
Business Models and Organizational Commitments: Evidence from IFRS 9

Francesco Grazioli*
ESCP Business School

Gabriel Pundrich*
University of Florida

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Abstract

This paper investigates whether and how the business model approach introduced by IFRS 9 creates organizational commitments that influence forecasters' judgments and expectations. We answer this research question by exploring whether banks' interest rate forecasts are aligned with their business models of sovereign debt under IFRS 9. Exploiting sovereign debt classifications from European Banking Authority transparency exercises matched with bank-level interest rate forecasts in the 2018-2024 period, we find that when banks face immediate income statement recognition (Held-for-Trading category), their interest rate forecasts underestimate future interest rates, consistent with the organizational commitment to market volatility. When banks are prevented from selling government bonds (Held-to-Maturity category), their forecasts miss turning points in interest rates, consistent with the organizational commitment to illiquid holding decisions. We also find that these forecast distortions are more pronounced among banks with lower regulatory capital, suggesting that regulatory capital considerations are a channel through which the business model approach creates organizational commitments. Finally, we document that these forecast distortions are muted when banks issue macroeconomic forecasts that are not directly related to their business models.

JEL Classifications: M41, G14, G32

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*Direct correspondence to Francesco Grazioli fgrazioli@escp.eu and Gabriel Pereira Pundrich gabriel.pundrich@warrington.ufl.edu.

1. Introduction

Organizations routinely adopt commitments that guide their decisions and provide a basis for interpreting information ([Akerlof and Dickens, 1982](#); [Kahneman et al., 1982](#); [Ayman and Georg, 2015](#)). Yet external audiences may have difficulty observing whether these commitments meaningfully shape organizational behavior. Business models can provide an observable representation of such commitments by formally indicating how organizations intend to manage particular assets. Prior accounting research primarily examines how business models of financial instruments affect reporting outcomes ([Beatty, 1995](#); [Kanodia, 2006](#); [Argimon et al., 2018](#)), investment decisions ([Hodder et al., 2002](#); [Chircop and Novotny-Farkas, 2016](#)), and lending choices ([Meder, 2015](#); [Kim et al., 2019](#)). Less is known, however, about whether business models are also aligned with the expectations that organizations communicate about the future.

Under IFRS 9, banks classify financial assets according to their intended business models, thereby formalizing organizational commitments concerning how those assets are managed. Once set by a bank’s investment committee in accordance with its strategic guidelines, these business models may influence how forecasters interpret and incorporate subsequent economic information. This paper therefore examines whether and how banks’ interest rate forecasts are aligned with their business models of sovereign debt under IFRS 9, beyond the information reflected in economic fundamentals.

This question matters because forecasters help market participants form expectations and are generally viewed as credible sources of information ([Cheng et al., 2021](#)). If banks’ forecasts partly align with organizational commitments, users may misinterpret these forecasts as independent signals about economic fundamentals. Such misinterpretation can distort asset prices and investment decisions. Moreover, forecasts aligned with organizational commitments may delay banks’ recognition of changing interest rate conditions and, consequently, alter their valuations, funding strategies, and credit policies. When adjustments to the ac-

tual economic backdrop eventually occur, their concentration may amplify procyclicality and contribute to a contraction in credit supply.

Despite the implications for real economic activity and capital market efficiency, prevailing research models forecast distortions as stemming from reputational concerns, revision rigidities, or cognitive biases (e.g., [Ottaviani and Sørensen, 2006](#); [Coibion and Gorodnichenko, 2012](#); [Gennaioli et al., 2016](#)), and treats forecasts as stemming from fundamental beliefs modified by incentives, rather than outputs aligned with reporting systems ([Beyer et al., 2010](#)). Behavioral models generally assume that forecasters observe external economic signals subject to processing biases, but rarely consider these agents as committed to their own institutions ([Sims, 2003](#)), and empirical studies on forecast behavior routinely attribute forecast distortions to trading motives or past performance, largely overlooking the role of organizational commitments (e.g., [Hong et al., 2000](#)). Consequently, whether such commitments influence forecast behavior remains an under-researched question that this paper addresses.

IFRS 9 renders banks' business models observable through their accounting classification of financial assets. Under this standard, government bonds managed with the objective of collecting contractual cash flows, analogous to the Held-to-Maturity (HTM) category, are measured at amortized cost (AC). For this category, changes in their fair value do not affect profits. By contrast, government bonds held for trading, analogous to the Held-for-Trading (HFT) category, are measured at fair value through profit or loss (FVTPL). For this category, changes in market prices are immediately recognized in the income statement.

Since a bank's investment committee sets business models according to its strategic guidelines, accounting classifications formally represent different ways in which banks commit to managing their government bond portfolios. They formalize strategic positions, communicate priorities throughout the organization, and create pressures to act accordingly when new information is evaluated. As a result, we argue that forecasts are deemed to be consistent with the organizational commitments stemming from the business models adopted. Once

a business model has been set, contradictory information can become increasingly costly to acknowledge because it challenges previously adopted beliefs. The consequence is not necessarily intentional manipulation. Instead, business models may shape forecasters' attention allocation, information updating, and sensemaking processes inside organizations. Therefore, we use the business model approach introduced by IFRS 9 to observe organizational commitments within a bank and investigate whether interest rate forecasts are aligned with those commitments.

To empirically test organizational commitments, we exploit a setting made possible by two concurrent developments. First, the adoption of IFRS 9 in January 2018 introduced the business model approach. Banks shall classify government bonds according to their intended use into standardized categories, with distinct consequences for profits and regulatory capital. Second, the European Banking Authority (EBA) transparency exercises include bank-level sovereign debt exposures, enabling us to observe how the same bank classifies government bonds from different sovereign issuers across different business models. Together, we are able to construct a novel dataset that combines banks' business models of sovereign debt with their interest rate forecasts sourced from Thomson Reuters Eikon. Our final sample consists of 953 interest rate forecasts matched with concurrent accounting classifications of sovereign debt for 30 systemically important banks over the period from 2018 to 2024.

Our empirical analysis supports our predictions that banks' interest rate forecasts are aligned with their business models of sovereign debt, suggesting that organizational commitments shape forecasters' judgment and expectations. On the one hand, banks with large Held-for-Trading exposures, which are measured at fair value through profit or loss, are committed to market volatility because they are not insulated from price fluctuations and face immediate market feedback in their income statements (e.g., [Kanagaretnam et al., 2003](#); [Liu and Ryan, 2006](#); [Kilic et al., 2013](#)). Since the consequences of unfavorable fair value changes immediately affect profits, information implying losses becomes particularly consequential. Banks with large HFT exposures thus pay closer attention to interest rate developments

and correctly identify the direction in which rates are moving. However, their forecasts do not incorporate the full magnitude of adverse future interest rate increases. They therefore forecast in the correct direction but insufficiently adjust the forecast level.

On the other hand, banks with large Held-to-Maturity exposures, which are measured at amortized cost, are committed to illiquid holding decisions ([Meder, 2015](#); [Chircop and Novotny-Farkas, 2016](#); [Kim et al., 2019](#)). This commitment stems from an holding rationale and, consequently, is likely to result in a weaker recognition of turning points in interest rates. Our results indicate that banks are less likely to recognize whether interest rates will increase or decrease at all. Because unrealized fair value changes on HTM exposures do not directly affect profit or equity, banks thus have less incentive to identify the direction of interest rate movements accurately. This, in the end, reduces directional accuracy without creating a systematic tendency to forecast rates above or below their realized levels.

Adverse valuation outcomes (fair value losses recognized in the income statement) are more consequential when capital buffers are smaller. Because mark-to-market losses directly reduce regulatory capital, banks with limited capital buffers have stronger incentives to avoid forecasts that imply adverse price changes. Consistent with this mechanism, the alignment between Held-for-Trading exposures and forecast distortions is more pronounced among capital-constrained banks. This evidence supports our interpretation that regulatory capital considerations constitute a channel through which the business model approach introduced by IFRS 9 creates organizational commitments that shape interest rate forecasts.

