Does Loan Loss Provision Timeliness Affect the Accuracy, Informativeness, and Predictability of Analyst Provision Forecasts?

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Abstract: We examine how the properties of equity analysts' bank loan loss provision forecasts differ with provision timeliness. We find that the accuracy of analyst provision forecasts relative to time-series provision forecasts is more pronounced for banks with more timely loan loss provisions. Consistent with the greater accuracy of analysts' provision forecast for timely banks, we find that, controlling for time series provision expectations, the equity market's incremental response to analysts' provision forecasts beyond earnings forecasts is greater for banks with more timely loan loss provisions. We further verify that the provision forecast is a better predictor of future non-performing assets for banks with timely provisions. Finally, we find a greater ability of analysts' provision forecasts to predict non-performing assets when analysts also provide a non-performing asset forecast that is larger for timely than for untimely banks.

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1. Introduction

Given the importance of accruals in predicting future earnings and cash flows (e.g., Dechow, 1994; Barth et al., 2001), the scarcity of research examining analysts' accruals forecasts seems surprising. We identify a setting where analysts issue explicit accruals forecasts and examine the accuracy of these forecasts, whether these accrual forecasts are incrementally useful to investors beyond earnings forecasts, and whether these forecasts predict future performance. Specifically, we examine financial analysts' explicit forecasts of loan loss provisions in banks, which Beatty and Liao (2014) argue is banks' most important accrual.[1] In addition, we consider whether analyst provision forecasts reflect banks' timeliness in loan loss provisioning by examining whether the accuracy, usefulness and predictability of these forecasts depend on the timeliness of banks' provision accounting. We focus on the relation between banks' timeliness in loan loss provisioning, among other accounting properties, and analyst forecasts, because of the important implication of provision timeliness in the current policy and accounting standards debate, in particular the significant economic consequences of provision timeliness at both the macro and micro levels.[2]

While the literature on sell-side analysts has established that analysts' earnings forecasts are more accurate than time-series (e.g., O'Brien, 1988), whether analysts'

[1]Beatty and Liao (2014) argue that relative to other accruals, the loan loss provision is large and explains much of the variability in total accruals. Specifically, for years ended 2005-2012 the ratio of the mean of the absolute values of the provision to that of total accruals is 56%, which is nearly twice the value of the next largest accrual. Consistent with the relative magnitudes, the percentage of the variance of total accruals explained by the provision of 34% is more than double the value of the accrual with the second highest explanatory power.

[2]Both IASB and FASB are drafting the final standards requiring the adoption of expected loss models for loan loss provision and expected loss models were once in the BASEL III discussions. In addition, Beatty and Liao (2011) find that provision timeliness affects pro-cyclicality of lending and Bushman and Williams (2012 and 2013) find that provision timeliness enhances market discipline in risk taking and affects contribution to systemic risk.

forecasts of earnings components such as cash flows are more accurate than time-series is under debate (e.g., Givoly et al., 2009). Nichols et al. (2009) argue that publicly traded banks provide timelier loan loss provisions to mitigate information asymmetry. This possibility could either advantage or disadvantage analysts relative to time-series forecasts, because it is inherently more difficult to predict expected losses compared to incurred losses. Therefore, to accurately predict provisions that are more timely, analysts may need to conduct more research on the banks' loan quality and predict borrowers' future performance. In addition, based on the earnings forecast literature, it is not clear whether analysts incorporate firms' timely loss recognition when forecasting earnings (e.g., Louis et al, 2008). Therefore, to shed light on this debate, we examine how analysts' relative provision forecast accuracy, measured as the difference between provision forecast errors based on the analysts' actual provision forecasts (i.e., absolute values of the difference between reported provisions and the median of analyst provision forecasts) versus predicted provisions based on time-series models (i.e., absolute values of the difference between reported provisions and predicted provisions based on time-series models), differs with the underlying timeliness of banks' provision accounting.

Using a sample collected from the SNL database ranging from 2008 Q3 to 2013 Q3, we identify 3,928 bank-quarters (representing 246 individual banks) with analysts forecasting both earnings and provisions. We find that provisions forecast errors are smaller when calculated using the actual provision forecast compared to various time-series models and that this differential is greater for banks with timely loan loss provisions. This suggests not only that analyst provision forecasts contain additional information about banks' loan quality and banks' overall information environments that cannot be simply replicated using time-series models, but that this information advantage is greater for banks that incorporate more expected losses in their loan loss provisions.

To evaluate the implications and usefulness of analyst provision forecasts for the equity market, we examine the three-day cumulative abnormal equity market reaction on earnings announcement dates., Previous research (e.g., Ahmed et al., 1999; Wahlen, 1994) examining the market response to unexpected provisions based on time series models have found that the market differentially reacts to the provision component of earnings although this differential reaction has been found to be either positive or negative depending on the period studied. First we document an incremental negative market response to the unexpected time-series provision component of earnings relative to other earnings components consistent with the results in more recent studies. Next, we find that, controlling for earnings surprises relative to earnings forecasts and for time-series provision expectations, banks whose actual loan loss provisions exceed the forecasted provisions experience a significant negative market return. This finding supports the notion that analyst provision forecasts help market participants form expectations of loan loss provisions beyond time-series models and therefore are important for valuation purposes. We also examine whether the market reaction differs for banks with more versus less timely loan loss provisioning. While we find no difference in the reaction to earnings forecasts between these two types of banks, we find that the market reacts more strongly to provision forecasts for banks with more timely loan loss provisions. This reaction is consistent with the improved accuracy of analysts' provision forecasts for banks with more timely loan loss provisions and suggests that these forecasts serve better market expectations of banks' loan losses.

To further support the notion that analysts incorporate banks' provision timeliness when forecasting provisions, we examine the association between analysts' provision forecasts and future non-performing assets to assess the predicting ability of loan loss provision forecasts. By construction the reported loan loss provision should have a higher association with future non-performing assets for more timely banks. However, it is not obvious whether analysts will have the necessary information to predict these expected future losses. We also examine the association between analysts' provision forecast errors and future non-performing assets to assess the extent to which analysts can predict expected future losses. We find that provision forecasts are more positively associated with future non-performing assets for banks with more timely provision accounting. This suggests that analysts are able at least in part to predict expected future losses, however we also find that provision forecast errors are associated with future non-performing loans indicating that analysts forecasts do not fully incorporate the expected losses reflected in the current period's provision.

One potential mechanism that increases the timeliness of analysts' provision forecasts is nonperforming assets forecasts. In our sample, about 44% of banks covered by analysts also receive forecasts of nonperforming assets. We argue that analysts that also forecast nonperforming assets are better able to provide timely provision forecasts because nonperforming assets are an important indicator for future losses (Beatty and Liao, 2011; Bushman and Williams, 2012). Therefore, we further explore the ability of provision forecasts to predict future non-performing assets by considering how these associations differ when analysts also forecast non-performing assets. Consistent with our expectations, we find a higher association between future non-performing assets and analyst provision forecasts in the presence of non-performing asset forecasts.

