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Pre-Publication Revisions of Bank Financial Statements:

A Novel Way to Monitor Banks?

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Abstract

We investigate whether pre-publication revisions of bank financial statements contain forward-looking information about bank risk. Using 7.4 million observations of monthly financial reports from all banks in Brazil during 2007-2019, we show that 78% of all revisions occur before the publication of these statements. The frequency, missing of reporting deadlines, and severity of revisions are positively related to future bank risk. Using machine learning techniques, we provide evidence on mechanisms through which revisions affect bank risk. Our findings suggest that private information about pre-publication revisions is useful for supervisors to monitor banks.

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1. Introduction

Bank financial reporting receives special attention by academia, financial markets, and policy makers for good reason. Bank balance sheets consist predominantly of opaque financial assets and liabilities, financial statement information is used in prudential bank regulation, and loan loss provisions constitute a dominant accrual in bank accounting. Moreover, research suggests a link between changes in accounting standards, banking regulations and banking crises (Beatty and Liao 2014). The experience from the Global Financial Crisis of 2007-09 suggests that inadequate financial reporting may have negatively affected bank supervision before and during the crisis (Acharya et al. 2009; Bank for International Settlements 2012; Bischof et al. 2021).

In this paper, we investigate a new source of information about bank risk. We examine whether pre-publication revisions of bank financial statements contain forward-looking information about bank risk. This is an important question because bank failures and systemic financial crisis are potentially costly but at the same time difficult to predict.[1] Our setting is novel as we analyze banks' revisions of financial statements *before* they are published rather than bank financial reporting to the public. In other words, we focus on the flow of private information from banks to their supervisor and investigate the link with bank risk. These revisions could provide early-stage private information that supervisors can use for monitoring "bad things to come."

We base our study on a unique dataset on bank regulatory reporting that, to the best of our knowledge, has never been used before. The data cover 1,812 banks that have to submit their financial statements to the Central Bank of Brazil every month. The main dataset contains 7,438,180 bank-month-item level observations resulting from a merge of four regulatory

[1] Laeven and Valencia (2018) provide a comprehensive overview of systemic banking crises and the associated costs.

datasets that include preliminary, revised, and final financial statements, as well as information on bank closures. Each observation contains information on a financial statement item reported by a certain bank in a given month.

These data allow us to compute the frequency and severity of the revisions by item, bank, and month. Interestingly, 78% of all revisions made by banks occur before the publication of the financial statements. After aggregating over all available accounting items at the bank-month level, the final dataset consists of 146,442 observations, spanning the period from January 2007 to March 2019. Our study is based on Brazilian data, but the general setting applies to virtually all countries, including the United States and the European Union where banks report balance sheet and credit risk information to their supervisors at a monthly frequency.

In our empirical analysis, we find that pre-publication revisions of financial statements contain significant private information about future bank risk. The frequency of revisions is negatively related to a bank's future average probability of default of its individual borrowers, the Capital, Asset quality, Management, Earnings, and Liquidity (CAMEL) rating and its distance to default (Z-score). The economic significance of these relations doubles for banks that revise their financial statements most frequently. Moreover, we find that banks that submit their financial statements faster and in fewer revision rounds, exhibit a relatively lower risk over the next six months. We then show for the subsample of revised financial statements, that not only the frequency but also the severity of revisions relates to future bank risk.

Using machine learning, we then analyze how the revision of individual accounts affect bank risk. We provide evidence on mechanisms at the accounting item level, through which revisions affect future bank risk. Moreover, we show that our main results are robust with regard to the choice of the lag length, the computation window of the bank risk proxies, using additional bank risk measures, and whether revisions are initiated by the supervisor or not.

Closely related to our paper is the study of Badertscher et al. (2018), which analyzes whether the publication of Call Reports by listed U.S. banks affects their stock returns and trading volume. These banks have to submit the reports to their bank supervisor in addition to the mandatory SEC filings. While they do not have access to the same confidential regulatory data that we use, they examine whether previously published versions of the same Call Report had been changed. They find that around one third of the published Call Reports are amended within the first three months after publication, but they do not find a statistically significant stock market reaction to amendments. They explain this with the fact that amendments are extremely small (0.2% of total assets, 0.4% of Tier 1 capital). Our study differs from Badertscher et al. (2018) in several important dimensions. We analyze (i) the flow of private information from banks to their supervisor that occurs *before* the publication of their financial reports, (ii) whether this information is related to future bank risk (rather than stock returns or trading volume) and (iii) a setting that is unique because there is no parallel flow of information (as in the U.S. the Call Reports and SEC filings).