We also examine banks' GDP growth forecasts as a falsification test. Notably, interest rates are set in capital markets and are a function of several factors such as the equilibrium between demand and supply of credit, expectations for future short-term interest rates, which partly depend on inflation and growth rates, expectations for future long-term interest rates, term premium, and sovereign debt issuance choices (see [Kaufman 1986](#) for a review). As a result, unlike interest rate forecasts, GDP growth forecasts are not directly related to the organizational commitments set by a bank's investment committee. Consistently, the

documented forecast distortions are substantially weaker for these macroeconomic forecasts.

Throughout our analyses, we include bank, country, and time fixed effects to control for bank-, country-, and time-invariant characteristics, and control variables for bank- and country-time-varying attributes. In particular, we control for other sources of public information such as consensus interest rate forecasts, current interest rates, change in interest rates, and policy rates. We also include the size of sovereign debt exposures to control for the turnover of banks' investments in government bonds. Finally, we perform a battery of robustness tests in which we use alternative specifications, include additional control variables, mitigate concerns regarding home bias in government bond portfolios (e.g., [Warnock and Burger, 2003](#); [Coeurdacier and Rey, 2013](#); [Enria et al., 2016](#)), remove unconventional loose monetary policies concurrent with the COVID-19 outbreak, and exclude the subsequent unprecedented monetary tightening cycle. Our findings are robust to these additional analyses.

Our paper contributes to the literature in two ways. First, we extend the literature on the real effects of financial reporting ([McCarthy, 1982](#); [Beyer et al., 2010](#); [Shroff, 2017](#); [Goldstein et al., 2023](#); [Garcia Osma et al., 2024](#)) by showing that business models are aligned with expectations that organizations such as banks communicate to capital markets. Our evidence suggests that organizational commitments can shape forecasters' judgments and expectations by creating pressures for consistency between internal business models and disclosed economic views. We thus document how these consistency pressures to align with organizational commitments shape a bank's information system. Prior work shows that fair value accounting disciplines managerial decisions ([Plantin et al., 2008](#); [Laux, 2016](#)). By identifying business models as a reflection of organizational commitments, we move beyond the standard view that forecasters' judgments and expectations are independent from fair value accounting.

Second, we contribute to the literature on the relationship between banks' portfolio holdings and their forecast behavior. [De Marco et al. 2022](#) document that banks with large

sovereign debt exposures produce better forecasts due to “skin in the game”. We refine this view by showing that the classification of financial instruments influences the forecast process itself. While prior research examines how the classification of financial instruments affects banks’ investment and lending decisions (Beatty, 1995; Hodder et al., 2002; Meder, 2015; Chircop and Novotny-Farkas, 2016; Argimon et al., 2018; Kim et al., 2019), this paper extends the literature on the informational externalities of fair value accounting and provides new evidence on its consequences on forecast behavior.

2. Prior Literature and Hypothesis Development

2.1. Institutional Setting

Under IFRS 9, which has been in place since January 2018, financial instruments (including government bonds) can be classified into three categories. First, the amortized cost category (AC), analogous to the Held-to-Maturity (HTM) category, which excludes fair value gains and losses from financial statements. Second, the fair value through other comprehensive income category (FVTOCI), analogous to the Available-for-Sale (AFS) category, which includes fair value gains and losses in the other comprehensive income section. Third, the fair value through profit and loss category (FVTPL), analogous to the Held-for-Trading (HFT) category, which includes fair value gains and losses in the income statement. As a result, these categories impact a bank’s profits and regulatory capital.¹

The choice of category is a consequence of the business models adopted by a bank’s investment committee according to its strategic guidelines. The FVTPL category shall be used for financial instruments held to generate trading income. The AC category shall be used for financial instruments held to generate interest income (collect contractual cash

¹Most European countries opted for the neutralization of unrealized gains and losses on sovereign debt until the implementation of IFRS 9 (see article 468 of EU Regulation no. 575/2013 for more details). Yet, the European Union reintroduced a temporal prudential filter for unrealized gains and losses on sovereign debt as a policy response to the COVID-19 pandemic (see Article 15 of EU Regulation no. 873/2020 for more details). Banks shall communicate their decision to regulators to apply new transitional arrangements.

flows of the financial instrument). Notably, banks are prevented from selling or divesting financial instruments in this category before maturity. Finally, the FVTOCI category shall be used for financial instruments held to realize cash flows from both contractual interests and divestitures.

Under IFRS 9, banks are prevented from reclassifying financial instruments of the Held-for-Trading category. For the other categories, a reclassification is required when the business model of certain financial instruments changes, rendering the previous classification obsolete. Since banks face intense scrutiny and numerous operational constraints, reclassifications are permitted only if the change in the business model of certain financial instruments is approved by the investment committee in accordance with its new strategic guidelines. As a result, reclassifications of financial instruments can be regarded as a one-off event.

Sovereign debt refers to financial instruments such as government bonds issued by and loans given to central government and governmental bodies. The business model approach of sovereign debt under IFRS 9 entails a trade-off between liquidity and market volatility. On the one hand, the Held-to-Maturity category imposes liquidity costs on banks by limiting their ability to sell the financial instrument, respond to market conditions, and fund loan demand (Meder, 2015; Chircop and Novotny-Farkas, 2016; Kim et al., 2019). On the other hand, this category hedges against market volatility because fair value changes are not accounted for in banks' profits and regulatory capital. Conversely, the Held-for-Trading category allows banks to sell the financial instrument without any constraints but fully embraces market volatility that can adversely affect banks' profits and regulatory capital.

Banks implement organizational structures and barriers to regulate informational flows (Michaely and Womack, 1999). Unlike funds, banks are not investment vehicles as their trading desks do not manage third parties' money but invest own capital. Informational flows may occur between trading and research departments within a bank, provided that checks and protocols such as insider lists that limit access to personnel directly involved in the discussions are in place to mitigate conflicts of interest. More precisely, inside informa-

tion can be disseminated internally to the personnel directly concerned by the discussions, after notifying those persons of its confidential nature. When placing individuals on an insider list, the organization should ensure that they understand their legal obligation not to disclose the information to other parties.² Empirical evidence has already documented informational flows within financial conglomerates. For instance, [Madureira and Underwood \(2008\)](#) document that analysts affiliated with banks that actively trade a security produce more accurate forecasts, suggesting that organizational commitments to trading activities generates positive informational externalities for the research function. Similarly, [Chen and Martin \(2011\)](#) and [Haselmann et al. \(2022\)](#) document informational flows across different functions within a bank.

2.2. Hypothesis Development

Under the *Rational Expectations Hypothesis* ([Muth, 1961](#); [Lucas, 1972](#)), agents form expectations by processing all available fundamental information. Accordingly, accounting classifications are merely a reporting convention that does not alter the fundamental economic characteristics of the underlying financial instrument. Consequently, banks' interest rate forecasts should be orthogonal to their business models. However, an emerging body of literature challenges this independent view. For example, forecasters could face pressures to align with their organizational view during the forecast process ([Kahneman et al., 1982](#); [Aymanns and Georg, 2015](#)). The *Cognitive Consistency Hypothesis* posits that agents strive to align beliefs and avoid institutional dissonance ([Akerlof and Dickens, 1982](#)). [Kanodia \(2006\)](#) argues that the reporting system can act as a mechanism that actively coordinates beliefs and creates organizational commitments. For example, when a bank classifies a significant portion of government bonds as Held-to-Maturity, it implicitly commits itself to an

²Insider lists include individuals working on behalf of the organization and who have access to undisclosed inside information, which is information that is of precise nature, has not yet been made public, and is likely to affect the price of financial instruments if it were made public. The regulatory framework include MiFID II Regulation (EU) 2017/565, which regulates conflicts of interest (art. 23) and investment research (art. 34–36), and MAR Regulation (EU) 596/2014, which oversees the flow of inside information.

illiquid investment decision. To maintain institutional consistency, it follows that interest rate forecasts should be aligned with the same economic assumptions that justify the illiquid holding decision.

