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Interest rate uncertainty and the predictability of bank revenues

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Abstract

This paper examines the predictive power of interest rate uncertainty over pre-provision net revenues (PPNR) in a large panel of bank holding companies (BHC). Utilizing a linear dynamic panel model, we show that supplementing forecasting models with interest rate uncertainty improves the forecasting performance with the augmented model yielding lower forecast errors in comparison to a baseline model which includes unemployment rate, federal funds rate, and spread variables. Further separating PPNRs into two components that reflect net interest and non-interest income, we show that the predictive power of interest rate uncertainty is concentrated on the non-interest component of bank revenues. Finally, examining the point predictions under a severely stressed scenario, we show that the model can successfully predict the negative effect on overall bank revenues with a rise in the non-interest component of income during 2009:Q1. Overall, the findings suggest that stress testing exercises that involve bank revenue models can benefit from the inclusion of interest rate uncertainty and the cross-sectional information embedded in the panel of BHCs.

JEL classification: C11; C14; C23; G21
Keywords: Bank stress tests; Empirical Bayes; Interest rate uncertainty; Out-of-sample forecasts

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1 Introduction

Following the introduction of the 2010 Dodd-Frank Act, stress tests have become the norm in the banking industry to conduct macroprudential regulation and supervision (Covas et al., 2014), allowing financial institutions and regulators to assess the resilience of the financial system to stressed macroeconomic and financial conditions. The top-down approach to stress testing offers a broad perspective, compared to the bottom-up approach that utilizes loan-level data, that is particularly useful for regulators by focusing on aggregate data at the balance sheet and income statement levels, thus allowing regulators to assess the resilience of the banking system cross-sectionally using publicly available financial statement data (Kapinos and Mitnik, 2016). At the heart of stress tests is forecasting models that are able to generate accurate predictions under the actual macroeconomic and financial conditions so that these models can be deemed reliable when it comes to generating projections under stressed scenarios.

Stress testing exercises, however, are often challenged by the lack of sufficiently long data as changes in the industry, such as mergers or acquisitions, and/or regulatory environment, as experienced following the global financial crisis in 2008, put limitations on the availability of data required to build reliable forecasting models. In a recent study, Liu et al. (2020) propose a method that allows to forecast short time series using information embedded in cross-sectional panel data and show that the empirical Bayes predictor generated from cross-sectional information in a dynamic panel setting performs well compared to various predictors in generating forecasts of bank revenues. Clearly, this is an issue of high importance for regulators as well as financial institutions during the post-global financial crisis era that experienced a wave of consolidation activity as well as regulatory changes which in turn imposed limitations on the availability of data analysts require in order to build reliable forecasting models.

We contribute to this debate in several novel aspects. First, we examine the role of interest rate uncertainty as a predictor of pre-provision bank revenues (PPNR) by comparing the forecasting performance of the baseline model of Liu et al. (2020) that includes unemployment rate, the federal funds rate, and an interest rate spread against an augmented model that also includes interest rate uncertainty as a predictor. The use of interest rate uncertainty as a predictor of bank revenues can be justified via the credit channel of the monetary transmission mechanism in which banks are forced to curtail loan supply in response to monetary tightening in order to satisfy the capital requirements imposed by regulators (e.g. Beutler et al., 2020) as well as the evidence that establishes a link between interest rate risk exposure and bank lending (e.g. Van den Heuven et al., 2007). Second, we distinguish between the interest and non-interest components of bank revenues and examine whether the predictive power of interest rate uncertainty is concentrated on a particular component of PPNRs. This is an important consideration given the evidence that banks have attempted to make up for the loss in interest income due to low interest rate environment during the post global crisis period by increasing their revenues from service charges and other nontraditional income activities (Haubrich and Young, 2019). Finally, we compare the forecasts from the augmented model under the actual and severely adverse macroeconomic conditions in order to assess the applicability of the model to stress testing exercises.