While descriptive in nature, our findings contribute to two literatures. First, our study adds to the large body of literature on sell-side analyst forecasts. We know very little from the literature about whether analysts engage in accruals forecasts. While Call et al. (2009) argue that analysts provide specific estimates of accounts receivables, accounts payables, inventories and depreciation to derive estimates of cash flow, evidence of whether analysts explicitly provide these forecasts to investors and of the information content of accruals forecasts is lacking in the existing literature. We add to this literature by showing that provision forecasts contain useful information that assists market participants in forming expectations of a bank's loan loss provision. We further add to this literature by showing that analysts attempt to incorporate banks' accounting practices, i.e., timely loss recognition, in their accrual forecasts, which enables analysts to outperform time-series models. While the provision forecasts do not completely predict future losses, we show that analysts research additional information including nonperforming assets to achieve more timely provision forecasts.

Our study also sheds light on the banking accounting literature. While the loan loss provision is the most important bank accrual, very little is known about how the equity market forms expectations about provisions and whether and how information intermediaries such as financial analysts disseminate provision information. We add to this literature by documenting that, beyond the provision component of earnings that is included in analysts' earnings forecasts, analysts make explicit provision forecasts that are informative to the market and to predicting future non-performing assets. We further find that the analysts' provision forecasts are more accurate and more informative to the market and in predicting future non-performing assets when loan loss provision accounting is more timely.

The rest of the paper is organized as follows. In section 2, we discuss the related literature and develop predictions on the determinants and consequences of loan loss provision forecasts. We describe research methodology in section 3. In section 4, we present sample descriptive statistics, empirical results and additional analyses. Section 5 concludes the paper.

2. Literature Review and Hypothesis Development

2.1. Loan Loss Provision Forecasts

While analysts do not provide explicit accruals forecasts for non-financial firms, they provide forecasts for loan loss provisions for banks. Because the loan loss provision is the most important accrual for banks and because of its significant economic consequences to the overall economy (Beatty and Liao, 2014), an examination of loan loss provision forecasts has the potential to expand the literature on sell-side financial analysts, which has not examined explicit accruals forecasts.

Call et al. (2009) argue that when analysts forecast individual components of earnings, they are likely to adopt a structured approach that includes analyses of a full set of financial statements, thereby imposing greater forecasting discipline. Similar to arguments made in Call et al. (2013) about forecasts of individual earnings components, we argue that when forecasting provisions, analysts need to further understand the bank's system for identifying, monitoring and addressing loan problems and predicting future loan quality, which cannot be replicated using time-series models. Therefore, we expect that the provision forecast errors calculated using actual forecasts should be lower in magnitude than using predicted provisions based on time-series models.

Further, we expect that the superiority of analysts forecast over time-series forecasts will depend on the extent to which the provision includes expected future losses in addition to incurred losses. Based on the argument in Nichols et al. (2009) that publicly traded banks provide timelier loan loss provisions to mitigate information asymmetry, we expect that analysts provision forecast accuracy relative to time-series models might differ for banks with more timely loan loss provision accounting. On the one hand analysts forecasts can incorporate their expectation of future losses that are not captured in the time-series models, while on the other hand provision accounting that is not based on incurred losses could be more difficult for analysts to predict. This ambiguity is consistent with the mixed findings in the literature on whether analysts incorporate firms' accounting conservatism when forecasting earnings. For example, while Louis et al. (2008) find that analysts do not fully incorporate firms' timely loss recognition into earnings forecasts, Helbok and Walker (2004) suggest that analysts base their earnings forecasts on firms' accounting conservatism.

Based on these arguments our first hypothesis (stated in the null form) is:

H1: *The accuracy of analysts provision forecasts relative to time-series provision forecasts does not differ based on provision timeliness.*

2.2. Market Reaction to Loan Loss Provision Forecasts

Although the loan loss provision negatively impacts reported earnings, previous several studies conducted in the early 1990s find a positive reaction to unexpected provisions. For example, examining the three-day returns centered on the earnings announcement dates, Wahlen (1994) finds that the market reacts positively to unexpected provisions and earnings at the earnings announcement date. Similarly, Griffin et al. (1991) and Elliot et al. (1991) find a positive market reaction for banks' additions to loan loss provisions. They interpret this as evidence that increased provisions provides credible signals about banks' intentions and abilities to resolve bad debt issues. However, Ryan (2007) states that the evidence since 1993 does not show a positive market reaction to increases in loan loss provisions. For example, Ahmed et al. (1999) find that the market values the provision negatively beyond valuation of the provision component of earnings. If the market responds more to the provision component than to other earnings components, then we would expect a negative reaction to the provision surprise beyond the response to the earnings surprise in our sample period.

If analyst forecasts help market participants form expectations about the loan loss provision component of earnings, then, following previous research, we argue that the short-term market returns around earnings announcements may depend on provision surprises, *i.e.*, actual provision minus the analyst median forecast. However, the direction of the market reaction is not entirely obvious based on the findings in the literature. For industrial firms with analyst cash flow forecasts, DeFond and Hung (2003) find a significant market response to cash flow forecast errors but no significant market response to the accrual component of earnings forecast errors. If the market responds less to the provision component of earnings than to other earnings components like non-financial firms, then this would suggest a positive reaction to the provision surprise after controlling for the earnings surprise.

Based on these arguments, our second hypothesis (stated in the null form) is:

H2: The equity market reactions to provision surprises calculated based on both time-series models and analyst provision forecasts (i.e. provision – provision forecasts) are not different from zero.

Ryan (2007) argues that the market reaction to loan loss provisions depends on the provisioning timeliness with more timely losses being perceived by the market as bad news about impending loan defaults. Consistent with this possibility, we expect a more negative reaction to provision forecast surprises for banks with more timely loan loss provision accounting.

Based on these arguments our third hypothesis (stated in the null form) is:

H3: The equity market reaction to provision surprises (i.e. provision – provision forecasts) does not differ based on provision timeliness.

2.3. Non-performing Assets Forecasts

To support the notion that analysts incorporate forward looking information in provision forecasts when the covered banks are more timely in reporting loan losses, we explore the predictive ability of loan loss provision forecasts by examining the association between analysts' provision forecasts and future non-performing assets. If the provision forecasts reflect forward looking news about expected future losses, then we expect the provision forecasts to be more positively associated with future non-performing assets for banks with more timely provision accounting. However, because of the inherent difficulty of incorporating forward-looking information in provision forecasts, we expect analysts may not fully incorporate forward-looking information. Therefore, we expect provision surprises (i.e., actual reported provisions minus analyst forecasts) to also contain information about future losses, i.e., future nonperforming assets especially for timely banks.

We further contend that, to better incorporate forward looking nonperforming assets into provision forecasts, analysts may need to conduct more research on banks' systems for managing problem loans and understanding the evolution of nonperforming loans. We argue that analysts that also provide non-performing asset forecasts are more likely to have conducted such research. Accordingly, we explore the ability of provision forecasts to predict future non-performing assets by considering how these associations differ when analysts also forecast non-performing assets. We expect that when analysts forecast non-performing loans, their provision forecasts are more likely to reflect future loan losses for banks with timely provisions. However, it is unclear whether the same is true for banks with untimely provisions, since the analysts may want to minimize the forecast error rather than best predict future loan losses.