We argue that organizational commitments stemming from the business models adopted are deemed to shape forecasters' judgments and expectations. Notably, accounting classifications of government bonds reflect organizational commitments in line with the business models adopted. Since mark-to-market does not insulated from price fluctuations and involves immediate market feedback in income statements (e.g., [Kanagaretnam et al., 2003](#); [Liu and Ryan, 2006](#); [Plantin et al., 2008](#); [Kilic et al., 2013](#)), we predict that banks with large Held-for-Trading exposures are committed to market volatility and issue forecasts that underestimate future interest rates. These banks thus pay closer attention to interest rate developments and correctly identify the direction in which rates will move. However, their forecasts do not incorporate the full magnitude of adverse future interest rate increases. They therefore forecast in the correct direction but insufficiently adjust the forecast level.

Hp I: Banks with large Held-for-Trading exposures are committed to market volatility and issue forecasts that underestimate future interest rates.

Conversely, the Held-to-Maturity category imposes liquidity costs by limiting the ability to sell financial instruments ([Meder, 2015](#); [Chircop and Novotny-Farkas, 2016](#); [Kim et al., 2019](#)). Since rising interest rate forecasts implicitly call into question the underlying illiquid holding strategy, which would yield lower returns, banks with large Held-to-Maturity exposures are committed to illiquid holding decisions and issue interest rate forecasts that exhibit a significant downward bias. This forecast behavior is consistent with pressures to avoid institutional dissonance. These banks thus have less incentive to identify the direction of interest rate movements accurately. This, in the end, reduces directional accuracy without creating a systematic tendency to forecast interest rates above or below their realized levels.

Hp II: Banks with large Held-to-Maturity exposures are committed to illiquid holding decisions

and issue forecasts that miss turning points in interest rates.

The Available-for-Sale category shall be used for financial instruments held to realize cash flows from both contractual interests and divestitures. This category allows both business models to co-exists together and is characterized by distinct features such as the exclusion of fair value gains and losses from the income statement and the contemporaneous ability to sell the financial instrument. Both business models are reflected simultaneously in the Available-for-Sale category. As a result, theoretical predictions become less straightforward because this category represents an intermediate case.

Forecasters' tendency to remain committed to a business models is stronger when the economic consequences of unfavorable price changes are more consequential. Banks with large Held-for-Trading exposures face immediate feedback in their income statements. Because mark-to-market losses directly affect prices and regulatory capital, banks with limited capital buffers face greater costs from interest rate forecasts that imply adverse price changes. We thus predict that the organizational commitment to market volatility is stronger for banks facing regulatory capital constraints. Accordingly, the alignment between Held-for-Trading exposures and forecast distortions should be more pronounced among constrained banks. Conversely, the Held-to-Maturity category already hedges banks' profits and regulatory capital from market volatility because fair value changes are automatically excluded from financial statements. As a result, the role of regulatory capital is likely muted for this category.

Hp III: The alignment between Held-for-Trading exposures and forecast distortions is stronger among banks with limited capital buffers.

3. Data and Descriptive Statistics

3.1. Data

We collect data on banks' accounting classifications of sovereign debt from EBA transparency exercises. Data are available only at the semester level (as of June 30 and December, 31), therefore, the frequency of observations in our analysis is semiannual. This setting is particularly well-suited for our analysis because banks hold massive sovereign debt exposures to manage interest rate risk and lock in a positive interest margin (Bowen, 1994; Argimon et al., 2018; Lamers et al., 2022). For example, according to EBA figures, sovereign debt exposures are, on average, 16% of banks' total assets. Because banks can use derivatives to hedge and offset risks, we use net sovereign debt exposures that already account for derivatives and other short positions. Notably, these derivatives represent on average less than 5% of gross sovereign debt exposures.³ Second, we collect interest rate forecasts and actual interest rates from Thomson Reuters Eikon. The forecast horizon of interest rate forecasts is one year. We retain only banks because other financial institutions, such as insurance companies, are not included in EBA transparency exercises. Third, we collect data on policy rates directly from the Central Bank websites.

As IFRS 9 has been in place since January 2018, our sample spans from 2018 to 2024. We match a bank's interest rate forecast for a specific country with its concurrent accounting classification of sovereign debt toward the same country. Exploiting data availability, the following countries are included in our sample: Australia, Canada, China, Germany, Japan, the United Kingdom, and the United States.⁴ We only include the non-missing variable

³More precisely, we directly collect data from the following sources: 2018, 2019, 2020, 2021, 2022, 2023, 2024 and 2025 EU-wide transparency exercise. Data are available upon request. It is not possible to track and assign derivatives and other short positions to a specific accounting category. In an untabulated test, we define our classification variables using gross exposures and find similar results.

⁴EBA transparency exercises include sovereign debt exposures toward several countries. Banks, however, issue forecasts for only key interest rates. As a result, we rely on available interest rate forecasts, and our sample is limited to these countries. Notably, since we collect data from EBA transparency exercises, in our sample, the most common interest rate forecast refers to the German sovereign yield.

filter. Our sample consists of 953 bank-country-time observations (953 interest rate forecasts issued by 30 unique banks). As we collect data from EBA transparency exercises, we acknowledge that our sample consists of only systemically important banks incorporated in Europe (including the European subsidiaries of US banking groups). Table 1 shows the sample distribution by year, by country, and by bank.

3.2. Descriptive Statistics

Classification HFT is equal to the ratio of sovereign debt at fair value through profit and loss over sovereign debt (sovereign debt at fair value through profit and loss_{*t*} / sovereign debt_{*t*}). *Classification HTM* is defined in the same way but considering the Held-to-Maturity category. *Classification HFT* and *Classification HTM* are defined at the bank-country-time level. Figure 1 illustrates an example of our classification variables.

EBA transparency exercises, unfortunately, do not provide detailed information (by country and by accounting category at a point in time) regarding accounting classifications for newly purchased, reimbursements of previously matured, divestitures of previously purchased, and reclassifications (which are, however, exceptional events). These data limitations limit our ability to address each factor separately.⁵ Market fluctuations translate into fair value gains and losses, which could influence our variables of interest. To control for these market fluctuations, throughout our analyses we include *Change interest rate*, which captures the variation in the fair value of government bonds. We also capture concomitant banks' investment decisions in government bonds by controlling for *Exposure*.

To test our predictions, we use the ten-year interest rate forecast for the following reasons. First, the maturity of banks' sovereign debt exposures is approximately ten years. More precisely, figures from EBA transparency exercises indicate that the weighted-average

⁵We measure our classification variables as the ratio of one category over sovereign debt at a point in time (see Figure 1 for an example). Since we cannot control for each factor separately, changes in one category over time (rather than the ratio at a point in time) are considered to increase, rather than reduce, noise.

residual maturity of HFT and HTM portfolios is 7 years.⁶ Second, seminal theoretical works document a linkage between short-term and long-term interest rates along the yield curve (Vasicek, 1977; Cox et al., 1985). This term structure linkage is also well supported empirically and operates in both directions: movements at the long end of the yield curve co-move with and influence the short end, and vice versa (Fama, 1976; Fama and Bliss, 1987; Gürkaynak et al., 2005; Hanson et al., 2021). In this vein, the ten-year interest rate is not only a key economic indicator but also a benchmark reference rate in capital markets, influencing the entire yield curve.

Figure 2 illustrates an example of interest rate forecasts. Our dependent variables capture different features of interest rate forecasts. *Directional bias* is a trinary indicator variable constructed as $(\text{Forecast}_t > \text{Actual}_t) - (\text{Forecast}_t < \text{Actual}_t)$ that takes the value of one if a bank overestimates the interest rate forecast, minus one if a bank underestimates the interest rate forecast, and zero otherwise. This variable captures the direction of a bank's interest rate expectations. *Correct direction* is a binary indicator variable equal to one if the sign of the forecasted interest rate change is equal to the sign of the actual interest rate change ($\text{sign}(\text{Forecast}_t - \text{Actual}_{t-1}) = \text{sign}(\text{Actual}_t - \text{Actual}_{t-1})$), and zero otherwise. This variable captures the likelihood of recognizing turning points in interest rates.