Our paper further relates to three broader strands of literature. The first one investigates bank risk taking and interactions with regulators. Ellul and Yerramilli (2013) show that banks with tighter risk controls exhibit less downside risk. Fahlenbrach et al. (2012) provide evidence that banks' inherent risk culture affects their risk taking and performance over a long-term horizon. Agarwal et al. (2014) document that lenient regulatory behavior can lead to costly outcomes and significantly impede the effectiveness of banking supervision and regulation. Gallemore (2022) investigates the link between financial reporting opacity, measured by delayed expected loan loss recognition, and regulatory interventions in U.S. banks during the financial crisis. He finds that reporting opacity is negatively related to regulatory intervention.

The second strand of literature examines banks' use of internal risk models. Banks report the output of these models internally (e.g., to loan officers, risk managers or the management) and externally (to bank supervisors or auditors). Concerning internal reporting, Hertzberg et al. (2010) provide evidence that loan officers' compensation scheme, career incentives and potential rotation schemes affect the quality of the internal risk ratings. Concerning external reporting, there is mixed evidence about whether banks over- or understate their market risk, which is measured by internal Value-at-Risk (VaR) models, to regulators and/or the public. Da Veiga et al. (2012) show that banks understate VaR to save costly capital, while Pérignon et al. (2008) provides evidence that banks overstate the VaR. The Basel II capital regulations also allow banks to use the internal-ratings based (IRB) approach to measure their level of credit risk. Mariathasan and Merrouche (2014) find that the risk-weight density becomes lower once regulatory approval to use the IRB approach is granted. Plosser and Santos (2018) provide evidence that within loan syndicates, low-capitalized banks report lower borrower risk estimates than high-capitalized banks. Behn et al. (2022) find that internal risk estimates employed for regulatory purposes understate actual default rates.

Third, the accounting literature has shown that delays and revisions in the regulatory filing of a financial statement is a sign of bad things to come. In a non-bank setting, Alford et al. (1994) and Bartov and Konchitchki (2017) show that firms delay their filings when they face unexpected negative events and that firm delaying their filings experience negative stock returns. Leuz et al. (2003) provide evidence that earnings management is more widespread in countries with weaker investor protection. Feroz et al. (1991) and Desai et al. (2006) provide empirical evidence of what forced accounting revisions imply for management turnover. Beatty and Liao (2014) provide a comprehensive overview of earnings management and restatements for banks. Jiang et al. (2016) find that intensified competition reduces abnormal accruals of loan loss provisions and the frequency with which banks restate financial statements. Herly (2019) shows that banks subject to restatements contribute more to systemic risk than other banks and have spillover effects on the financial system. Costello et al. (2019) use the

Badertscher et al. (2018) approach and show that strict regulators are more likely to enforce income-reducing reporting choices by forcing banks to restate their overly aggressive call reports. Huizinga and Laeven (2012) show that banks overstated the value of distressed assets and their regulatory capital during the financial crisis.

Our paper contributes to the literature above in the following ways. First, we investigate the regulatory reporting of banks to their supervisor, which involves private information as it takes place before banks publish financial statements. Second, banks' regulatory reporting is more frequent (monthly instead of quarterly or yearly) and significantly more detailed than their financial reporting to the public. Both features of regulatory reporting enable supervisors to observe information earlier than the public and take actions if necessary. Third, our results differ to Badertscher et al. (2018) because we use revisions of privately available data for all banks (including non-listed ones), the severity of revisions are several magnitudes larger compared to their results, and we focus on the predictive power of these measures for future bank risk rather the immediate stock market impact.

2. Institutional background

The National Financial System (SFN) of Brazil is structured in three functions: regulatory, supervisory, and operational. The operational function is performed by intermediary institutions that provide financial services. The financial system is dominated by banking institutions. In addition, it is highly concentrated with the five largest banks accounting for more than 70 percent of total lending (for an overview, see Cortes and Marcondes, 2018). The credit market experienced significant growth in the last two decades. According to World Bank data, bank credit to private sector increased from 31% of GDP in 2005 to almost 64% of GDP in 2019. This vast expansion of credit is attributed to several reforms in the 2000s, a fostering credit policy after the Global Financial Crisis of 2007-09, and a declining trend of the policy interest rates.