Our analysis suggests that supplementing forecasting models with interest rate uncertainty indeed improves the forecasting performance with the augmented model generating lower forecast errors in comparison to a baseline model which includes unemployment rate, federal funds rate, and spread variables only. Further separating PPNRs into the net interest and non-interest components, we find that the predictive power of interest rate uncertainty is concentrated on the non-interest component of bank revenues. We argue that a combination of factors including the effect of interest rate risk exposure and funding uncertainty on bank lending and increasing use of nontraditional revenue generating activities as a hedge against the fall in the interest component of revenues drives the predictive relationship between interest rate uncertainty and the non-interest component of PPNRs. Finally, examining the point predictions under a severely stressed scenario, we find that the model can successfully predict the negative effect on overall bank revenues with a rise in the non-interest component of income during the first quarter of 2009. While the findings provide strong support for the predictive information captured by interest rate uncertainty over bank revenues, they also highlight the importance of the cross-sectional information embedded in the panel of bank holding companies in order to generate reliable projections in stress testing exercises.

The remainder of the paper is organized as follows. Section 2 provides the data description and the methodological details of the dynamic panel model utilized in the forecasting application. Section 3 presents the empirical findings on the performance of the empirical Bayes predictor under the actual and severely distressed scenarios as well as the findings for the interest and non-interest components of PPNRs. Finally, Section 4 concludes with suggestions for future research.

2 Data and Methodology

2.1 Data

The construction of our data is based on Liu et al. (2020) who examine pre-provision net revenues (PPNR) from a panel of bank holding companies (BHC) with average assets above $500m. Using quarterly financial statements of BHCs, obtained from the web portal of the Federal Reserve Bank of Chicago, PPNR relative to assets is computed as the sum of the net interest income (NII) and total non-interest income (TNII) less total non-interest expenses (TNIE), divided by the value of consolidated assets.[1] This ratio is then multiplied by 400 to obtain annualized percentages.[2].

Following Liu et al. (2020), our benchmark stress test scenarios utilize quarterly data on unemployment rate, federal funds rate and spread variables to represent stressed macroeconomic conditions. This also allows us to compare our findings to those of Liu et al. (2020). In order to explore the predictive value of interest rate uncertainty in the forecasting models, we augment our forecasting models by including the interest

[1] Data obtained from https://www.chicagofed.org/api/sitecore/BHCHome/

[2] For further details about the dataset, see online appendix of Liu et al. (2020).

rate uncertainty index of Istrefi and Mouabbi (2018) which measures the uncertainty on the 3-month government bond interest rate at a 3-month forecast horizon. Based on Consensus Economics survey data, this index offers a subjective measure of interest rate uncertainty representing disagreement among forecasters as well as the perceived variability of future aggregate shocks.[3] The sample period is 2002:Q1 to 2014:Q4.

2.2 Methodology

We utilize a linear dynamic panel model which allows the interaction of unobserved individual heterogeneity, denoted by the vector λ_i, with observed predictors W_{it-1}:

$$Y_{it} = \lambda_i' W_{it-1} + \rho' X_{it-1} + \alpha' Z_{it-1} + U_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T \tag{1}$$

where Y_{it} is the pre-provision net revenue (relative to assets) for BHC i in quarter t, X_{it-1} is a predetermined vector of variables which may contain lags of Y_{it}, Z_{it-1} is a vector of strictly exogenous variables, λ_is are considered as random variables that are possibly correlated with some of the predictors and U_{it} is the idiosyncratic error component. The cross-sectional dimension N varies from sample to sample and ranges from 613 to 920.

In order to generate point forecasts of Y_{iT+1}, we employ an empirical Bayes approach to take into account the information captured both cross-sectionally and in time series. Given that the distribution $\pi(\lambda_i|\cdot)$ of the heterogenous coefficients λ_i and the common coefficients (ρ, α) are not known[4], we employ Tweedie's formula that defines the posterior mean of λ_i as a function of the cross-sectional information[5]. This yields an empirical Bayes estimate of λ_i and for a given (ρ, α), the empirical Bayes predictor of Y_{iT+1} at time T is given by :

$$\mathbb{E}(Y_{iT+1}|Y, \rho, \alpha) = \rho Y_{iT} + \mathbb{E}(\lambda_i|Y, \rho, \alpha) \tag{2}$$

[3] Data is available at https://sites.google.com/site/istrefiklodiana/interest-rate-uncertainty.