Interest rate forecasts have a one-year ahead forecast horizon (see Figure 2 for an example). Figures from EBA transparency exercises indicate that the weighted-average residual maturity of banks' HFT and HTM portfolios is 7 years. Data limitations, unfortunately, render complex the process of measuring the investment horizon of a bank's sovereign debt portfolio. This is not a source of concerns because business models of sovereign debt under IFRS 9 entail forward-looking views, regardless of the exact investment horizon of the

⁶EBA transparency exercises include sovereign debt exposures by country, accounting category, and residual maturity. In particular, seven different maturity baskets are available (see Figure 1 for more details). We express the residual maturity in years as the midpoint of each maturity basket (for baskets beyond ten years, we use the conservative value of twenty years). Then, we compute the weighted-average residual maturity for each category, with weights proportional to exposure size.

underlying exposures. As a result, both interest rate forecasts and concurrent accounting classifications of sovereign debt reveal forward-looking interest rate expectations even if they might have different underlying time horizons. Notably, instead of using forecast error or accuracy, our forecast variables capture features related to the direction of banks' interest rate expectations, which is consistent with our predictions and with the possibility that underlying time horizons might be different.

We provide descriptive statistics and the correlation matrix in Tables 2 and 3, respectively. All continuous variables are winsorized at the 1st and 99th percentiles. Refer to Appendix 1 for detailed variable definitions. The Held-to-Maturity category represents, on average, 35% of government bonds (*Classification HTM*). *Classification HFT* is an average equal to 51%.⁷ We can also draw some descriptive evidence on actual interest rates. *Interest rate* equals 1.7%, on average, ranging from -0.6% to +4.4%. It shows negative values due to loose monetary policies. *Change interest rate* and *Policy rate* display enough variation. Finally, *Exposure*, defined as the ratio of a country's sovereign debt to the sovereign debt portfolio, is, on average, 12%, ranging from 0.01% to 83%.

The correlation matrix provides insights into the associations between banks' interest rate forecasts, accounting classifications, and other variables. Notably, the correlation between classification (*Classification HFT* and *Classification HTM*) and forecast variables (*Directional bias* and *Correct direction*) is below the 10% threshold.

⁷Since we use net sovereign debt exposures, the values of our classification variables may exceed 1. We provide an example from the EBA 2022 EU-wide transparency exercise. As of the 31st of December 2021, BNP Paribas had a net sovereign debt exposure to Japan equal to EUR 9,219 million (p. 23). The Japanese sovereign debt in the Held-for-Trading category was equal to EUR 12,363 million. As a result, *Classification HFT* is equal to 1.34 ($= 12,363/9,219$).

4. Main Analyses

4.1. Main Analyses

We argue that organizational commitments stemming from the business models adopted shape forecasters' judgments and expectations within a bank. To test our predictions, we employ a multivariate regression framework that links banks' interest rate forecasts to their concurrent business models of sovereign debt under IFRS 9. To test the first and second hypotheses (*Hp I and Hp II*), we estimate the following OLS regression:

$$Y_{i,c,t} = \beta_0 + \beta_1 \text{Classification}_{i,c,t} + \beta_\gamma \text{Controls} + FE + \varepsilon \quad (1)$$

where $Y_{i,c,t}$ is the forecast variable for bank i toward country c at time t . We test distinct forecast variables. *Directional bias* captures the direction of a bank's interest rate expectations: a negative value indicates that forecasts underestimate future rates and vice versa. *Correct direction* measures the likelihood of missing turning points in interest rates. To account for unobserved heterogeneity, we include bank, country, and time fixed effects. As our variables of interest are defined at the bank-country-time level, standard errors are clustered at the country level.

We additionally control for bank- and country-level time-variant characteristics that may relate to banks' interest rate forecasts and their accounting classifications of sovereign debt. Unless stated otherwise, control variables are current values and capture public information available at the time decisions are made. First, we add consensus variables capturing market expectations for future interest rates. We therefore add *Consensus forecast*, *Consensus estimates*, and *Consensus uncertainty*. These variables, defined at the country-time level, proxy for interest rate forecasts issued by other financial institutions and capture the median, the number, and the standard deviation of available forecasts, respectively. Second, we include macroeconomic indicators that capture the economic outlook of a country. We

therefore control for *Change interest rate*, *Interest rate*, and *Policy rate*. *Change interest rate* is defined at the country-time level and controls for the change in a country’s interest rate (Hodder et al., 2002). We include *Policy rate*, defined at the country-time level, to control for the monetary policy in place that affects the availability of funds (Bernanke and Blinder, 1992). We control for *Exposure*, defined at the bank-country-time level, as a proxy for a bank’s investment decisions in government bonds (De Marco et al., 2022).

We first predict that banks with large Held-for-Trading exposures are committed to market volatility and issue forecasts that underestimate future interest rates. We tabulate the results of the *Directional bias* analysis in Table 4. The coefficient on *Classification HFT* is negative and statistically significant in the Held-for-Trading model (Column 1). More precisely, a 1% increase in banks’ sovereign debt at fair value through profit and loss (*Classification HFT*) is associated with a 2.3% decrease in *Directional bias* (Column 1), representing a 8% reduction compared to the mean value of -0.284. The coefficient on *Classification HTM* is negative but not statistically significant in the Held-to-Maturity model (Column 2). These results indicate that banks with large Held-for-Trading exposures, whose positions are subject to immediate feedback in the income statement, underestimate future interest rates in their forecasts. *Consensus estimates* and *Consensus uncertainty* have a positive and statistically significant coefficient (Columns 1 and 2).

We next test whether organizational commitments to illiquid holding decision shape forecasters’ willingness to revise underlying economic assumptions of their investment decisions. We tabulate the results of the *Correct direction* analysis in Table 5. The coefficient on *Classification HTM* is negative and statistically significant in the Held-to-Maturity model (Column 2). More precisely, a 1% increase in banks’ sovereign debt at amortized cost (*Classification HTM*) is associated with a 10% decrease in *Correct direction* (Column 2), representing a 21% reduction compared to the mean value of 0.476. The coefficient on *Classification HFT* is negative and not statistically significant in the Held-for-Trading model (Column 1). These results indicate that banks with large Held-to-Maturity exposures tend to miss turn-

ing points and are implicitly aligned with the economic assumptions that justify concurrent illiquid investment decisions. Our expectations are borne out. The results of Tables 4 and 5 are consistent with our predictions: different organizational commitments stemming from the business models adopted shape forecasters' judgments and expectations in line with the business models adopted.

5. Additional Analyses

5.1. Cross-sectional Analysis by Regulatory Capital

To better understand the dynamics underlying our findings, we examine regulatory capital. Because mark-to-market losses directly affect regulatory capital, banks with limited capital buffers face greater costs from forecasts that imply adverse price changes. We thus predict that the organizational commitment to market volatility is stronger for banks facing regulatory capital constraints. Accordingly, the alignment between Held-for-Trading exposures and forecast distortions should be more pronounced among constrained banks (*H_p III*). In this vein, we examine whether forecasters' tendency to remain aligned with business models adopted is stronger when the economic consequences of unfavorable price changes are more consequential.⁸

We use *Regulatory capital*, the ratio of Tier 1 capital over risk-weighted total assets, to identify constrained and unconstrained banks. We then test the difference in coefficients between the two subsamples. Banks whose Tier 1 capital ratio is below or above the first tercile (the 33% level) are assigned to the constrained and unconstrained subsamples, respectively. We provide the results in Panels A and B of Table 6.

In the constrained subsample (Panel A), the coefficient on *Classification HFT* is negative and statistically significant in the *Directional bias* model (Column 1). The coefficient on

⁸Notably, as the Held-to-Maturity category shields automatically banks' profits and regulatory capital from market volatility, we do not perform the cross-sectional analysis by regulatory capital for this category.

Classification HFT is positive and not statistically significant in the unconstrained subsample across the models (Columns 1 and 2 of Panel B). The t-test comparing the coefficients between the two subsamples is statistically significant at the 10% level in the *Directional bias* model. Overall, this evidence supports our prediction that the alignment between Held-for-Trading exposures and forecast distortions is stronger among banks with limited capital buffers.