Brazil's financial system has been characterized by high interest rates and high spreads. Nonetheless, the interest rates have fallen significantly in the last five years. The Selic rate, which is the policy interest rate, dropped from 14% in 2015 to 2% in 2020. As of December 2019, the average interest rate on loans was 22.6% whereas the banks' funding cost was about 11%. The high lending rates can be explained by the high-risk environment. Brazilian banks held non-performing loans of 7.3% and provisions expenses of 2.9% of the credit portfolio. The provisions maintained by the banks covered more than 80% of their delinquent loans, which is an important mitigator in the case of risk materialization. Furthermore, more than 60% of loans were secured by collateral (Haas Ornelas et al., 2022). Despite the high-risk environment, Brazilian banks are highly profitable. In 2019, the banking system reported an average Return on Equity (ROE) of 16.5%.

The Central Bank of Brazil (BCB), is responsible for executing the monetary, credit and exchange rate policies, and regulating and supervising the National Financial System. It has the mandate of assuring the soundness and efficiency of the financial system. Banks are required to report to the regulator on several aspects, including accounting information. The banks report monthly accounting information to the Financial System Monitoring Department (Desig) of the Central Bank. The accounting plan and governing principles thereof are stipulated in the regulatory guidelines (COSIF). The data submitted by the banks form the COSIF database.

Desig issues the submission schedule of the financial statements at the beginning of each year. The banks are required to report their accounting information, before the respective submission deadline, via an online system of the Central Bank. When a bank submits its report, an initial screening takes place. This screening involves two types of checks: pre-processing checks and post-processing checks. The pre-processing checks are embedded in the system. They identify common errors and mistakes, such as account balance errors. If any parameter of the pre-processing checks is not satisfactory, the system automatically rejects the report[2]. Such rejected data do not enter the COSIF database. The data that meets the pre-processing checks become part of the COSIF data. In the next step, Desig performs post-processing checks and evaluates quality of the data. In case of any anomaly, it asks the bank, via the online system, for explanation and/or rectification. The system automatically shares a copy of the message with the Banking Supervision Department (Desup) for information and further investigation. If significant inconsistencies are observed, Desig informs the Conduct Supervision Department (Decon).

The Central Bank publishes selected financial information of the banks on its website on a fixed date, which is 90 days after the reference date for the annual accounts of December and 60 days after the reference date for all the other months. The COSIF dataset has several levels of detail, with level-5 being the most detailed. The data is made public only up to level-3 of detail.

The banks are allowed to submit, and re-submit the financial statements *before* the publishing of the data without any restriction. For example, for the month of January 2018, the deadline to submit the report is 18/02/2018, and the publishing date is 01/04/2018. The banks can freely revise and substitute the initially submitted reports until 01/04/2018.

Banks do not need approval of the Central Bank to make changes and substitute the initially submitted data with a new version. The history of all the initially submitted reports is stored in a separate database, which is never published. We have access to this database. If banks make changes after the financial statements are published, only then it is necessary to

[2] The pre-processing checks are a possible bank rationale for sending financial statements early instead of just meeting the supervisor deadline.

resubmit the statements with explanatory notes on the reason of changes. If changes are made in the statements of June or December, in addition to the explanatory notes, it is necessary to have the financial statements audited again. Each month the Central Bank updates the last six months of data, which reflect any updates made by the banks in the meantime.

3. Data

3.1. Data sources

Our analysis is based on four datasets obtained from the BCB. Three datasets are obtained from Desig and one from the Department of Financial System Organization (Deorf). The data come from 1,812 banks during the period from January 2007 to March 2019.

Our first dataset is a registration database for the supervised financial institutions (Unicad). This dataset includes key information such as incorporation date, corporate control, ownership, type of institution, and segment of operation. It is continuously updated to reflect the latest characteristics of a supervised entity.

Our second dataset contains accounting data of the financial institutions (COSIF). Some banks are required to submit the accounting statements on a monthly basis and others on a quarterly basis. The Central Bank uses COSIF data for the purpose of monitoring, analysis, and evaluation of the financial system.

Our third dataset, revisions history data, is a confidential database that contains the history of all preliminary accounting information submitted to the Central Bank. This database basically contains all initial versions of the accounting information reported to the Central Bank as per regulatory guidelines in the COSIF manual. When a bank first submits its accounting information, it becomes part of the COSIF data. However, if a bank substitutes its initially reported accounting information with an updated version, before the publishing date, the initially submitted version is transferred to the revisions history data and only the final version becomes part of the COSIF database. The former is never made public while the latter is published according to a pre-determined schedule. The publishing date is 90 days after the reference date for the annual accounts of December and 60 days after the reference date for all the other months.

Our fourth dataset is a compilation of the cases of bank closures as a consequence of license cancellations. It includes the reason of the bank closure (e.g., bankruptcy, extrajudicial settlement or judicial decision). Bank license cancelations requested by the bank and related to non-distress acquisitions are not considered a distress event. Our sample includes 262 cases of bank closures.