[4] Hence, we change the unkonwn parameters by a consistent estimator.

[5] For Tweedie's formula and its applications, see Brown and Greenshtein (2009), Efron (2011), Gu and Koenker (2017).

We compare the performance of the empirical Bayes predictor under actual and stressed scenarios with two benchmark predictors that have different assumptions about the distribution of the λ_is, i.e. the plug-in predictor and the pooled OLS predictor. The former is obtained by estimating λ_i conditional on (ρ, α) via maximum likelihood for each unit i, while the latter assumes absence of heterogeneity, i.e $\lambda_i = \lambda$ for all i.

As a novel aspect of our analysis, we examine whether the inclusion of interest rate uncertainty to the forecasting model increases the predictive performance by comparing our results with the model in Liu et al. (2020) which employs as predictors the unemployment rate, federal funds rate and an interest rate spread only. In order to gain further insight to the predictability patterns, we further separate PPNRs into two categories: net interest income and net non-interest income. This allows us to compare the predictive information captured by interest rate uncertainty over the interest vs non-interest components of PPNRs separately. Finally, we analyze the effect of severely adverse macroeconomic conditions on BHC revenues by replacing the observed values of model covariates by hypothetical values that reflect stressed conditions.

3 Empirical results

Following Liu et al. (2020), we begin the analysis by generating rolling samples that include T+2 observations where the size of the estimation sample (T) takes values T=6, 8, 10 quarters. To initialize the lag in the first period and calculate the error of the one-step-ahead forecast, the additional two observations are added to the rolling samples obtained. For instance, if the sample size is selected as T=6, we can generate M=45 rolling samples with forecast origins running from τ=2003:Q3 to τ=2014:Q3 given that our sample covers the period 2002:Q1 to 2014:Q4. We compute the mean-squared error (MSE) across BHCs using the formula:

$$\text{MSE}\left(\widehat{Y}^{N}_{\tau+1}\right) = \frac{\frac{1}{N_\tau}\sum_{i=1}^{N_\tau}\left(Y_{i\tau+1} - \widehat{Y}_{i\tau+1}\right)^2}{\frac{1}{N_\tau}\sum_{i=1}^{N_\tau}} \tag{3}$$

3.1 Forecast results under actual macroeconomic conditions

In Figure 1, we present the MSE differentials, computed as percent reduction in MSE, for the empirical Bayes and pooled-OLS predictors relative to that of the benchmark plug-in predictor, for various sample sizes including T=6, T=8, and T=10, respectively.[6] A negative value for the relative MSE (y-axis) implies that the selected predictor produces better PPNR forecasts compared to the plug-in predictor. The findings depicted in Figure 1 support the results in Liu et al. (2020), confirming that the empirical Bayes predictor performs well against the plug-in and pooled-OLS predictors in the model that includes the unemployment rate, federal funds rate, interest rate spread and interest rate uncertainty. We observe that the empirical Bayes predictor outperforms the plug-in predictor for almost all sample sizes and also dominates the pooled-OLS estimator in a large fraction of samples with T=10, indicating that the shrinkage induced by estimated correlated random effects distribution results in an improvement in forecast accuracy[7]. This establishes the preliminary assessment of the empirical Bayes predictor, confirming that the results reported in Liu et al. (2020) regarding the performance of the Bayes predictor also hold for the augmented model that includes interest rate uncertainty.

– Insert Figure 1 about here. –

Having established the baseline evidence on the performance of the empirical Bayes predictor within the augmented model, we next examine the predictive contribution of interest rate uncertainty in the forecasting models. Panels A and B in Table 1 present the MSEs for PPNR forecasts under the actual macroeconomic conditions from the baseline model of Liu et al. (2020) which includes the unemployment rate, federal funds rate, interest rate spread only and the augmented model that also includes interest rate uncertainty, respectively. We observe that the inclusion of interest rate uncertainty

[6] We modify Equation (3) as $\Delta\left(\widehat{Y}^N_{\tau+1}\right) = \frac{\text{MSE}\left(\widehat{Y}^N_{\tau+1}\right) - \text{MSE(plug-in)}}{\text{MSE(plug-in)}}$.