5.2. GDP Growth Rate Forecasts

Next, as a falsification test, we investigate whether and how other banks' macroeconomic forecasts are aligned with their accounting classifications under IFRS 9. We focus on GDP growth rate forecasts because they are not directly related to the organizational commitments set stemming from the business models adopted. Notably, interest rates are set in capital markets and are a function of several factors such as the equilibrium between demand and supply of credit, expectations for future short-term interest rates, which partly depend on inflation and growth rates, expectations for future long-term interest rates, term premium, and sovereign debt issuance choices (see [Kaufman 1986](#) for a review). Moreover, GDP growth forecasts are common macroeconomic forecasts available. We thus match banks' GDP growth rate forecasts sourced from Thomson Reuters Eikon with their concurrent accounting classifications of sovereign debt. In this analysis, the sample consists of 753 bank-country-time observations (753 GDP growth rate forecasts issued by 43 unique banks). *Directional bias* is a trinary indicator variable constructed as $(\text{Forecast}_t > \text{Actual}_t) - (\text{Forecast}_t < \text{Actual}_t)$ that takes the value of one if a bank overestimates the GDP growth rate forecast, minus one if a bank underestimates the GDP growth rate forecast, and zero otherwise. *Correct direction* is a binary indicator variable equal to one if the sign of the forecasted GDP growth rate is equal to the sign of the actual GDP growth rate ($\text{sign}(\text{Forecast}_t - \text{Actual}_{t-1}) = \text{sign}(\text{Actual}_t - \text{Actual}_{t-1})$), and zero otherwise.

We include the full set of control variables capturing bank- and country-time-variant characteristics that relate to banks' accounting classifications and their GDP growth rate

forecasts (see also the previous sections for the related literature). Notably, the consensus variables (*Consensus forecast*, *Consensus estimates*, and *Consensus uncertainty*) use the same definitions as before but now refer to GDP growth rate forecasts. We repeat the main analyses and tabulate the results in Table 7. The coefficient on *Classification HFT* is not statistically significant in the *Directional bias* model (Column 1). Moreover, the coefficient on *Classification HTM* is not statistically significant in the *Correct direction* model (Column 2). Overall, these results suggest that our findings are limited to interest rate forecasts and cannot be generalized to GDP growth rate forecasts. This analysis serves as a falsification test: when organizational commitments stemming from the business models adopted become muted, other banks' macroeconomic forecasts such as GDP growth rates are no longer aligned with their concurrent accounting classifications of sovereign debt.

5.3. Robustness Tests

We perform a battery of robustness tests to further validate our results. First, we add the Available-for-Sale category (*Classification AFS*) in the regression model as a control variable. The Available-for-Sale category is characterized by distinct features such as the exclusion of fair value gains and losses from the income statement and simultaneously the ability to sell the financial instrument, which make theoretical predictions regarding this category less straightforward. We now include this category as a control variable. Notably, it is not possible to include all three categories in a single regression model due to perfect multicollinearity. We tabulate the results in Panel A of Table 8. The coefficient on *Classification HFT* is negative and statistically significant in the *Directional bias* model (Column 1). The coefficient on *Classification HTM* is negative and statistically significant in the *Correct direction* model (Column 2). These results indicate that our findings are robust to the inclusion of the Available-for-Sale category as a control variable.

Second, prior research documents the so-called “home bias”, namely the tendency of banks to overweight domestic sovereign debt exposures (Warnock and Burger, 2003; Coeurdacier and Rey, 2013; Enria et al., 2016; Ongena et al., 2019). Consistently, it could be argued that

the organizational commitments stemming from the business model approach introduced by IFRS 9 apply mainly to domestic exposures. Throughout our analyses, we control for *Exposure*, the ratio of a country’s sovereign debt to its sovereign debt portfolio (De Marco et al., 2022). Yet, to rule out these concerns, we exclude domestic exposures (111 bank-country-time observations, equal to 12% of our sample) and repeat the analysis. We tabulate the results in Panel B of Table 8. The coefficient on *Classification HFT* is negative and statistically significant in the *Directional bias* model (Column 1). Moreover, the coefficient on *Classification HTM* is negative and statistically significant in the *Correct direction* model (Column 2). These results indicate that our findings are robust to foreign exposures.

In the third tabulated robustness test, we exclude observations with negative interest rates (127 bank-country-time observations, equal to 13% of our sample). As the COVID-19 pandemic unfolded, policymakers adopted unconventional loose monetary policies. To rule out the effects of these unconventional measures, we limit the sample to positive interest rates and repeat the analysis. We tabulate the results in Panel C of Table 8. The coefficient on *Classification HFT* is negative and statistically significant in the *Directional bias* model (Column 1). The coefficient on *Classification HTM* is negative and statistically significant in the *Correct direction* model (Column 2). These results indicate that our findings are not driven by the unconventional loose monetary policies adopted by policymakers as a response to the COVID-19 pandemic.

Lastly, in the fourth tabulated robustness test, we exclude observations of the year 2022 in which central banks started the sharpest monetary tightening cycle in recent times (166 bank-country-time observations, equal to 17% of our sample). To rule out the effects of these hikes in policy rates, we repeat the analysis without the observations of the year 2022. We tabulate the results in Panel D of Table 8. The coefficient on *Classification HFT* is negative and statistically significant in the *Directional bias* model (Column 1). The coefficient on *Classification HTM* is negative and statistically significant in the *Correct direction* model (Column 2). These results indicate that our findings are not driven by unconventional tight

monetary policies.

6. Discussion and Conclusions

We investigate whether organizational commitments stemming from the business model approach introduced by IFRS 9 influence forecasters' judgments and expectations. We argue that accounting classifications of sovereign debt reflect organizational commitments in line with the business models adopted. Our empirical analysis supports our predictions that banks' interest rate forecasts are aligned with their business models of sovereign debt.

First, we find that banks with large Held-for-Trading exposures are more likely to issue forecasts that underestimate future interest rates. These results indicate that when fair value changes immediately affect income statement, forecasters are committed to market volatility and predict the correct direction but insufficiently adjust the interest rate forecast level. Second, we show that banks with large Held-to-Maturity exposures exhibit a significant higher likelihood of missing turning points, which is consistent with the organizational commitment to illiquid holding decisions. This, in the end, reduces directional accuracy without creating a systematic tendency to forecast interest rates above or below their realized levels.

Cross-sectionally, we show that the organizational commitment to market volatility is stronger for banks with regulatory capital constraints. More precisely, our findings indicate that the documented forecast distortions are more pronounced among banks with lower capital buffers, suggesting that regulatory capital considerations are a channel through which the business model approach creates organizational commitments that shape interest rate forecasts. As a falsification test, we investigate banks' GDP growth rate forecasts and do not find major forecast distortions for this macroeconomic indicator that is not directly related to organizational commitments stemming from the business models adopted. Finally, our results are robust to additional analyses.

Our findings are subject to certain caveats. First, EBA transparency exercises do not

provide detailed information on the accounting classification of newly purchased government bonds, reimbursements of previously matured government bonds, divestitures of previously purchased government bonds, and reclassifications of government bonds.⁹ Second, since interest rates are set in capital markets and depend on many factors (see [Kaufman 1986](#) for a review) that we cannot observe separately, data limitations also impair our ability to investigate the nature and sources of banks’ information sets.

Our paper contributes to the literature in two ways. We extend the literature on the real effects of financial reporting ([McCarthy, 1982](#); [Beyer et al., 2010](#); [Shroff, 2017](#); [Goldstein et al., 2023](#); [Garcia Osma et al., 2024](#)) by showing that business models are aligned with expectations that organizations such as banks communicate to capital markets. Our evidence suggests that organizational commitments can shape forecasters’ judgments and expectations by creating pressures for consistency between internal business models and disclosed economic views. Moreover, we refine the view that “skin in the game” produces better interest rate forecasts ([De Marco et al., 2022](#)) by showing that the classification of financial instruments influences the forecast process itself. While prior research examines how the classification of financial instruments affects banks’ investment and lending decisions ([Beatty, 1995](#); [Hodder et al., 2002](#); [Meder, 2015](#); [Chircop and Novotny-Farkas, 2016](#); [Argimon et al., 2018](#); [Kim et al., 2019](#)), our findings provide new evidence on the consequences of this classification on forecast behavior.