Based on these arguments our fourth and fifth hypotheses (stated in the null form) are:

H4: *The ability of analyst provision forecasts to predict future non-performing loans does not differ based on provision timeliness.*

H5: *The ability of analyst provision forecasts to predict future non-performing loans in the presence of non-performing asset forecasts does not differ based on provision timeliness.*

3. Research Methodology

3.1 Equity Analysts' Provision Forecasts vs. Time-Series Provision Forecasts

To explore whether analyst provision forecasts provide sophisticated information that cannot be replicated by investors using publicly available information, we first examine whether analyst provision forecasts are more accurate in predicting loan loss provisions than various time-series models and whether provision timeliness affects this difference in accuracy. Specifically, we compare the forecast errors calculated using actual analyst provision forecasts to forecast errors using predicted values based on various time-series models.

The first time-series model we consider is an AR1 time-series model (1):

$$Provision_t = \alpha_0 + \alpha_1 Provision_{t-1} + \varepsilon_{t.} \qquad (1)$$

Based on Beatty and Liao (2011), the second time-series model (2) that we consider includes other backward looking information including past non-performing loans, lagged earnings before provision and Tier 1 capital ratio in addition to last quarter provisions.

$$LLP_t = \alpha_0 + \alpha_1 \Delta NPL_{t-2} + \alpha_2 \Delta NPL_{t-1} + \alpha_3 TIER1_{t-1} + \alpha_4 {*} EBP_{t-1} + \alpha_5 LLP_{t-1} + \varepsilon_{t,} \quad (2)$$

where

LLP: Loan loss provision (COMPUSTAT "pllq") divided by lagged total assets").
ΔNPL: Change in non-performing loans (COMPUSTAT "npatq") divided by lagged total assets (COMPUSTAT "atq").
TIER1: The tier one risk-adjusted capital ratio (COMPUSTAT "capr1q").
EBP: Earnings before loan loss provision, defined as (COMPUTAT "ibq" plus COMPUSTAT "pllq", scaled by lagged COMPUSTAT "atq").

Specifically, we use the estimated coefficients from these time-series regressions using the past 20 quarters before the quarter in question to calculate the predicted provision for the current quarter.[3] In an alternative model, we also allow the time-series prediction model to include forward-looking information ΔNPL_{t+1}, one quarter ahead change in nonperforming assets, as an explanatory variable.

[3] We also replace the previous quarter provisions with four-quarter lagged provisions or add macro-variables in alternative time-series models. All results continue to hold.

We then compare the forecast errors based on analyst forecasts versus these three time-series models depending on the bank's timeliness in recognizing provision using the following model (3).

$$Inaccuracy_t = \beta_0 + \beta_1 Untimely_t + \beta_2 SIZE_{t-1} + \beta_3 NPL_{t-1} + \beta_4 {*} TIER1_{t-1} + \beta_5 EBP_{t-1} + \beta_6 Charge\text{-}Off_{t-1} + \beta_7 LOAN_{t-1} + \beta_8 Q4_t + \varepsilon_{t,} \quad (3)$$

where

Inaccuracy: absolute value of *LLPSurprise* minus the absolute value of either $LLP\text{-}PLLP_1$, $LLP\text{-}PLLP_2$ or $LLP\text{-}PLLP_3$.

LLPSurprise: the actual reported provision (COMPUSTAT "pllq"), scaled by lagged total assets (COMPUSTAT "atq") minus *LLPForecast.*

$LLP\text{-}PLLP_1$: the actual reported provision (COMPUSTAT "pllq") minus the predicted value of provision based on the AR1 time-series model (1) using the data from past 20 quarters on a rolling basis, scaled by lagged total assets (COMPUSTAT "atq").

$LLP\text{-}PLLP_2$: the actual reported provision (COMPUSTAT "pllq") minus the predicted value of provision based on a time-series model (2), where the explanatory variables include one-quarter lagged provision, ΔNPL_{t-1}, ΔNPL_{t-2}, one-quarter lagged EBP and TIER1, scaled by lagged total assets (COMPUSTAT "atq").

$LLP\text{-}PLLP_3$: the actual reported provision (COMPUSTAT "pllq") minus the predicted value of provision based on a time-series model where the explanatory variables include lagged provisions, ΔNPL_{t-1}, ΔNPL_{t-2}, ΔNPL_{t+1}, one-quarter lagged EBP, TIER1 and one-quarter ahead , scaled by lagged total assets (COMPUSTAT "atq").

Untimely : An indicator variable equal to one when *Timeliness* is below the sample median, zero otherwise.

Timeliness: Measured as the adjusted R-squared of EQ(a) minus adjusted R-squared of EQ(b) using the data from the past 20 quarters on a rolling basis, where

EQ(a): $LLP_t = \alpha_0 + \alpha_1 \Delta NPL_{t+1} + \alpha_2 \Delta NPL_t + \alpha_3 \Delta NPL_{t-1} + \alpha_4 \Delta NPL_{t-2} + \alpha_5 TIER1_t + \alpha_6 {*} EBP_t + \varepsilon_t$

EQ(b): $LLP_t = \alpha_0 + \alpha_1 \Delta NPL_{t-1} + \alpha_2 \Delta NPL_{t-2} + \alpha_3 TIER1_t + \alpha_4 {*} EBP_t + \varepsilon_t$

LLP: Loan loss provision (COMPUSTAT "pllq") divided by lagged total assets (COMPUSTAT "atq");

ΔNPL: Change in non-performing loans (COMPUSTAT "npatq") divided by lagged total assets (COMPUSTAT "atq");

TIER1: The tier one risk-adjusted capital ratio (COMPUSTAT "capr1q");

EBP: Earnings before loan loss provision, defined as (COMPUTAT "ibq" plus COMPUSTAT "pllq", scaled by lagged COMPUSTAT "atq").

Charge-Off: net charge offs (COMPUSTAT "ncoq") scaled by lagged total assets.

LOAN: Total loans (COMPUSTAT "lntalq") scaled by total assets.
Q4: An indicator variable equal to 1 for the 4th fiscal quarter.

In Model (3), in addition to the independent variable of interest (*Untimely*) that captures the timeliness of loan loss provisioning, we also control for bank characteristics that potentially affect analyst forecasts without specific predictions. Based on H1, we expect the coefficient on *Untimely* to differ from zero..

3.2 Market Reactions to Provision Forecast Errors at Earnings Announcements

To test whether market participants form provision expectations based on analysts' provision forecasts, we use the following OLS estimation (4) where we regress 3-day (-1, +1) market adjusted cumulative returns around earnings announcements on both earnings surprises and provision surprises calculated using analyst median earnings and provision forecasts.

$$RETURN_t = \beta_0 + \beta_1 * NISurprise_t + \beta_2 * LLPSurprise_t + \beta_3 * \Delta NI_t + \beta_4 * LLP\text{-}PLLP_1 + \beta_5 * \Delta SIZE_t + \beta_6 * \Delta NPL_t + \beta_7 * \Delta TIER1_t + \beta_8 * Q4_t + \varepsilon_t \quad (4)$$

where

RETURN: 3-day (-1, 1) cumulative abnormal returns around earnings announcements, where abnormal returns is measured as bank daily return minus bank sector equal weighted return.

NIForecast: the median analyst net income forecast, scaled by lagged total assets (COMPUSTAT "atq").

LLPForecast: the median analyst provision forecast, scaled by lagged total assets (COMPUSTAT "atq").

NISurprise: the actual reported net income (COMPUSTAT"niq"), scaled by lagged total assets (COMPUSTAT "atq") minus *NIForecast*.

