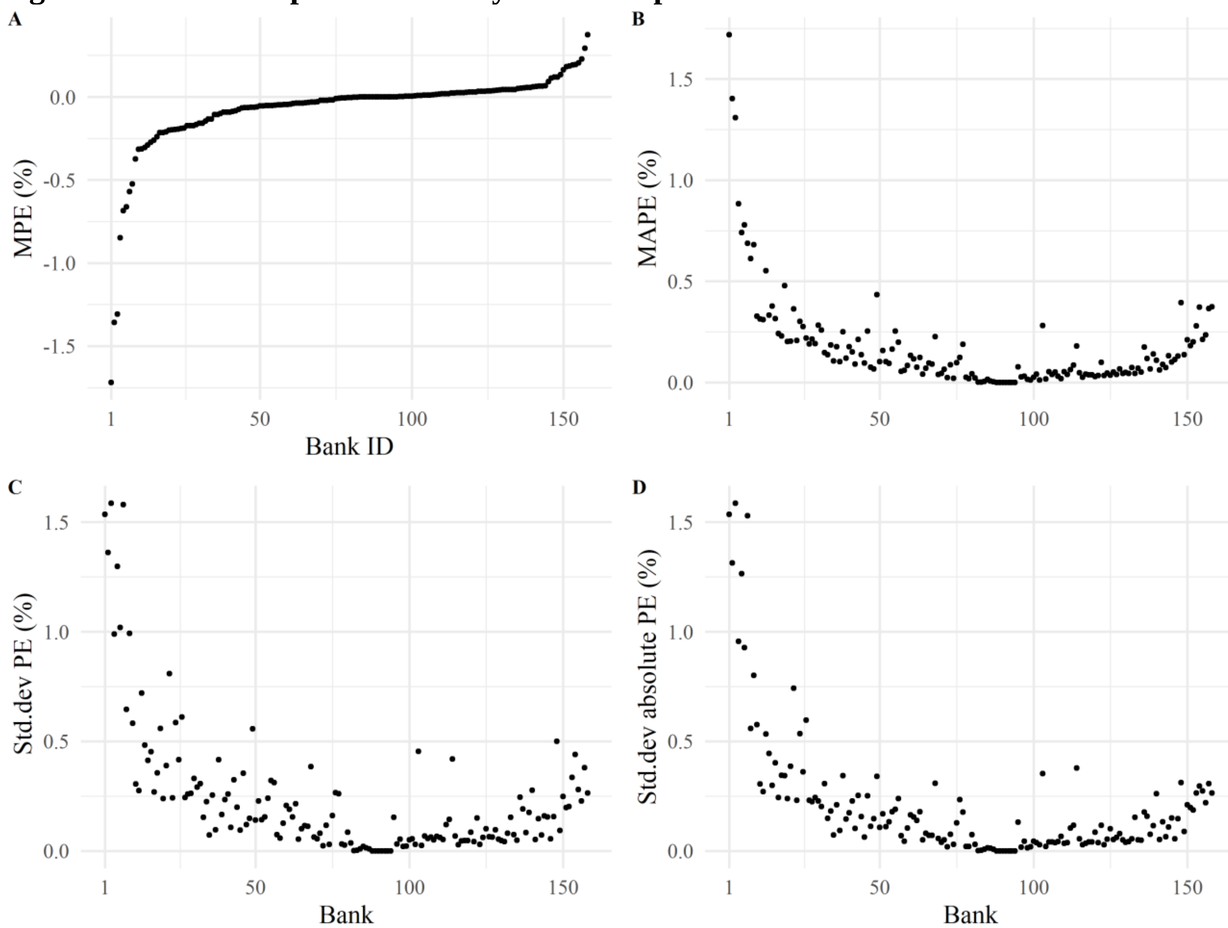


Figure A.3: Forecast performance by bank – CET1 capital

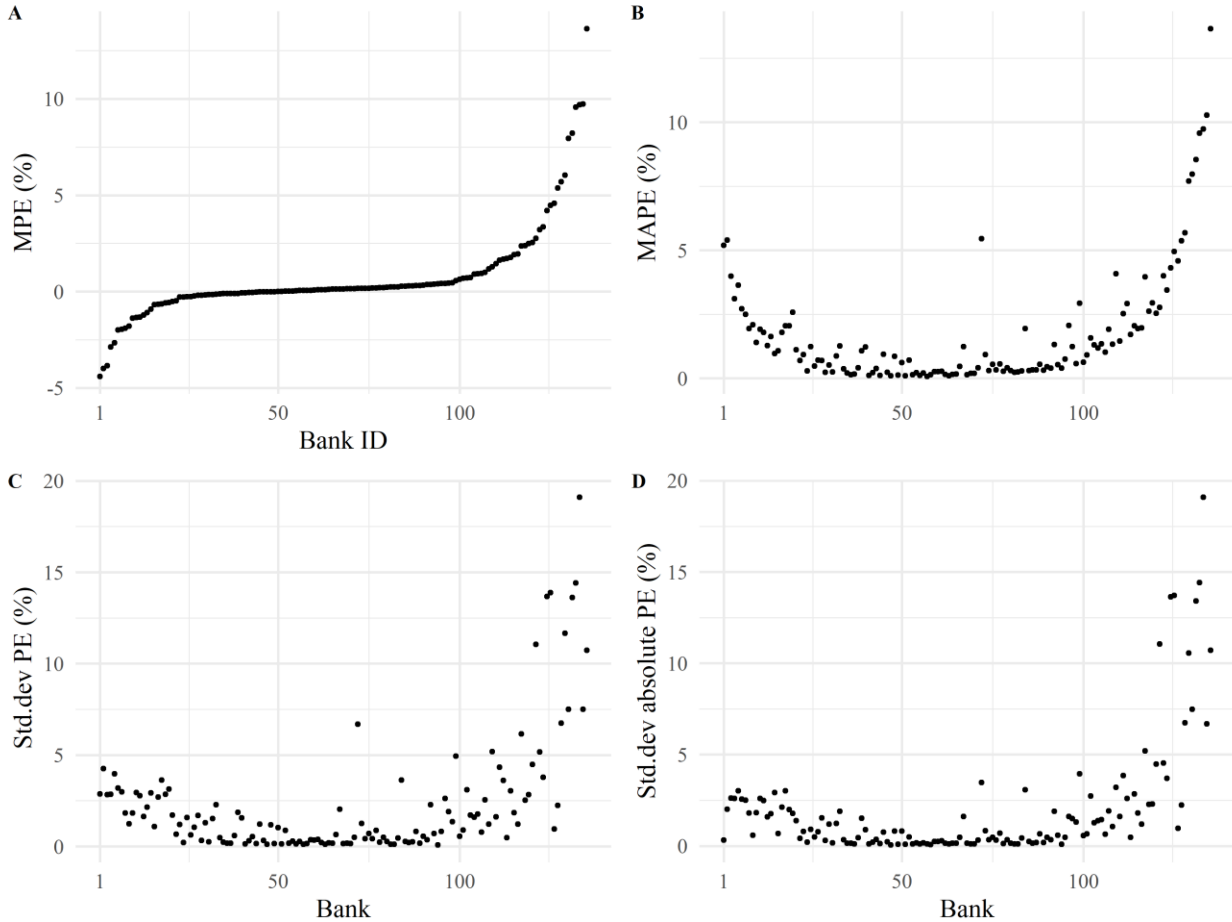


Table A.2: Determinants of CET1 forecasting errors

	Dependent variable:								
	|PE CT1|								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tenure board + exec average (quarters)	-0.031			-0.011					0.044
	(0.027)			(0.028)					(0.035)
Age board + exec average (years)		-0.034**		-0.027					-0.010
		(0.017)		(0.018)					(0.028)
Female proportion board + exec			0.039**	0.035*					0.023
			(0.019)	(0.019)					(0.021)
Tenure CEO (quarters)					-0.085***			-0.072***	-0.082***
					(0.021)			(0.021)	(0.025)
Age CEO (years)						-0.045***		-0.036**	-0.035
						(0.017)		(0.017)	(0.024)
Female CEO							0.251*	0.225*	0.201
							(0.136)	(0.134)	(0.137)
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of banks	154	154	154	154	153	153	151	151	151
N	2439	2439	2439	2439	2413	2404	2385	2376	2376
R2	0.106	0.107	0.107	0.108	0.11	0.109	0.099	0.104	0.105

Note: *p<0.1; **p<0.05; ***p<0.01

Clustered standard errors (bank-level) are in parentheses.

All continuous right-hand side variables (aside from the forecast horizon) are mean-centred and scaled by 1 standard deviation.