⁹Notably, it could also be argued that banks’ sovereign debt classification might partly be driven by concomitant investment decisions *unrelated* to interest rate expectations, such as managerial biases. However, similar investment decisions and managerial biases are not a concern because they do not contradict our results.

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Appendix A Variable Definitions

Variable	Definition	Source
Classification HFT	Sovereign debt at fair value through profit and loss _t / sovereign debt _t . The variable is defined at bank-country-time level and captures banks' Held-for-Trading exposures.	EBA
Classification HTM	Sovereign debt at amortized cost _t / sovereign debt _t . The variable is defined at bank-country-time level and captures banks' Held-to-Maturity exposures.	EBA
Classification AFS	Sovereign debt at fair value through other comprehensive income _t / sovereign debt _t . The variable is defined at bank-country-time level and captures banks' Available-for-Sale exposures.	EBA
Directional bias	Trinary indicator variable constructed as $(\text{Forecast}_t > \text{Actual}_t) - (\text{Forecast}_t < \text{Actual}_t)$. It takes the value of one if the bank overestimates the interest rate forecast, minus one if the bank underestimates the interest rate forecast, and zero otherwise. The variable is defined at bank-country-time level and captures the direction of a bank's interest rate expectations.	Thomson Reuters Eikon
Correct direction	Binary indicator variable constructed as $(\text{sign}(\text{Forecast}_t - \text{Actual}_{t-1}) = \text{sign}(\text{Actual}_t - \text{Actual}_{t-1}))$. It takes the value of one if the sign of the forecasted interest rate change is equal to the sign of the actual interest rate change, and zero otherwise. The variable is defined at bank-country-time level and captures the likelihood of missing turning points in interest rates.	Thomson Reuters Eikon
Consensus forecast	Median consensus forecasted interest rate _t . The variable is defined at country-time level.	Thomson Reuters Eikon
Consensus estimates	Number of forecasted interest rate _t . The variable is defined at country-time level.	Thomson Reuters Eikon
Consensus uncertainty	Standard deviation of the forecasted interest rate _t . The variable is defined at country-time level.	Thomson Reuters Eikon
Change interest rate	Interest rate _t - interest rate _{t-1} . The variable is defined at country-time level.	Thomson Reuters Eikon
Exposure	Sovereign debt _t / sovereign debt portfolio _t . The variable is defined at bank-country-time level.	EBA
Interest rate	Ten-year interest rate _t . Sovereign yields are implied by the prices at which government bonds are traded on capital markets. The variable is defined at country-time level.	Thomson Reuters Eikon
Policy rate	Central bank policy rate _t . The variable is defined at country-time level.	Central bank websites

Figure 1. 2022 EU-wide Transparency Exercise

ING Groep N.V. is a bank included in EBA transparency exercises. This table is from its 2022 EU-wide Transparency Exercise (p. 23). It provides sovereign debt exposures by country and by accounting category at a point in time. As of the 31th of December 2021, the net sovereign debt exposure toward Japan is equal to EUR 158 million. The Japanese sovereign debt at fair value through profit and loss is equal to EUR 112 million (Classification HFT = $0.71 = 112/158$). The Japanese sovereign debt at amortized cost is equal to EUR 46 million (Classification HTM = $0.29 = 46/158$).



2022 EU-wide Transparency Exercise											
General governments exposures by country of the counterparty											
ING Groep N.V.											
As of 31/12/2021											
Direct exposures											
Residual Maturity	Country / Region	On balance sheet						Derivatives			
		Total gross carrying amount of non-derivative financial assets	Total carrying amount of non-derivative financial assets (net of short positions)	Non-derivative financial assets by accounting portfolio				Derivatives with positive fair value		Derivatives with negative fair value	
				of which: Financial assets held for trading	of which: Financial assets designated at fair value through profit or loss	of which: Financial assets at fair value through other comprehensive income	of which: Financial assets at amortised cost	Carrying amount	Notional amount	Carrying amount	Notional amount
(mn EUR)	Japan	46	46	0	0	0	46	0	0	0	0
		0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0
		0	0	0	0	0	0	0	0	0	0
		112	112	112	0	0	0	0	0	0	0
		158	158	112	0	0	46	0	0	0	0

Figure 2. 2025 Interest Rate Forecasts

ING Groep N.V. is a bank included in EBA transparency exercises. This table is from its June 2025 Economic Forecasts (p. 4). It provides interest rate forecasts by country and by forecast horizon at a point in time. As of the 30th of June 2025, the expected 10-year interest rate is equal to 4.25% in the United States.

ING Economic Forecasts June 2025

10Y Bond Yield Forecasts

(end period, %)	4Q25F	1Q26F	2Q26F	3Q26F	4Q26F
US: Fed funds	3.75	3.50	3.25	3.25	3.25
3M	3.70	3.50	3.30	3.30	3.30
2Y	3.45	3.30	3.30	3.30	3.30
5Y	3.70	3.75	3.75	3.70	3.70
10Y	4.25	4.50	4.50	4.25	4.25
30Y	4.90	5.15	5.15	4.90	4.90
ECB refi*	2.00	2.00	2.00	2.00	2.00
3M	2.00	2.00	2.10	2.10	2.10
2Y	1.95	1.95	2.00	2.00	2.00
5Y	2.30	2.30	2.40	2.45	2.45
10Y	2.80	2.80	2.90	3.00	3.00
30Y	3.45	3.50	3.60	3.65	3.65
Japan	1.75	1.75	1.80	1.80	2.00
France	3.70	3.70	3.75	3.85	3.90
Italy	3.65	3.65	3.70	3.80	3.80
Spain	3.35	3.35	3.45	3.55	3.55
UK	4.60	4.50	4.40	4.30	4.30
Netherlands	2.95	2.95	3.05	3.15	3.15
Belgium	3.40	3.40	3.45	3.55	3.55
Austria	3.10	3.10	3.20	3.30	3.30
Ireland	3.05	3.05	3.15	3.25	3.25
Portugal	3.20	3.20	3.30	3.40	3.40
Switzerland	0.30	0.30	0.40	0.50	0.50
Sweden	2.90	3.00	3.10	3.20	3.20
Finland	3.20	3.20	3.30	3.40	3.45
Canada	3.25	3.25	3.25	3.50	3.50
Australia	4.20	4.20	4.20	4.10	4.10

Table 1. Sample Distribution by Year, by Country, and by Bank

This table reports the sample distribution by year, by country, and by bank. The sample consists of 953 bank-country-time observations over the 2018–2024 period. Refer to Appendix 1 for variable definitions.

Panel A: Distribution of observations by year

Year	Observations	%
2018	101	10.59%
2019	114	11.96%
2020	127	13.33%
2021	137	14.37%
2022	166	17.41%
2023	159	16.68%
2024	149	15.63%
Total	953	100%

Panel B: Distribution of observations by country

Country	Observations	%
Australia	27	2.83%
Canada	53	5.56%
China	19	1.99%
Germany	316	33.16%
United Kingdom	162	16.99%
Japan	95	9.96%
United States	281	29.48%
Total	953	100%

Panel C: Distribution of observations by bank

Bank	Observations	%
ABN Amro Bank NV	16	1.68%
BNP Paribas	40	4.19%
Bank of America Europe	31	3.25%
Barclays Bank Ireland plc	25	2.62%
Bayerische Landesbank	22	2.30%
Commerzbank AG	42	4.40%
Danske Bank A/S	38	3.98%
DekaBank Deutsche	57	5.97%
Deutsche Bank AG	69	7.23%
Erste Group Bank AG	22	2.30%
Goldman Sachs Bank Europe SE	30	3.14%
Groupe Credit Agricole	24	2.51%
HSBC Continental Europe	16	1.68%
ING Groep NV	91	9.53%
Intesa Sanpaolo S.p.A.	28	2.93%
J.P. Morgan AG	24	2.51%
Jyske Bank A/S	15	1.57%
KBC Groep	45	4.71%
Landesbank Baden-Württemberg	44	4.61%
Morgan Stanley Europe Holding SE	5	0.52%
National Bank of Greece SA	30	3.14%
Natwest Group plc	15	1.57%
Norddeutsche Landesbank	42	4.40%
Nykredit Realkredit A/S	20	2.09%
Skandinaviska Enskilda Banken	36	3.77%
Société Générale SA	28	2.93%
Standard Chartered Plc	15	1.57%
Svenska Handelsbanken – group	32	3.35%
UBS Europe SE	23	2.41%
Unicredit S.p.A.	28	2.93%
Total	953	100%

Table 2. Descriptive Statistics

This table reports the descriptive statistics of the sample. The sample consists of 953 bank-country-time observations over the 2018–2024 period. Refer to Appendix 1 for variable definitions and data sources. All continuous variables are winsorized at the 1st and the 99th percentiles.