[7] In the online appendix of the paper, we also present bank holding company-specific forecast error differentials relative to the plug-in predictor. Furthermore, for a robustness check, we also examine the performance of predictors on three different periods starting from 2007:Q1, 2009:Q1, and 2012:Q1.

as an additional predictor can improve the predictive performance of models, implied by smaller forecasting errors, compared to the baseline model. Considering the evidence that links interest rate risk exposure and bank lending (e.g. Van den Heuven, 2007), one can argue that the predictive power of interest rate uncertainty over PPNRs is driven by the sensitivity of loan growth rates on interest rate uncertainty. Indeed, in a recent study, applying a dynamic panel model to 297 Swiss banks, Beutler et al. (2020) show that realized interest rate risk affects bank lending with the effect mainly driven by the capital channel rather than liquidity, driving banks to reduce its lending to satisfy the capital requirements imposed by regulators. Building on Ritz and Walther (2015), one can also argue that funding uncertainty, in part driven by interest rate uncertainty, also serves as a determinant of lending activities, thus contributing to the predictive information captured by interest rate uncertainty over bank revenues over and above the predictors in the baseline model of Liu et al. (2020). Nevertheless, the findings clearly suggest that supplementing forecasting models with interest rate uncertainty can help improve the forecast accuracy of revenue models, which is an important consideration for stress testing exercises.

– Insert Table 1 about here. –

3.2 Interest income component vs non-interest income component

It can be argued that the predictive relationship between bank revenues and macroeconomic/financial factors largely depends on the nature of the income as interest or non-interest based.[8] While the interest income component of revenues can be driven by the yield curve and credit spreads (Schuermann, 2014), the non-interest component of income can be harder to model as banks have to compete with a wide range of financial intermediaries like hedge funds and insurance companies to capture market share. Indeed, DeYoung and Roland (2001) show that non-interest revenue is more volatile than

[8] Non-interest income can roughly be defined as the income attributable to sources that are not related to interest payments such as investment banking fees and commissions or income from trading and securitization, among others.

the more stable interest revenue and also more sensitive to economic fluctuations. Confirming this finding, Brunnermeier et al. (2020) further show that non-interest income is positively related to banks' tail risk, while it has an insignificant or positive relationship with a bank's exposure to macroeconomic/financial factors. Against this backdrop, we extend our tests by distinguishing between the interest and non-interest components of PPNRs and examine whether the predictive power of interest rate uncertainty is driven by a particular component of bank revenues.

Table 2 presents the mean-squared errors (MSE) for the interest and non-interest components of PPNRs under the actual macroeconomic conditions. Similar to Table 1, we compare the forecasting performance of the baseline model (Panel A) without interest rate uncertainty with the augmented model (Panel B) that includes uncertainty as an additional predictor. In each panel, we report the MSEs for the net-interest and non-interest components of PPNRs. Interestingly, we observe that the predictive value of interest rate uncertainty is largely driven by the non-interest component of revenues. The comparison of the MSEs in panels A1 and B1 indicates smaller forecast errors for the baseline model, suggesting that interest rate uncertainty does not play a significant role in predicting the net interest component of bank revenues. Considering that the baseline model performs better for most sample sizes, particularly for the short term forecast horizon (T=6), the use of interest rate hedging strategies may limit the predictive contribution of interest rate uncertainty in the forecasting model as hedging mitigates the sensitivity of earnings to interest rate fluctuations (e.g. Purnanandam, 2007).

– Insert Table 2 about here. –

On the other hand, we observe smaller forecasting errors in panel B2 compared to those in A2, suggesting that the predictive power of interest rate sensitivity is largely concentrated on the non-interest component of PPNRs. In a recent study, Baum et al. (2018) show that inflation uncertainty curtails banks' lending capacity to the private sector, which in turn increases their reliance on non-interest income activities. It is thus possible that the predictive power of interest rate uncertainty on the non-interest component of PPNRs is driven by the increased reliance of bank revenues on non-interest related activities due to uncertainty in inflationary expectations. Indeed, Haubrich and Young (2019) note that, during the post-global crisis period, banks have attempted to make up for the loss in interest income due to low interest rate environment by increasing their revenues from service charges and other nontraditional income activities. One can thus argue that the predictive power of interest rate uncertainty over the non-interest component of PPNRs captures the increasing use of non-traditional revenue generating activities as a hedge against against the loss in the interest component of revenues.