LLPSurprise: the actual reported provision (COMPUSTAT "pllq"), scaled by lagged total assets (COMPUSTAT "atq") minus *LLPForecast.*

LLP-PLLP$_1$: the actual reported provision (COMPUSTAT "pllq") minus the predicted value of provision based on the AR1 time-series model using the data from past 20 quarters on a rolling basis, scaled by lagged total assets (COMPUSTAT "atq").

Δ*NI:* change in net income (COMPUSTAT"niq") scaled by lagged total assets (COMPUSTAT "atq").

Δ*SIZE*: change in bank size, where bank size is measured as the natural log of total asset (COMPUSTAT "atq").

ΔNPL: change in non-performing loan that is measured as the ratio of non-performing assets over lagged assets (COMPUSTAT "atq").
$\Delta TIER1$: change in Tier 1 regulatory capital.
Q4: an indicator variable equal to 1 for the fourth calendar quarter in a year, and 0 otherwise.

Based on prior research, we expect the coefficient on *NISurprise*, earnings surprises, to be positive. In addition, if analysts' provision forecasts are used to form expectations about loan loss provisions and the market responds differ for the loan loss provision component of earnings than for other earnings components then the coefficient on *LLPSurprise*, provision surprises should differ from zero.. In addition to these two main test variables, we control for change in net income (ΔNI) and $LLP\text{-}PLLP_1$ to ensure that we capture earnings and provision surprises incremental to that suggested by time-series models.[4] Based on H2 and prior research, we also expect the coefficient on $LLP\text{-}PLLP_1$ to differ from zero.[5] We also control for the change in size ($\Delta SIZE$), the change in non-performing loans (ΔNPL) and the change in regulatory capital ($\Delta TIER1$) to ensure we are not capturing the underlying change in banks' financial conditions. We expect the coefficients on $\Delta SIZE$ and $\Delta TIER1$ to be positive and the coefficient on ΔNPL to be negative. Finally, we also control for whether the quarter in which the earnings is measured is the 4^{th} quarter (*Q4*) without particular predictions.

To test whether analyst provision forecasts are more informative to the market in forming provision expectations when the banks' provision is more forward looking, we allow *Untimely* to be interacted with both *NISurprise* and *LLPSurprise*. In Model (4a) we expect that the coefficient on *LLPSurprise*Untimely* to differ from zero based on the

[4]To be consistent, we also alternatively control for the change in provisions instead of $LLP\text{-}PLLP_1$ .The results continue to hold.
[5] Alternatively, we control for $LLP\text{-}PLLP_2$ *or* $LLP\text{-}PLLP_3$ instead. We continue to find the same results.

argument that analyst forecasts are more informative of future losses when the bank is more timely in recognizing loan losses, while we do not expect the coefficient on *NISurprise*Untimely* to be significantly different from zero if the timeliness of the provision does not affect the informativeness of the non-provision earnings components.

$$RETURN_t = \beta_0 + \beta_1{*}Untimely_t + \beta_2{*}NISurprise_t + \beta_3{*}LLPSurprise_t + \beta_4{*}NISurprise{*}Untimely_t + \beta_5{*}LLPSurprise{*}Untimely_t + \beta_6{*}\Delta NI_t + \beta_7{*}\,LLP\text{-}PLLP_{1t} + \beta_8{*}\Delta SIZE_t + \beta_9{*}\Delta NPL_t + \beta_{10}{*}\Delta TIER1_t + \beta_{11}{*}Q4_t + \varepsilon_t \quad (4a)$$

3.3 Analysts Provision Forecasts and Future Non-performing Assets

To test whether analysts provision forecasts predict future non-performing assets we estimate the following model (5):

$$\Delta NPL_{t-+1} = \beta_0 + \beta_1\, LLPForecast_t + \beta_2\, Untimely_t + \beta_3\, LLPForecast{*}Untimely_t + \beta_4 \Delta NPL_{t-1} + \beta_5 SIZE_t + \beta_6 TIER1_{t-1} + \beta_7 Charge\text{-}off_{t-1} + \beta_8 EBP_{t-1} + \beta_9 LOAN_{t-1} + \beta_{10} Q4_t + \varepsilon_t \quad (5)$$

In Model (5), *LLPForecast* is measured as analyst provision forecasts scaled by lagged total assets. We expect the coefficient on *LLPForecast*Untimely* to differ from zero if the ability of analyst provision forecasts to predict future nonperforming assets differs for timely versus untimely banks. We also control for bank characteristics that are likely to affect future nonperforming loans without particular predictions. Other variables are defined as above or as in Appendix A.

To examine how the associations between future non-performing loans and provision forecasts differs in the presence of non-performing loan forecasts we estimate Model (5) separately for banks with nonperforming loans forecasts versus without such forecasts. We expect the coefficients on *LLPForecast* and on $LLPForecast{*}Untimely_t$ to differ for banks with nonperforming loan forecasts.

4. Samples and Findings

4.1 Samples and Databases

Our provision forecast information is acquired from SNL, which contains both analyst provision and net income forecasts for banks starting from the third quarter of 2008. We require the bank to be publicly traded and covered by CRSP for market reaction analyses. Finally, other bank characteristics are acquired from COMPUSTAT. Based on the intersection of these databases and the requirement of non-missing values for test and control variables, we end up with 3,928 bank-quarters with provision forecasts (representing 246 banks) for the period from the third quarter of 2008 through the third quarter of 2013.

Table 1 shows bank characteristics and our main variables partitioned by provision timeliness. We find that on average banks' earnings are lower than the forecasts while banks' provisions tend to be higher than the analyst forecast. We also find that consistent with our expectation, for both timely and untimely banks, analyst provision forecast errors (0.0008 and 0.0007, respectively) are lower than forecast errors based on time-series (0.0014 and 0.0012 for the first time series model, 0.0020, and 0.0016 for the second time series model, and 0.0021 and 0.0018, respectively, for the third time series model) at the 1% significance level (the test is not tabulated), suggesting that analyst provision forecasts contain useful information beyond what can be learned from time-series models. We also find that based on all three time series models, provision forecast errors are larger for timely banks than untimely banks, suggesting that it is more difficult to predict the provision when the bank's provisioning is more timely. Further, we find that timely banks are larger, have more nonperforming assets, and have lower regulatory capital compared to untimely banks. We present Pearson correlations among test and control variables in Table 2. We find that consistent with our expectation, the 3-day abnormal returns around earnings announcement are positively correlated with *NISurprise* while negatively correlated with *LLPSurprise*.

4.2 Empirical Findings

4.2.1 Analysts versus Time-Series Provision Forecasts

In Table 3 we explore whether the advantage of analyst provision forecasts over time-series models depends on banks' timeliness of loan loss provisioning. We find that provision forecast relative inaccuracy, measured as $|LLPSurprise| - |LLP\text{-}PLLP_1|$, $|LLPSurprise| - |LLP\text{-}PLLP_2|$, *or* $|LLPSurprise| - |LLP\text{-}PLLP_3|$, is significantly higher for banks with less timely loan loss recognition, significant at the 5% for time-series model 1) and 1% levels for time-series models 2) and 3). This finding suggests that analysts have a comparative advantage forecasting provisions when the underlying provision is timely. Analysts' forecast advantage for timely banks holds for all three time series models we consider and interestingly is the smallest for the simplest AR1 time series model.