Variable	Obs.	Mean	Median	Sd	Min	Max
<i>Independent variables</i>						
Classification HFT	953	0.508	0.119	1.119	0.000	9.967
Classification HTM	953	0.354	0.231	0.373	0.000	1.000
Classification AFS	953	0.288	0.148	0.348	0.000	1.009
<i>Dependent variables</i>						
Directional bias	953	−0.284	−1.000	0.959	−1.000	1.000
Correct direction	953	0.476	0.000	0.250	0.499	1.000
<i>Controls</i>						
Consensus forecast	953	0.100	0.057	0.731	−2.471	2.199
Consensus estimates	953	38.220	37.000	18.390	6.000	78.000
Consensus uncertainty	953	0.966	1.018	0.235	0.350	1.331
Change interest rate	953	0.328	0.243	0.927	−1.715	3.068
Exposure	953	0.117	0.043	0.183	0.001	0.825
Interest rate	953	1.723	1.673	1.491	−0.572	4.361
Policy rate	953	1.850	1.250	2.012	−0.100	5.250

Table 3. Correlation Matrix

This table reports the correlation matrix of the sample. The sample consists of 953 bank-country-time observations over the 2018-2024 period. Refer to Appendix 1 for variable definitions and data sources. All continuous variables are winsorized at the 1st and the 99th percentiles.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Classification HFT	1.000										
(2) Classification HTM	-0.222	1.000									
(3) Directional bias	-0.051	-0.002	1.000								
(4) Correct direction	0.006	-0.061	-0.086	1.000							
(5) Consensus forecast	0.006	-0.006	-0.063	-0.075	1.000						
(6) Consensus estimates	-0.103	-0.112	0.220	-0.028	0.039	1.000					
(7) Consensus uncertainty	-0.106	0.053	0.039	-0.066	-0.123	0.240	1.000				
(8) Change interest rate	0.007	0.088	-0.401	-0.273	0.019	-0.147	0.108	1.000			
(9) Exposure	-0.130	0.064	0.043	0.005	-0.100	0.125	0.196	-0.014	1.000		
(10) Interest rate	-0.023	-0.023	-0.160	-0.153	0.008	-0.006	0.177	0.456	-0.110	1.000	
(11) Policy rate	-0.022	0.033	-0.158	-0.065	-0.134	-0.168	0.200	0.385	-0.026	0.905	1.000

Table 4. Directional Bias Analysis

This table reports the results of the directional bias analysis. The variable $Directional\ Bias_{i,c,t}$ is a trinary indicator variable constructed as $(Forecast_t > Actual_t) - (Forecast_t < Actual_t)$. It takes the value of one if the bank overestimates the interest rate forecast, minus one if the bank underestimates the interest rate forecast, and zero otherwise. The variable $Classification_{i,c,t}$ refers to the specific accounting category indicated in the column header (Held-for-Trading in Column 1 and Held-to-Maturity in Column 2). Refer to Appendix 1 for variable definitions and data sources. All continuous variables are winsorized at the 1st and the 99th percentiles. All regressions include bank, country, and time fixed effects. Standard errors are clustered at the country level (t-statistics in parentheses). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	$Directional\ Bias_{i,c,t}$	
	(1)	(2)
Column		
Model	Held-for-Trading	Held-to-Maturity
$Classification_{i,c,t}$	-0.023** (-3.04)	-0.049 (-0.82)
$Consensus\ forecast_{c,t}$	0.026 (0.70)	0.030 (0.76)
$Consensus\ estimates_{c,t}$	0.011** (2.51)	0.011* (2.41)
$Consensus\ uncertainty_{c,t}$	0.939* (2.23)	0.882* (2.07)
$Change\ interest\ rate_{c,t}$	-0.050 (-0.73)	-0.047 (-0.69)
$Exposure_{i,c,t}$	0.225 (1.65)	0.244 (1.74)
$Interest\ rate_{c,t}$	-0.103 (-1.76)	-0.112 (-1.83)
$Policy\ rate_{c,t}$	0.038 (0.89)	0.041 (0.94)
Observations	953	953
Adjusted R-squared	0.6271	0.6266
Bank FE	Yes	Yes
Country FE	Yes	Yes
Time FE	Yes	Yes

Table 5. Correct Direction Analysis

This table reports the results of the correct direction analysis. The variable $Correct\ Direction_{i,c,t}$ is a binary indicator variable constructed as $(\text{sign}(\text{Forecast}_t - \text{Actual}_{t-1}) = \text{sign}(\text{Actual}_t - \text{Actual}_{t-1}))$. It takes the value one if the sign of the forecasted interest rate change is equal to the sign of the actual interest rate change, and zero otherwise. The variable $Classification_{i,c,t}$ refers to the specific accounting category indicated in the column header (Held-for-Trading in Column 1 and Held-to-Maturity in Column 2). Refer to Appendix 1 for variable definitions and data sources. All continuous variables are winsorized at the 1st and the 99th percentiles. All regressions include bank, country, and time fixed effects. Standard errors are clustered at the country level (t-statistics in parentheses). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable	$Correct\ Direction_{i,c,t}$	
	(1)	(2)
Column	Held-for-Trading	Held-to-Maturity
Model		
$Classification_{i,c,t}$	-0.002 (-0.20)	-0.100*** (-3.92)
$Consensus\ forecast_{c,t}$	-0.026 (-0.89)	-0.025 (-0.91)
$Consensus\ estimates_{c,t}$	-0.003 (-0.89)	-0.003 (-0.87)
$Consensus\ uncertainty_{c,t}$	0.501 (1.72)	0.444 (1.55)
$Change\ interest\ rate_{c,t}$	-0.031 (-0.60)	-0.028 (-0.54)
$Exposure_{i,c,t}$	0.035 (0.88)	0.041 (0.97)
$Interest\ rate_{c,t}$	-0.131 (-0.92)	-0.135 (-0.94)
$Policy\ rate_{c,t}$	0.016 (0.30)	0.018 (0.33)
Observations	953	953
Adjusted R-squared	0.3754	0.3782
Bank FE	Yes	Yes
Country FE	Yes	Yes
Time FE	Yes	Yes

Table 6. Regulatory Capital Analysis

This table reports the results of the cross-sectional analysis by regulatory capital. Panel A presents results for constrained banks, while Panel B presents results for unconstrained banks. Test A = B is a t-test of equality of the coefficients between the two subsamples. The dependent variables are *Directional Bias* in Column 1 and *Correct Direction* in Column 2. Refer to Appendix 1 for variable definitions and data sources. All continuous variables are winsorized at the 1st and the 99th percentiles. All regressions include bank, country, and time fixed effects. Standard errors are clustered at the country level (t-statistics in parentheses). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Constrained Banks		
Variable	(1) Directional Bias	(2) Correct Direction
<i>Classification_{i,c,t}</i>	-0.072*** (-4.44)	-0.031 (-1.68)
<i>Consensus forecast_{c,t}</i>	0.087* (2.04)	-0.034 (-0.94)
<i>Consensus estimates_{c,t}</i>	-0.002 (-0.41)	0.000 (0.13)
<i>Consensus uncertainty_{c,t}</i>	-0.113 (-0.08)	-0.786 (-0.63)
<i>Change interest rate_{c,t}</i>	-0.161 (-1.47)	-0.033 (-0.52)
<i>Exposure_{i,c,t}</i>	0.083 (0.40)	0.297** (2.70)
<i>Interest rate_{c,t}</i>	0.035 (0.19)	-0.348 (-1.76)
<i>Policy rate_{c,t}</i>	0.012 (0.16)	0.128 (1.53)
Observations	313	313
Adjusted R-squared	0.6462	0.4084
P-value t-test (A vs B)	0.089	0.269
Bank FE	Yes	Yes
Country FE	Yes	Yes
Time FE	Yes	Yes