3.3 Forecast results under stressed macroeconomic conditions

Clearly, stress tests are aimed to assess the resilience of a bank's operations under stressed macroeconomic/financial conditions and the value of a forecasting model in this context depends on the reliability of its forecasts under such scenarios. Therefore, in this section, we compare the forecasts under the actual economic conditions, presented in the previous section, to the forecasts obtained under a particular stress scenario. For this purpose, we design a stress scenario that represents severely adverse macroeconomic conditions by increasing the unemployment rate, federal funds rate, interest rate spread and interest rate uncertainty by 5%. This can be interpreted as an environment in which aggressive monetary tightening, high unemployment and an elevated interest rate uncertainty induce a slowdown in economic activity.

Given that the global financial crisis had a dramatic impact on macroeconomic conditions and financial markets, we focus on 2009:Q1 in the midst of the Great Recession as our target for point predictions under the stressed scenario. Figure 2 displays the predictions for 2009:Q1 (for sample size T=10) with each circle representing a one-quarter ahead point forecast for a particular BHC. Point predictions of PPNRs under the actual macroeconomic conditions and the stressed scenario are displayed on the y- and x-axis, respectively. The institutions with assets greater than 50 billion dollars are highlighted by green circles while the other BHCs are represented as black circles. Interestingly, we find that the pooled-OLS estimator does not forecast any impact on BHCs revenues, implied by the points that are very close to the 45-degree line. This suggests that the pooled-OLS estimator does a poor job in predicting the impact of the great crash on bank revenues by predicting essentially no effect on PPNRs. In contrast, the plug-in predictor forecasts a more heterogeneous reaction across the BHCs by predicting that 45% of the institutions are expected to experience lower revenues in comparison to the actual macroeconomic conditions. Finally, in the case of the empirical Bayes predictor, which is the preferable model with the lowest MSE in the actual scenario, we find that 30% of BHCs are predicted to suffer a decrease in revenues under the severely stressed scenario. This implies that the plug-in estimator predicts more bank losses than the Bayes predictor during the market crash period.

– Insert Figure 2 about here. –

In Figure 3, we present the point predictions for the net interest and non-interest components of PPNRs. We observe that the drop in revenues is generally more pronounced in the case of the net interest income component as the actual-versus-stressed predictions generally cluster below the 45-degree line. This is not unexpected given the observation by Haubrich and Young (2019) that, during the post global crisis period, banks have attempted to make up for the loss in interest income due to low interest rate environment by increasing their revenues from service charges and other nontraditional income activities. On the other hand, examining the plots for the non-interest component of PPNRs, presented in the lower panel of Figure 3, we see that all BHCs are predicted to be able to raise their non-interest revenues according to the pooled-OLS predictor, in line with the argument by Haubrich and Young (2019). A similar pattern, although not as consistent as in the case of the pooled-OLS estimator, is also observed for the empirical Bayes estimator in which a majority of BHCs are predicted to raise their non-interest income relative the actual conditions. Overall, the findings suggest that forecasting models supplemented by interest rate uncertainty perform quite well in generating point predictions for stressed scenarios, however distinguishing between the interest and non-interest components of revenues can add to the forecasting performance of the models, particularly under stressed scenarios that are the focus of stress testing exercises.

– Insert Figure 3 about here. –

4 Conclusion

This paper examines the predictive power of interest rate uncertainty over pre-provision net revenues (PPNR) in a large panel of bank holding companies (BHC). Utilizing a linear dynamic panel model that allows the interaction of unobserved individual heterogeneity across the panel of BHCs and the interest rate uncertainty index recently developed by Istrefi and Mouabbi (2018), we show that supplementing forecasting models with interest rate uncertainty indeed improves the forecasting performance. The augmented model is found to generate lower forecast errors for various sample sizes in comparison to a baseline model which includes unemployment rate, federal funds rate, and spread variables.