4.2.2 Market Reaction to Provision Forecasts

Table 4 presents the results of our analysis of the market reactions to provisions and earnings announcements. The findings in Panel A Model 1 are consistent with recent findings in prior studies that the market reacts more strongly to the unexpected loan loss provision component of earnings than to other earnings components. In model 2 where the earnings surprise based on analyst earnings forecasts (*NISurprise*) is added there is a significant market reaction to the analyst forecast surprise and the market reaction to the time-series earnings forecast surprise becomes insignificant. The time-series provision forecast surprise remains significant however suggesting that the analyst earnings forecast surprise does not capture all of the time-series information about the provision. In model 3 where the analyst provision surprise (*LLPSurprise*) is also added, there is a significant market reaction to the analyst provision forecast surprise and the market reaction to the time-series provision forecast surprise becomes insignificant. This suggests that analyst provision forecast provides information to the market beyond what is provided by either the analyst earnings forecast or the time-series provision forecast. This indicates that separately forecasting the provision provides useful information beyond what is learned from the provision component of earnings.

In Panel B we extend our Panel A analysis to consider whether our findings differ based on banks' provision timeliness. In model 1 we find limited evidence that provision timeliness affects the markets' reaction to either time-series earnings or provision surprises. When we add analyst forecast surprises in models (2) and (3) and allow the coefficients on the earnings and provision surprises to differ for banks with more and less timely provision accounting, we find no difference in the coefficient on earnings forecast errors across this partition, but we find a significantly larger negative response to the provision forecast errors for more timely versus less timely banks. These results suggest that.analysts forecast surprises for banks with timely loan loss provisioning are informative to the market but those for banks with untimely provisions are not.

4.2.3 Analysts Provision Forecasts and Future Non-performing Assets

The first column of Table 5 provides the results of our analysis of the association between future non-performing assets and analysts' loan loss provision forecasts.

Consistent with the accuracy and usefulness of the provision forecasts being greater for banks with more timely loss recognition, we find that the provision forecasts are positively associated with future non-performing assets for banks with timely provision accounting and that the association is significantly lower for those with less timely provisions. This suggests that analysts attempt to map provision forecasts into future performance when providing forecasts for timely banks.

To further investigate whether analysts fully incorporate the loan loss provision timeliness in capturing future performance, we examine whether provision surprises predict one-quarter ahead nonperforming loans. In the second column of Table 5, we find that when the provision is timely, provision surprises are better able to predict future nonperforming loans, suggesting that despite their efforts to incorporate future performance in provision forecasts, analysts cannot fully incorporate the expected losses recognized in the provision. This again reflects the inherent difficulty of forecasting forward looking provisions.

In Panel A of Table 6, we examine whether the timeliness of analyst provision forecasts depend on the presence of nonperforming loan forecasts using the overall sample. We allow these coefficients on *LLPForecast* in Model (5) to also vary based on the existence of a non-performing asset forecasts. We find that, relative to untimely banks, the association between provision forecasts for timely banks and next period's non-performing assets becomes stronger in the presence of a non-performing asset forecast. This result suggests that analysts can improve their timeliness in provision forecasts for timely banks by understanding the factors that affect nonperforming loans, including banks' systems for identifying, addressing and monitoring loan problems. This finding may also suggest that analysts do not choose to incorporate those expectations into their forecasts for untimely banks that only provide for incurred losses. The lower association between future non-performing loans and provision forecasts for untimely banks is consistent with the market finding those forecasts less informative.

4.3 Additional Analyses and Robustness Checks

The presence of nonperforming asset forecasts may be an endogenous choice, which may affect the inference of results in the previous section. To address this issue, we employ a propensity score matching approach. In the first stage model of predicting nonperforming asset forecasts, we use the following logistic model (6):

$$NonPerfForecast = \beta_0 + \beta_1 LOAN\_RE_{t-1} + \beta_2 LOAN\_COM_{t-1} + \beta_3 NPL_{t-1} + \beta_4 SIZE_{t-1} + \beta_5 TIER1_{t-1} + \beta_6 EBP_{t-1} + \beta_7 Charge\text{-}Off_{t-1} + \beta_8 Q4_t + \varepsilon_{t,}, \qquad (6)$$

where

NonPerForecast :	An indicator variable equal to one for banks with nonperforming loan forecasts.
LOAN_RE :	Measured as the ratio of real estate loans divided by total loans.
LOAN_COM :	Measured as the ratio of commercial loans divided by total loans.

In Panel B of Table 6, we find the coefficients on *LOAN_RE* and *LOAN_COM* to be positive suggesting that the demand for nonperforming loan forecasts is higher for more heterogeneous loans. We also find that this nonperforming loan forecast is more likely for larger firms. Based on the propensity score calculated using this prediction model, we form a matched sample and conduct the estimation of the same model (5). In the last two columns of Table 6, we find that, based on the matched sample, the results continue to hold, suggesting that selection bias is not likely driving our findings. That is, analyst provision forecasts are more likely to predict future nonperforming loans in the presence of nonperforming loan forecasts.

As an additional analysis on the usefulness of analyst provision forecasts, we also examine whether the trading volume is affected by analyst provision forecasts. In untabulated results, we find that around the earnings and provision announcement dates, abnormal trading volume increases with both earnings forecast errors and provision forecast errors, further suggestive of the usefulness of analyst provision forecasts in forming market expectations. Further, in the market return analysis, the results also continue to hold when *RETURN* is defined alternatively using the market equal or value weighted return in CRSP as the benchmark as opposed to using the bank sector average return as the benchmark. We also follow prior research by scaling variables in the market reaction analysis using market value of equity instead of total assets. The results continue to hold. Finally, we define *RETURN* using 5-day (-2, 2) cumulative abnormal returns, and the results continue to hold.

5. Conclusion

In this paper, we study analyst loan loss provision forecasts, which have not been explored in previous research. We first examine the relative accuracy of analyst provision forecasts relative to three time-series provision forecast models and find that analysts are more accurate for banks with more timely provisioning relative to those with less timely provisioning.

We next examine the information content of provision forecasts by studying the market returns to earnings and provisions announcements for both time-series and analyst forecasts. We find that the 3-day abnormal returns increase with earnings surprises and decrease with provision surprises based on time-series models, indicating that the market applies a greater multiple to the provision component of earnings than to other earnings components. The time-series provision surprise continues to be associated with abnormal returns when we add analyst earnings surprise to the model but becomes insignificant when we include analyst provision surprise. This suggests that the provision forecasts provide information that cannot be gleaned from either the analyst earnings forecast or the time-series provision forecast.

When we examine how the market response varies with provision timeliness, we find limited evidence that the response to time-series forecasts of either earnings or the provision differs by timeliness. The market response to analyst earnings forecast errors similarly does not differ based on provision timeliness, but the response to the analyst provision forecast errors is more negative for more timely versus less timely banks. These results suggest that analyst provision forecasts contain more forward looking information as a benchmark for provisions.

To further investigate whether analysts' forecasts incorporate the expected losses recognized in the loan loss provision, we examine the association between future non-performing assets and analyst loan loss provision forecasts. We find that provision forecasts are positively associated with future non-performing assets for banks with timely loss recognition, but that the association is much lower for those with less timely provisions. We further find that analyst provision surprises are also more positively associated with future non-performing assets for timely banks. These results are consistent with the accuracy and usefulness of the prevision forecasts being greater for banks with more timely loss recognition, but also with the forecast not fully incorporating the expected losses recognized in the provision.