Table A.3: Determinants of impairments forecasting errors

	Dependent variable:								
	Dependent variable: |PE impairments|								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tenure board + exec average (quarters)	0.058			0.085*					0.087
	(0.043)			(0.048)					(0.058)
Age board + exec average (years)		-0.021		-0.047					-0.029
		(0.035)		(0.039)					(0.045)
Female proportion board + exec			0.027	0.022					0.028
			(0.035)	(0.035)					(0.035)
Tenure CEO (quarters)					-0.004			0.004	-0.021
					(0.025)			(0.027)	(0.032)
Age CEO (years)						-0.039		-0.048	-0.038
						(0.031)		(0.034)	(0.037)
Female CEO							-0.462***	-0.486***	-0.490***
							(0.123)	(0.125)	(0.126)
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Number of banks	154	154	154	154	153	153	151	151	151
N	1273	1273	1273	1273	1260	1255	1243	1238	1238
R2	0.113	0.112	0.112	0.114	0.11	0.113	0.117	0.12	0.122

Note: *p<0.1; **p<0.05; ***p<0.01

Clustered standard errors (bank-level) are in parentheses.

All continuous right-hand side variables (aside from the forecast horizon) are mean-centred and scaled by 1 standard deviation.

Table A.4: Relationship between CET1 forecast performance and bank outcomes

	Dependent variable:								
		ROA			PIF			NPL	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
| PE CT1 |	0.029	-0.006	-0.038	0.112^{***}	0.082^{***}	0.026^{**}	-0.029^{**}	0.015	0.048^{**}
	(0.046)	(0.043)	(0.025)	(0.021)	(0.031)	(0.013)	(0.014)	(0.024)	(0.023)
Number banks	157	122	122	176	133	133	126	101	101
Control variables included	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank fixed effects	N	N	Y	N	N	Y	N	N	Y
N	2276	1454	1454	2590	1438	1438	1792	873	873
R2	0.035	0.186	0.885	0.104	0.353	0.871	0.148	0.44	0.886

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

All continuous variables are mean-centred and scaled by 1 standard deviation (aside from the forecast horizon).

All right-hand side variables are lagged 1 quarter.

Standard errors are clustered at the bank-level.

Table A.5: Relationship between impairments forecast performance and bank outcomes

	Dependent variable:								
	ROA			PIF			NPL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
| PE Impairments |	-0.075**	-0.105**	-0.040	0.181***	0.110***	0.062**	0.106***	0.107***	0.068**
	(0.036)	(0.042)	(0.040)	(0.026)	(0.025)	(0.028)	(0.029)	(0.039)	(0.032)
Number banks	178	137	137	173	129	129	153	116	116
Control variables included	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank fixed effects	N	N	Y	N	N	Y	N	N	Y
N	2900	2071	2073	1700	1154	1154	2115	1456	1458
R2	0.032	0.084	0.638	0.059	0.327	0.803	0.036	0.189	0.628

Note: *p<0.1; **p<0.05; ***p<0.01

All continuous variables are mean-centred and scaled by 1 standard deviation (aside from the forecast horizon).

All right-hand side variables are lagged 1 quarter.

Standard errors are clustered at the bank-level.

Table A.6: Robustness check – arc distance error metric

	Dependent variable:								
	ROA			PIF			NPL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
| Arc distance profit |	-0.149^{***}	-0.150^{***}	-0.042^{**}	0.257^{***}	0.152^{***}	0.039^{**}	0.114^{***}	0.100^{***}	0.052^{***}
	(0.021)	(0.023)	(0.017)	(0.026)	(0.029)	(0.019)	(0.025)	(0.025)	(0.018)
Number banks	187	139	139	174	130	130	154	120	120
Control variables included	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank fixed effects	N	N	Y	N	N	Y	N	N	Y
N	2833	2070	2071	1773	1225	1225	1978	1381	1382
R2	0.032	0.095	0.693	0.097	0.359	0.814	0.04	0.177	0.633

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
All continuous variables are mean-centred and scaled by 1 standard deviation.
All right-hand side variables are lagged 1 quarter.
Standard errors are clustered at the bank-level.

Table A.7: Regression robust – four quarter lag

	Dependent variable:								
	ROA			PIF			NPL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
| PE profit |	-0.127***	-0.186***	-0.097**	0.166***	0.095***	0.063***	0.024	0.086**	0.047*
	(0.040)	(0.045)	(0.039)	(0.022)	(0.023)	(0.018)	(0.025)	(0.039)	(0.026)
Number banks	184	138	138	175	130	130	151	118	118
Control variables included	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank fixed effects	N	N	Y	N	N	Y	N	N	Y
N	3118	2261	2263	2206	1549	1549	2161	1499	1501
R2	0.027	0.081	0.691	0.052	0.312	0.806	0.022	0.2	0.712

Note: *p<0.1; **p<0.05; ***p<0.01

All continuous variables are mean-centred and scaled by 1 standard deviation (aside from the forecast horizon).