Further separating PPNRs into two components that reflect the net interest and non-interest income, we show that the predictive power of interest rate uncertainty is concentrated on the non-interest component of bank revenues. We argue that a combination of factors including the effect of interest rate risk exposure and funding uncertainty on bank lending and increasing use of nontraditional revenue generating activities as a hedge against the fall in the interest component of revenues drives the predictive relationship between interest rate uncertainty and the non-interest component of PPNRs.

Finally, examining the point predictions under a stressed scenario implied by a 5% rise in the unemployment rate, federal funds rate, interest rate spread and uncertainty, we show that the model can successfully predict the negative effect on overall bank revenues with a rise in the non-interest component of income during the first quarter of 2009. However, the choice of the estimator is found to be critical in the accuracy of the forecasts with the empirical Bayes predictor performing relatively well compared to its counterparts. Overall, the findings suggest that stress testing exercises for bank revenue models can benefit from the inclusion of interest rate uncertainty and the cross-sectional information embedded in the panel of bank holding companies. For future research, it would be interesting to explore whether bank lending activity indeed serves as a channel that facilitates the predictive relationship between interest rate uncertainty and bank revenues, particularly during stressed market conditions. Furthermore, given the finding in Brunnermeier et al. (2020) that links non-interest income to banks' tail risk, our findings could be extended to build tail risk forecasting models with interest rate uncertainty utilized as a predictor.

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Table 1: Forecast results for bank pre-provision net revenues.

Sample Size	Empirical Bayes	Pooled OLS	Plug-in
Panel A: Baseline model			
T=10	0.332	0.810	1.287
T=8	0.348	0.429	1.387
T=6	0.361	0.475	1.427
Panel B: Model with interest rate uncertainty			
T=10	**0.325**	**0.381**	**1.193**
T=8	**0.338**	0.431	**1.255**
T=6	0.372	**0.471**	**1.379**

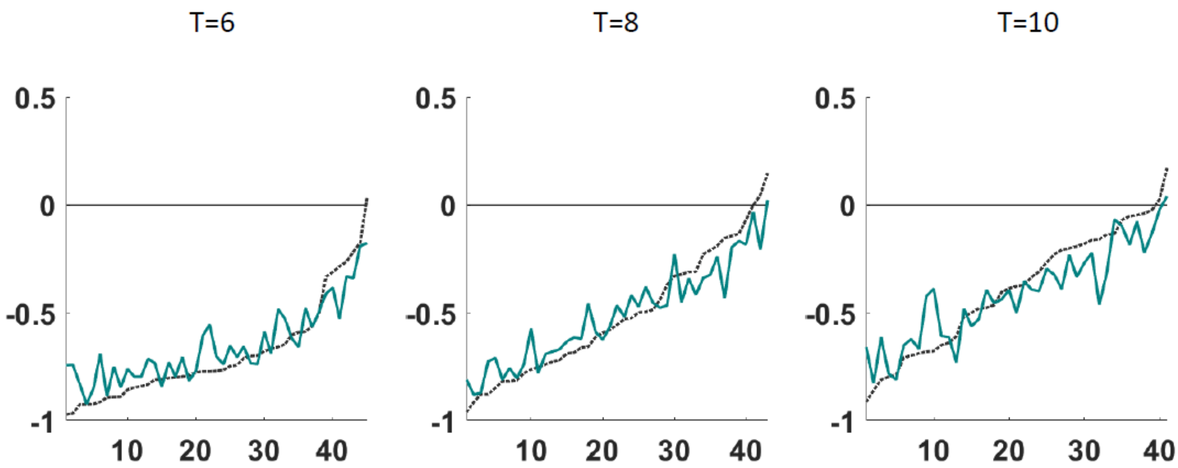
Note: The table presents the mean-squared errors (MSE) for PPNRs under the actual macroeconomic conditions. Panels A and B present the results for the baseline model of Liu et al. (2020) which includes the unemployment rate, federal funds rate, interest rate spread only and the augmented model that also includes interest rate uncertainty, respectively. MSE values highlighted in bold represent cases for which the augmented model that includes interest rate uncertainty yields smaller forecasting errors than the baseline model of Liu et al. (2020).