Our study makes two major contributions to the literature. We add to the literature on sell-side financial analysts by expanding our understanding of the properties of analyst accruals forecasts, which have largely been ignored in the analyst literature. In addition, we expand the literature on loan loss provisions by providing a new perspective on how and whether analyst provision forecasts form market expectations about provisions and on how provision timeliness affects the markets' response to those forecasts. We also expand our understanding of the timely provision recognition practice in relation to analyst provision forecasts.

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Appendix A: Variable Definitions

Timeliness Measures:

Untimely: An indicator variable equal to one when *Timeliness* is below the sample median, zero otherwise.

Timeliness: measured as the adjusted R-squared of EQ(a) minus adjusted R-squared of EQ(b) using the data from the past 20 quarters on a rolling basis, where

EQ(a): $LLP_t = \alpha_0 + \alpha_1 \Delta NPL_{t+1} + \alpha_2 \Delta NPL_t + \alpha_3 \Delta NPL_{t-1} + \alpha_4 \Delta NPL_{t-2} + \alpha_5 TIER1_t + \alpha_6 {*} EBP_t + \varepsilon_t$

EQ(b): $LLP_t = \alpha_0 + \alpha_1 \Delta NPL_{t-1} + \alpha_2 \Delta NPL_{t-2} + \alpha_3 TIER1_t + \alpha_4 {*} EBP_t + \varepsilon_t$

LLP: Loan loss provision (COMPUSTAT "pllq") divided by lagged total assets (COMPUSTAT "atq");

ΔNPL: Change in non-performing loans (COMPUSTAT "npatq") divided by lagged total assets (COMPUSTAT "atq");

TIER1: The tier one risk-adjusted capital ratio (COMPUSTAT "capr1q");

EBP: Earnings before loan loss provision, defined as (COMPUTAT "ibq" plus COMPUSTAT "pllq", scaled by lagged COMPUSTAT "atq").

Dependent and Test Variables:

RETURN: 3 day (-1, 1) cumulative abnormal returns around earnings announcements, where abnormal returns is measured as bank daily return minus bank sector equal weighted return.

NIForecast: the median analyst net income forecast, scaled by lagged total assets (COMPUSTAT "atq").

LLPForecast: the median analyst provision forecast, scaled by lagged total assets (COMPUSTAT "atq").

NISurprise: the actual reported net income (COMPUSTAT"niq") , scaled by lagged total assets (COMPUSTAT "atq") minus NIForecast.

LLPSurprise: the actual reported provision (COMPUSTAT "pllq"), scaled by lagged total assets (COMPUSTAT "atq") minus LLPForecast

$LLP\text{-}PLLP_1$: the actual reported provision (COMPUSTAT "pllq") minus the predicted value of provision based on the AR1 time-series model using the data from past 20 quarters on a rolling basis, scaled by lagged total assets (COMPUSTAT "atq").

$LLP\text{-}PLLP_2$: the actual reported provision (COMPUSTAT "pllq") minus the predicted value of provision based on a time-series model, where the explanatory variables include one-quarter lagged provision, ΔNPL_{t-1}, ΔNPL_{t-2}, one-quarter lagged EBP and TIER1, scaled by lagged total assets (COMPUSTAT "atq").

$LLP\text{-}PLLP_3$: the actual reported provision (COMPUSTAT "pllq") minus the predicted value of provision based on a time-series model where the explanatory variables include lagged provisions, $\Delta \mathrm{NPL}_{t-1}$, $\Delta \mathrm{NPL}_{t-2}$, ΔNPL_{t+1}, one-quarter lagged EBP, TIER1 and one-quarter ahead , scaled by lagged total assets (COMPUSTAT "atq").

Inaccuracy: absolute value of *LLPSurprise* minus the absolute value of either *$LLP\text{-}PLLP_1$, $LLP\text{-}PLLP_2$ or $LLP\text{-}PLLP_3$* .

Bank Characteristic Control Variables

SIZE: the natural log of lagged total asset (COMPUSTAT "atq").
NPL: the lagged ratio of non-performing assets over total assets (COMPUSTAT "atq").
*TIER*1: lagged tier one risk-adjusted capital ratio (COMPUSTAT "capr1q");
LOAN: total loans (COMPUSTAT "lntalq") scaled by total assets,.
Charge-Off: net charge offs (COMPUSTAT "ncoq") scaled by lagged total assets.
EBP: the ratio of earnings before loan loss provision, defined as (COMPUTAT "ibq" plus COMPUSTAT "pllq", scaled by lagged COMPUSTAT "atq").
Δ*NI:* change in net income (COMPUSTAT"niq") scaled by lagged total assets (COMPUSTAT "atq").
Δ*NPL*: change in non-performing loan that is measured as the ratio of non-performing assets over total assets (COMPUSTAT "atq").
Δ*SIZE*: change in bank size, where bank size is measured as the natural log of total asset (COMPUSTAT "atq").
Δ*TIER1*: change in Tier 1 regulatory capital.
Q4: an indicator equal to one for the fourth fiscal quarter in a year, zero otherwise.

Table 1: Descriptive Statistics Partitioned by Provision Timeliness

Variables	Timely		Untimely	
	Mean	Standard Deviation	Mean	Standard Deviation
Timeliness	0.2368	0.1537	-0.0195***	0.0554
RETURN	0.0009	0.0579	0.0006	0.0495
NISurprise	-0.00029	0.0026	-0.00026	0.0026
LLPSurprise	0.00028	0.0015	0.00025	0.0015
$LLP\text{-}PLLP_1$	-0.00028	0.0025	-0.00034	0.0023
$LLP\text{-}PLLP_2$	-0.00021	0.0037	-0.00016	0.0032
$LLP\text{-}PLLP_3$	-0.00006	0.0038	-0.00011	0.0035
| LLPSurprise |	0.0008	0.0014	0.0007	0.0014
$\lvert LLP\text{-}PLLP_1 \rvert$	0.0014	0.0025	0.0012**	0.0023
$\lvert LLP\text{-}PLLP_2 \rvert$	0.0020	0.0035	0.0016***	0.0032
$\lvert LLP\text{-}PLLP_3 \rvert$	0.0021	0.0037	0.0018**	0.0036
ΔNPL_{t+1}	0.0003	0.0045	-0.0004***	0.0039
SIZE	8.7591	1.7810	8.5278***	1.5639
NPL	0.0237	0.0200	0.0211***	0.0185
TIER1	12.6733	3.0309	13.0466***	3.2849
LOAN	0.6285	0.1161	0.6287	0.1269
Charge-Off	0.0018	0.0020	0.0017	0.0021
EBP	0.0036	0.0044	0.0036	0.0042
ΔNI	0.0001	0.0039	0.0001	0.0043
ΔNPL	0.0005	0.0047	-0.0002***	0.0039
ΔSIZE	0.0112	0.0428	0.0116	0.0469
ΔTIER1	0.1696	0.9775	0.1056**	1.0682
NPLForeError	0.0049 (N=845)	0.0067	0.0035*** (N=893)	0.0058
N	1,964		1,964	

Note: ***, **, and * indicate whether the means of the timely and untimely banks are significantly different at the 1%, 5% and 10% levels, respectively. See Appendix A for variable definitions.