All right-hand side variables are lagged 4 quarters.

Standard errors are clustered at the bank-level.

Table A.8: Regression robust – risk measures from market prices

	Dependent variable:					
	Stock price volatility			Tail risk		
	(1)	(2)	(3)	(4)	(5)	(6)
| PE profit |	0.043	0.096**	-0.019	0.118***	0.162***	0.072**
	(0.037)	(0.047)	(0.033)	(0.027)	(0.038)	(0.032)
Number banks	70	59	59	68	59	59
Control variables included	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y
Bank fixed effects	N	N	Y	N	N	Y
N	1164	823	823	1313	984	984
R2	0.029	0.069	0.48	0.188	0.191	0.481

Note: *p<0.1; **p<0.05; ***p<0.01
All continuous variables are mean-centred and scaled by 1 standard deviation.
All right-hand side variables are lagged 1 quarter.
Standard errors are clustered at the bank-level.

Table A.9: Regression robust – pre-Covid data

	Dependent variable:								
		ROA			PIF			NPL	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
| PE profit |	-0.234***	-0.210***	-0.179***	0.191***	0.068***	0.042**	0.013	0.073***	0.067***
	(0.034)	(0.038)	(0.028)	(0.021)	(0.023)	(0.018)	(0.020)	(0.028)	(0.022)
Number banks	199	150	150	186	142	142	161	121	121
Control variables included	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank fixed effects	N	N	Y	N	N	Y	N	N	Y
N	4261	3135	3137	3029	2175	2175	2540	1790	1792
R2	0.075	0.106	0.667	0.053	0.306	0.807	0.021	0.181	0.584

Note: *p<0.1; **p<0.05; ***p<0.01

Regression results for relationship between absolute profit percentage error and bank outcomes, using full sample of data (i.e. including post-Covid observations).

All continuous variables are mean-centred and scaled by 1 standard deviation. All right-hand side variables are lagged 1 quarter. Standard errors are clustered at the bank-level.

Table A.10: Asymmetric relationship of CET1 forecasting errors and bank outcomes

	Dependent variable:								
	ROA			PIF			NPL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Positive errors	0.042	0.003	-0.046	0.118***	0.106***	0.030**	-0.015	0.049**	0.054**
	(0.053)	(0.048)	(0.029)	(0.022)	(0.029)	(0.014)	(0.014)	(0.025)	(0.023)
Negative errors	-0.044***	-0.043**	0.019**	0.038**	-0.064***	-0.011	-0.060***	-0.113***	-0.003
	(0.015)	(0.017)	(0.010)	(0.017)	(0.019)	(0.015)	(0.017)	(0.018)	(0.019)
Number banks	167	134	134	179	147	147	132	108	108
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank fixed effects	N	N	Y	N	N	Y	N	N	Y
N	3378	2362	2362	3668	2323	2323	2380	1364	1364
R2	0.054	0.153	0.794	0.075	0.314	0.849	0.116	0.394	0.866

Note: *p<0.1; **p<0.05; ***p<0.01
All continuous variables are mean-centred and scaled by 1 standard deviation.
All right-hand side variables are lagged 1 quarter.
Standard errors are clustered at the bank-level.

Table A.11: Asymmetric relationship of impairment forecasting errors and bank outcomes

	Dependent variable:								
	ROA			PIF			NPL		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Positive errors	-0.008	-0.034	-0.003	0.046^{**}	0.011	-0.007	0.033^{*}	0.023	-0.018
	(0.022)	(0.023)	(0.019)	(0.021)	(0.019)	(0.018)	(0.018)	(0.022)	(0.018)
Negative errors	-0.076^{**}	-0.103^{**}	-0.041	0.183^{***}	0.116^{***}	0.071^{**}	0.106^{***}	0.108^{***}	0.076^{**}
	(0.036)	(0.042)	(0.040)	(0.027)	(0.026)	(0.030)	(0.030)	(0.041)	(0.033)
Number banks	189	145	145	179	136	136	157	118	118
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Bank fixed effects	N	N	Y	N	N	Y	N	N	Y
N	3537	2559	2561	2315	1619	1619	2320	1608	1610
R2	0.037	0.068	0.618	0.044	0.335	0.803	0.041	0.192	0.609

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
All continuous variables are mean-centred and scaled by 1 standard deviation.
All right-hand side variables are lagged 1 quarter.
Standard errors are clustered at the bank-level.

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