Table 2: Forecast results for interest and non-interest components of PPNRs.

Sample Size	Empirical Bayes	Pooled OLS	Plug-in
Panel A: Baseline model without uncertainty			
A1. Total net interest income			
T=10	0.104	0.067	0.324
T=8	0.092	0.069	0.346
T=6	0.099	0.076	0.355
A2. Total net non-interest income			
T=10	0.158	0.251	0.651
T=8	0.163	0.272	0.736
T=6	0.165	0.274	0.747
Panel B: Model with interest rate uncertainty			
B1. Total net interest income			
T=10	0.106	0.067	**0.319**
T=8	0.094	**0.069**	**0.315**
T=6	0.116	0.084	0.371
B2. Total net non-interest income			
T=10	**0.156**	**0.250**	**0.627**
T=8	0.164	0.275	**0.715**
T=6	**0.162**	**0.261**	**0.702**

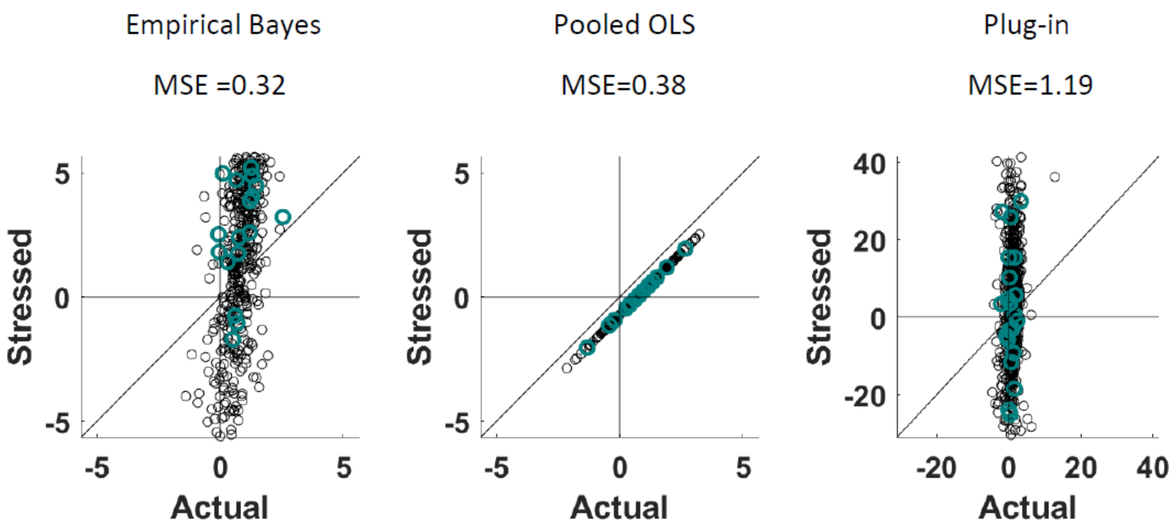
The table presents the mean-squared errors (MSE) for the interest and non-interest components of PPNRs under the actual macroeconomic conditions. Panels A and B present the results for the baseline model of Liu et al. (2020) which includes the unemployment rate, federal funds rate, interest rate spread only and the augmented model that also includes interest rate uncertainty, respectively. MSE values highlighted in bold represent cases for which the augmented model that includes interest rate uncertainty yields smaller forecasting errors than the baseline model of Liu et al. (2020).