Note: See Appendix A for variable definitions.

Table 2: Pearson Correlations (and p-values) among Main Variables

	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Untimely (1)	-0.003 (0.836)	0.007 (0.658)	-0.009 (0.564)	-0.022 (0.169)	-0.077 (0.001)	-0.069 (0.001)	-0.065 (0.001)	0.059 (0.001)	0.000 (0.956)	-0.023 (0.142)	-0.002 (0.903)	-0.002 (0.885)	-0.083 (0.001)	0.005 (0.765)	-0.031 (0.050)
RETURN (2)		0.282 (0.001)	-0.268 (0.001)	-0.178 (0.001)	-0.040 (0.012)	-0.060 (0.001)	-0.017 (0.274)	0.014 (0.382)	0.008 (0.609)	-0.020 (0.200)	-0.001 (0.948)	0.182 (0.001)	-0.186 (0.001)	0.044 (0.006)	0.056 (0.001)
NI Surprise (3)			-0.593 (0.001)	-0.529 (0.001)	-0.085 (0.001)	0.021 (0.194)	-0.145 (0.001)	0.136 (0.001)	-0.074 (0.001)	-0.168 (0.001)	0.102 (0.001)	0.583 (0.001)	-0.151 (0.001)	0.122 (0.001)	0.122 (0.001)
LLP_ Surprise (4)				0.809 (0.001)	0.157 (0.001)	-0.053 (0.001)	0.165 (0.001)	-0.103 (0.001)	0.147 (0.001)	0.166 (0.001)	-0.056 (0.002)	-0.317 (0.001)	0.207 (0.001)	-0.018 (0.270)	-0.091 (0.001)
| LLP_ Surprise | (5)					0.063 (0.001)	-0.126 (0.001)	0.345 (0.001)	-0.103 (0.001)	0.200 (0.001)	0.322 (0.001)	-0.012 (0.001)	-0.229 (0.001)	0.115 (0.001)	-0.084 (0.001)	-0.054 (0.000)
ΔNPL_{t+1} (6)						0.001 (0.959)	-0.192 (0.001)	-0.113 (0.001)	0.097 (0.001)	-0.061 (0.001)	-0.020 (0.201)	-0.009 (0.569)	0.263 (0.001)	0.065 (0.001)	0.078 (0.001)
SIZE (7)							-0.226 (0.001)	-0.166 (0.001)	-0.359 (0.001)	-0.009 (0.580)	0.055 (0.001)	-0.006 (0.687)	-0.011 (0.477)	-0.006 (0.728)	-0.000 (0.976)
NPL (8)								-0.055 (0.001)	0.296 (0.001)	0.528 (0.001)	-0.131 (0.001)	0.023 (0.145)	-0.140 (0.001)	-0.198 (0.001)	0.002 (0.927)
TIER1 (9)									-0.274 (0.001)	-0.118 (0.001)	0.127 (0.001)	-0.028 (0.076)	-0.119 (0.001)	0.036 (0.026)	-0.194 (0.001)
LOAN (10)										0.197 (0.001)	-0.018 (0.265)	-0.008 (0.621)	0.127 (0.001)	-0.009 (0.588)	0.025 (0.118)
Charge-Off (11)											-0.132 (0.001)	0.168 (0.001)	-0.014 (0.382)	-0.183 (0.001)	0.059 (0.001)
EBP (12)												-0.443 (0.001)	0.019 (0.244)	0.034 (0.031)	0.003 (0.864)
ΔNI (12)													-0.082 (0.001)	0.065 (0.001)	0.131 (0.001)
ΔNPL (13)														0.125 (0.001)	0.131 (0.001)
ΔSIZE (14)															-0.087 (0.001)
ΔTIER1 (15)															

Note: See Appendix A for variable definitions.

Table 3: Accuracy of Analyst Provision Forecasts Compared to Provision Forecasts Based on Time Series Models

$$Inaccuracy_t = \beta_0 + \beta_1 Untimely_t + \beta_2 SIZE_{t-1} + \beta_3 NPL_{t-1} + \beta_4 {*}TIER1_{t-1} + \beta_5 EBP_{t-1} + \beta_6 Charge\text{-}Off_{t-1} + \beta_7 LOAN_{t-1} + \beta_8 Q4_t + \varepsilon_t,, \quad (3)$$

	Model 1 (Inaccuracy = | LLPSurprise | - | *LLP-PLLP*$_1$ |)	Model 2 (Inaccuracy = | LLPSurprise | - | *LLP-PLLP*$_2$ |)	Model 3 (Inaccuracy = | LLPSurprise | - | *LLP-PLLP*$_3$ |)
Variables	Coefficients (p-value)	Coefficients (p-value)	Coefficients (p-value)
Intercept	-0.0006 (0.032)**	-0.0003 (0.675)	-0.0003 (0.667)
Untimely	0.0001 (0.046)**	0.0003 (0.002)***	0.0002 (0.085)***
SIZE	0.0006 (0.001)***	0.0006 (0.035)**	0.0007 (0.021)**
NPL	0.0094 (0.004)***	0.0023 (0.412)	0.0045 (0.2561)
TIER1	-0.0000 (0.983)	-0.0000 (0.137)	-0.0000 (0.111)
EBP	0.0180 (0.392)	0.0709 (0.108)	0.0730 (0.092)*
Charge-Off	-0.3822 (0.000)***	-0.5298 (0.000)***	-0.5867 (0.000)***
LOAN	-0.0003 (0.264)	-0.0008 (0.052)*	-0.0009 (0.023)**
Q4	0.0002 (0.064)*	0.0001 (0.223)	0.0002 (0.053)*
N	3,928	3,928	3,928
R-Squared	0.1751	0.1976	0.2055

Note: ***, **, and * represent 1%, 5% and 10% significance levels, respectively (two- or one-tailed when appropriate). Standard errors are double-clustered at the bank and quarter levels. See Appendix A for variable definitions.

Table 4: Market Reactions to Earnings and Provisions Announcements

$$RETURN_t = \beta_0 + \beta_1 * NISurprise_t + \beta_2 * LLPSurprise_t + \beta_3 * \Delta NI_t + \beta_4 * LLP\text{-}PLLP_1 + \beta_5 * \Delta SIZE_t + \beta_6 * \Delta NPL_t + \beta_7 * \Delta TIER1_t + \beta_8 * Q4_t + \varepsilon_t \qquad (4)$$

PANEL A:

	Model 1	Model 2	Model 3
Variables	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)
Intercept	-0.0007 (0.527)	0.0009 (0.429)	0.0021 (0.059)*
NISurprise		4.7828 (0.000)***	3.3108 (0.000)***
LLPSurprise			-4.7691 (0.000)***
ΔNI	1.4601 (0.000)***	0.0188 (0.957)	0.4235 (0.227)
$LLP\text{-}PLLP_1$	-2.2744 (0.000)***	-1.5574 (0.003)***	-0.0068 (0.991)
ΔNPL	-2.121 (0.000)***	-1.8195 (0.000)***	-1.6737 (0.000)***
ΔSIZE	0.0802 (0.000)***	0.0478 (0.025)**	0.0462 (0.031)**
ΔTIER1	0.0018 (0.024)**	0.0012 (0.148)	0.0011 (0.189)
Q4	-0.0083 (0.725)	0.0014 (0.585)	0.0015 (0.554)
N	3,928	3,928	3,928
R-Squared	0.0748	0.1062	0.1144