Table 6 (*Continued*)

Panel B: Unconstrained Banks		
Variable	(1) Directional Bias	(2) Correct Direction
<i>Classification_{i,c,t}</i>	0.018 (0.58)	0.007 (0.38)
<i>Consensus forecast_{c,t}</i>	-0.011 (-0.31)	-0.029 (-0.84)
<i>Consensus estimates_{c,t}</i>	0.017*** (3.81)	-0.004 (-1.52)
<i>Consensus uncertainty_{c,t}</i>	1.302** (2.89)	0.626 (1.73)
<i>Change interest rate_{c,t}</i>	-0.025 (-0.26)	-0.001 (-0.03)
<i>Exposure_{i,c,t}</i>	0.312 (1.80)	-0.022 (-0.23)
<i>Interest rate_{c,t}</i>	-0.112 (-1.52)	-0.061 (-0.5)
<i>Policy rate_{c,t}</i>	0.041 (0.95)	-0.041 (-0.95)
Observations	639	639
Adjusted R-squared	0.5965	0.4056
P-value t-test (A vs B)	0.089	0.269
Bank FE	Yes	Yes
Country FE	Yes	Yes
Time FE	Yes	Yes

Table 7. GDP Growth Rate Analysis

This table reports the results of the GDP growth rate analysis. The dependent variables are *Directional Bias* in Column 1 and *Correct Direction* in Column 2. Consensus control variables are measured using GDP growth rate forecasts. Refer to Appendix 1 for variable definitions and data sources. All continuous variables are winsorized at the 1st and the 99th percentiles. All regressions include bank, country, and time fixed effects. Standard errors are clustered at the country level (t-statistics in parentheses). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Column Dependent Variable	(1) Directional Bias	(2) Correct Direction
<i>Classification_{i,c,t}</i>	-0.113 (-1.50)	0.036 (1.34)
<i>Consensus forecast_{c,t}</i>	0.005** (2.64)	0.000 (-0.01)
<i>Consensus estimates_{c,t}</i>	0.021 (1.13)	0.005 (0.99)
<i>Consensus uncertainty_{c,t}</i>	0.010 (0.21)	-0.018* (-2.15)
<i>Exposure_{i,c,t}</i>	-0.357*** (-5.34)	-0.038 (-1.03)
<i>GDP growth rate_{c,t}</i>	-0.028* (-2.21)	0.003 (0.62)
<i>Policy rate_{c,t}</i>	-0.097 (-1.76)	0.045 (1.14)
Observations	753	753
Adjusted R-squared	0.1839	0.4519
Bank FE	Yes	Yes
Country FE	Yes	Yes
Time FE	Yes	Yes

Table 8. Robustness Tests

This table reports the results of robustness tests. Panel A includes Available-for-Sale exposures as additional control variable, Panel B focuses on foreign sovereign debt exposures, Panel C restricts the sample to observations with positive interest rates, and Panel D excludes observations with hikes in policy rates. The dependent variables are *Directional Bias* in Column 1 and *Correct Direction* in Column 2. Refer to Appendix 1 for variable definitions and data sources. All continuous variables are winsorized at the 1st and the 99th percentiles. All regressions include bank, country, and time fixed effects. Standard errors are clustered at the country level (t-statistics in parentheses). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Available-for-Sale Exposures		
Variable	(1) Directional Bias	(2) Correct Direction
<i>Classification_{i,c,t}</i>	-0.022** (-2.54)	-0.103** (-2.80)
<i>Classification AFS_{i,c,t}</i>	0.064 (1.13)	-0.009 (-0.21)
<i>Consensus forecast_{c,t}</i>	0.028 (0.74)	-0.026 (-0.90)
<i>Consensus estimates_{c,t}</i>	0.011* (2.44)	0.000 (0.04)
<i>Consensus uncertainty_{c,t}</i>	0.936* (2.19)	0.443 (1.58)
<i>Change interest rate_{c,t}</i>	-0.049 (-0.72)	-0.028 (-0.54)
<i>Exposure_{i,c,t}</i>	0.211 (1.82)	0.044 (0.99)
<i>Interest rate_{c,t}</i>	-0.102 (-1.71)	-0.135 (-0.94)
<i>Policy rate_{c,t}</i>	0.040 (0.91)	0.018 (0.33)
Observations	953	953
Adjusted R-squared	0.6269	0.3776
Bank FE	Yes	Yes
Country FE	Yes	Yes
Time FE	Yes	Yes

Table 8 (*Continued*)

Panel B: Foreign Sovereign Debt Exposures		
Variable	(1) Directional Bias	(2) Correct Direction
<i>Classification_{i,c,t}</i>	−0.014* (−2.24)	−0.115** (−3.22)
<i>Consensus forecast_{c,t}</i>	0.040 (0.79)	−0.024 (−0.69)
<i>Consensus estimates_{c,t}</i>	0.010* (2.23)	−0.003 (−1.16)
<i>Consensus uncertainty_{c,t}</i>	1.140* (2.38)	0.302 (0.87)
<i>Change interest rate_{c,t}</i>	−0.062 (−1.02)	−0.032 (−0.57)
<i>Exposure_{i,c,t}</i>	0.726* (2.16)	0.138 (1.70)
<i>Interest rate_{c,t}</i>	−0.068 (−1.12)	−0.131 (−0.98)
<i>Policy rate_{c,t}</i>	0.014 (0.35)	0.012 (0.23)
Observations	842	842
Adjusted R-squared	0.6272	0.3650
Bank FE	Yes	Yes
Country FE	Yes	Yes
Time FE	Yes	Yes

Table 8 (*Continued*)

Panel C: Positive Interest Rates		
Variable	(1) Directional Bias	(2) Correct Direction
<i>Classification_{i,c,t}</i>	−0.022** (−3.50)	−0.104** (−3.22)
<i>Consensus forecast_{c,t}</i>	0.044 (0.71)	−0.058 (−1.39)
<i>Consensus estimates_{c,t}</i>	0.011* (2.38)	−0.003 (−0.99)
<i>Consensus uncertainty_{c,t}</i>	0.806 (1.53)	1.204* (1.97)
<i>Change interest rate_{c,t}</i>	−0.070 (−0.98)	−0.072 (−1.27)
<i>Exposure_{i,c,t}</i>	0.294 (1.65)	0.028 (0.38)
<i>Interest rate_{c,t}</i>	−0.055 (−0.92)	−0.050 (−0.56)
<i>Policy rate_{c,t}</i>	0.009 (0.23)	−0.037 (−1.02)
Observations	828	828
Adjusted R-squared	0.5895	0.3564
Bank FE	Yes	Yes
Country FE	Yes	Yes
Time FE	Yes	Yes

Table 8 (*Continued*)

Panel D: Without Rate Hikes		
Variable	(1) Directional Bias	(2) Correct Direction
<i>Classification_{i,c,t}</i>	−0.024* (−2.06)	−0.100*** (−4.23)
<i>Consensus forecast_{c,t}</i>	0.065 (1.04)	−0.020 (−0.44)
<i>Consensus estimates_{c,t}</i>	0.014** (3.02)	−0.002 (−0.40)
<i>Consensus uncertainty_{c,t}</i>	0.997* (1.95)	−0.058 (−0.16)
<i>Change interest rate_{c,t}</i>	0.025 (0.40)	0.036 (1.00)
<i>Exposure_{i,c,t}</i>	0.268 (1.60)	0.082 (1.70)
<i>Interest rate_{c,t}</i>	−0.153* (−2.20)	−0.273 (−1.51)
<i>Policy rate_{c,t}</i>	0.051 (1.22)	0.078 (0.93)
Observations	787	787
Adjusted R-squared	0.5969	0.3517
Bank FE	Yes	Yes
Country FE	Yes	Yes
Time FE	Yes	Yes