Figure 1: Percentage Change in MSE relative to plug-in predictor



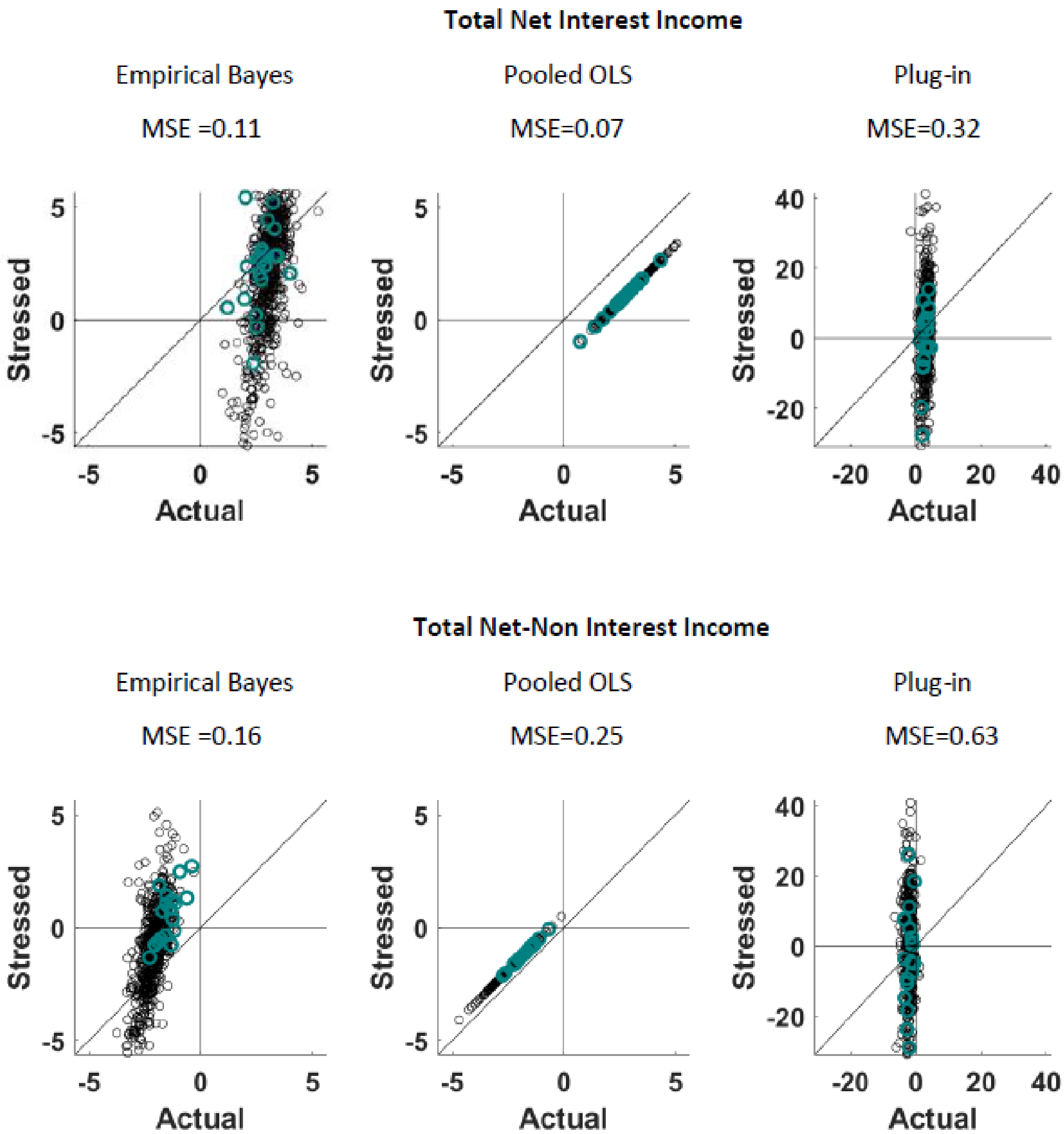
Note: The plug-in predictor is the benchmark. y-axis displays the percentage change in MSE with a negative value indicating improvement compared to the plug-in predictor. Time periods are sorted to monotonically increase the MSE of pooled OLS. The empirical Bayes predictor is plotted in solid teal and the pooled OLS predictor is represented by dotted black.

Figure 2: Predictions of PPNRs under actual and stressed scenarios (T=10).



Note: Each dot represents a BHC in our dataset with the institutions that have assets greater than 50 billion dollars highlighted by green circles. Point predictions of PPNRs under the actual macroeconomic conditions and a stressed scenario are displayed on the y- and x-axis, respectively. Also reported on top of each plot are the MSEs based on the predictions under the actual macroeconomic conditions.

Figure 3: Predictions of net interest and non-interest components of PPNRs under actual and stressed scenarios (T=10)



Notes: See notes to Figure 2.