PANEL B: Interaction with Timeliness Measures

	Model 1	Model 2	Model 3
Variables	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)
Intercept	0.0003 (0.867)	0.0035 (0.016)**	0.0038 (0.008)***
Untimely	-0.0019 (0.267)	-0.0028 (0.076)*	-0.0034 (0.031)**
NISurprise		3.0728 (0.000)***	2.5797 (0.018)**
NISurprise* Untimely		0.4838 (0.671)	1.3721 (0.381)
LLPSurprise		-7.1665 (0.000)***	-7.9294 (0.000)***
LLPSurprise* Untimely		4.6508 (0.008)***	6.2667 (0.004)***
ΔNI	2.0798 (0.000)***	0.4071 (0.249)	0.9474 (0.098)*
ΔNI* Untimely	-1.1103 (0.089)*		-0.9808 (0.236)
LLP-PLLP$_1$	-2.0984 (0.004)***	0.0169 (0.978)	0.7935 (0.306)
LLP-PLLP$_1$* Untimely	-0.2648 (0.8027)		-1.6643 (0.141)
ΔNPL	-2.1222 (0.000)***	-1.5957 (0.000)***	-1.5896 (0.000)***
ΔSIZE	0.0805 (0.000)***	0.0468 (0.029)**	0.0476 (0.025)**
ΔTIER1	0.0018 (0.025)	0.0010 (0.198)	0.0011 (0.188)
Q4	-0.0009 (0.867)	0.0017 (0.517)	0.0016 (0.543)
N	3,928	3,928	3,928
R-Squared	0.0767	0.1182	0.1192

Note: ***, **, and * represent 1%, 5% and 10% significance levels, respectively (two- or one-tailed when appropriate). Standard errors are double-clustered at the bank and quarter levels. See Appendix A for variable definitions.

Table 5: Analyst Provision Forecasts' Predictability of Future Nonperforming Loans

$$\Delta NPL_{t-+1} = \beta_0 + \beta_1\, LLPForecast_t + \beta_2\, Untimely_t + \beta_3\, LLPForecast*Untimely_t$$
$$+\ \beta_4 \Delta NPL_{t-1} + \beta_5 SIZE_t + \beta_6 TIER1_{t-1} + \beta_7 Charge\text{-}off_{t-1} + \beta_8 EBP_{t-1}$$
$$+\ \beta_9 LOAN_{t-1} + \beta_{10} Q4_t + \varepsilon_t \qquad (5)$$

	Provision Forecast	Provision Surprise
Variables	Coefficients (p-values)	Coefficients (p-values)
Intercept	-0.001 (0.487)	-0.001 (0.521)
LLPForecast	0.411 (0.006)***	
LLPSurprise		0.406 (0.000)***
Untimely	0.0000 (0.951)	-0.0004 (0.008)***
LLPForecast* Untimely	-0.297 (0.011)**	
LLPSurprise* Untimely		-0.188 (0.091)*
ΔNPL_{t-1}	0.177 (0.000)***	0.183 (0.000)***
SIZE	0.0000 (0.514)	0.0001 (0.206)
TIER1	-0.0001 (0.062)*	-0.0001 (0.054)*
Charge-Off	-0.296 (0.000)***	-0.213 (0.000)***
EBP	-0.021 (0.329)	-0.018 (0.413)
LOAN	0.002 (0.028)**	0.002 (0.027)**
Q4	0.001 (0.399)	0.000 (0.448)
N	3,928	3,928
R-Squared	0.0869	0.0927

Note: ***, **, and * represent 1%, 5% and 10% significance levels, respectively (two- or one-tailed when appropriate). Standard errors are double-clustered at the bank and quarter levels. See Appendix A for variable definitions. *LLPForecast* is measured as the median of analyst provision forecasts scaled by lagged total assets (COMPUSTAT "atq").

Table 6: The Effect of Nonperforming Loan Forecasts on Timeliness in Provision Forecasts

PANEL A: Prediction of Future Nonperforming Loans

	Overall Sample		Propensity Score Matching	
Nonperforming Loan Forecasts:	YES	NO	YES	NO
Variables	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)	Coefficients (p-values)
Intercept	0.0012 (0.435)	-0.0016 (0.173)	-0.0003 (0.899)	-0.0006 (0.710)
LLPForecast	0.9297 (0.000)***	0.0850 (0.311)	1.0506 (0.000)***	0.0086 (0.486)
Untimely	0.0004 (0.047)**	-0.0002 (0.340)	0.0007 (0.024)**	-0.0003 (0.3717)
LLPForecast* Untimely	-0.4187 (0.006)***	-0.2533 (0.061)*	-0.5489 (0.005)***	-0.1212 (0.308)
ΔNPL_{t-1}	0.1445 (0.006)***	0.1857 (0.000)***	0.1050 (0.120)	0.1442 (0.001)***
SIZE	-0.0001 (0.362)	0.0001 (0.144)	-0.0000 (0.765)	0.0000 (0.971)
TIER1	-0.0001 (0.067)*	-0.0001 (0.129)	-0.0001 (0.246)	-0.0001 (0.084)*
Charge-Off	-0.4516 (0.002)***	-0.2163 (0.004)***	-0.586 (0.001)***	-0.2372 (0.063)*
EBP	-0.0201 (0.515)	-0.0239 (0.400)	-0.0181 (0.628)	-0.0369 (0.153)
LOAN	0.0004 (0.651)	0.0033 (0.003)***	0.0018 (0.204)	0.0046 (0.002)***
Q4	0.0005 (0.469)	0.0006 (0.283)	0.0008 (0.269)	0.0005 (0.502)
Difference in Coefficients on *LLPForecast*	X^2=14.0624 (p-value=0.000)		X^2=7.1289 (p-value=0.008)	
N	1,739	2,189	871	871
R-Squared	0.1199	0.0082	0.1175	0.0862

Note: ***, **, and * represent 1%, 5% and 10% significance levels, respectively (two- or one-tailed when appropriate). Standard errors are double-clustered at the bank and quarter levels. See Appendix A for variable definitions. *LLPForecast* is measured as the median of analyst provision forecasts scaled by lagged total assets (COMPUSTAT "atq").

PANEL B: Logit Estimation of Determinants of Nonperforming Loan Forecasts

Variables	Coefficients	p-values
Intercept	-9.699	0.000***
LOAN_RE	4.790	0.000***
LOAN_COM	5.785	0.000***
NPL	-0.132	0.998
SIZE	0.571	0.000***
TIER1	0.022	0.507
EBP	5.327	0.678
Charge-Off	-63.277	0.100*
N	3,365	
Pseudo R-Squared	0.0944	

Note: ***, **, and * represent 1%, 5% and 10% significance levels, respectively (two- or one-tailed when appropriate). Standard errors are clustered at the bank level. See Appendix A for variable definitions. *LOAN_RE* is measured as the ratio of real estate loans over total loans and *LOAN_COM* is measured as the ratio of the commercial loans over total loans, both measured at the beginning of the quarter.