3.2. Data samples

We prepare two data samples for our analysis, a master dataset and an aggregated dataset. We construct our master dataset by merging the above four regulatory datasets at item-bank-time level. Our master dataset consists of 7,438,180 observations, where each row contains information on accounting item *i* reported by bank *b* at time *t*. For each of these accounting items, we have information on whether, when and to what extent the initially reported value is substituted with an updated value. This unique dataset allows us to compare the preliminary accounting information that never becomes public with the final accounting information that becomes public. Our master dataset offers several advantages for the empirical analysis. First, it allows us to identify and zoom in on the accounting items that are most frequently revised by the banks. Second, we are able to utilize each reported accounting item for computation of our measures of revisions.

We aggregate our master dataset at the bank-time level to construct our aggregated dataset. Our aggregated dataset consists of 146,442 bank-time level observations, where each row contains aggregated information on revisions of bank *b* at time *t*. All our multivariate results are based on our aggregated dataset.

3.3. Main variables

We measure revisions of banks' regulatory reporting using the two key metrics $Frequency_{bt}$ and $Severity\ to\ Assets_{bt}$. $Frequency_{bt}$ captures the ratio of total items revised to total items reported in a given month. It is defined as:

$$Frequency_{bt} = \frac{\sum_{i=1}^{I} Count_{\{Revision_{ibt} \neq 0\}}}{Total\ Items_{bt}} \quad (1)$$

where $Revision_{ibt}$ is a condition testing if the final value of an accounting item *i* of bank *b* at time *t* is different than the initial value of the accounting item *i*. *Count* is a dummy variable which equals one in case of a revised item and $Total\ Items_{bt}$ counts the total number of reported accounting items. Since the revision of one accounting item likely triggers other revision(s) in one or more accounting items via accounting identities[3], we acknowledge that $Frequency_{bt}$ is at least double counted in the revision metrics used in the paper.

$Severity\ to\ Assets_{bt}$ measures the intensities of revised accounting items scaled by bank size. It is computed only for the items for which $Revision_{ibt}$ is equal to one. It is defined as:

$$Severity\ to\ Assets_{bt} = \frac{\sum_{i=1}^{I} |Item\ Post_{ibt} - Item\ Pre_{ibt}|}{Total\ Assets_{bt}} \quad (2)$$

where $Item\ Post_{ibt}$ is the value of an item i of bank b at time t after revision, $Item\ Pre_{ibt}$ is the value of an item i of bank b at time t before revision, and $Total\ Assets_{bt}$ are the total assets of bank b at time t.

We also use two further independent variables that capture the timing and complexity of revisions. Both are defined in Section 4.1.

[3] For example, a revision that increases an asset item should at least trigger one more revision that increases a liability item or a revision that diminishes another asset item.

We employ three key indicators of bank risk. Our risk indicators are a proxy for the average *Probability of Default* (*PD*) of a bank's individual borrowers, the *CAMEL* rating, and the bank *Z-Score*.

The *PD* is based on the micro-level loan ratings data in the credit registry (SCR) from the Central Bank of Brazil. Banks rely on these ratings for the loan approval decision, loan pricing, and credit risk transfer. The *PD* is calculated as the weighted average of default probabilities of bank b's loans at time t[4].

CAMEL is the average rating of $Capital_{bt}$, $Asset\ quality_{bt}$, $Management_{bt}$, $Earnings_{bt}$, *and* $Liquidity_{bt}$ of bank *b* at time *t*, computed as an average rating over six months, *t*-5 to *t.* It takes values from 1 to 5 where 5 is the best rating.

The $Z\text{-}Score_{bt-5:t}$ captures the distance-to-default, i.e., the number of standard deviations a bank's (six-month rolling window) return of assets has to decline to entirely deplete its equity, of bank *b* at time *t.* Since the *Z-Score* is highly skewed, we use the natural logarithm of the Z-Score as in Laeven and Levine (2009).[5] All variables are defined in the Online Appendix, Table OA.1.

Our three key risk measures are bank-specific and time-varying and therefore, unlike a dummy variable of bank default, capture the continuous time variation in default risk during the pre-default time. Stated differently, our measures capture ex ante (and not ex post) bank risk. The Central Bank of Brazil has used this information, including the *PD* from the loan ratings, for on-going monitoring of banks.

[4] This measure can be interpreted as the weighted average minimum provision percentage across the bank's loan portfolio. The risk cohorts and provision allocations for each rating category align with the regulatory buckets outlined in Resolution 2,682 from 1999. Given that internal ratings used by banks in managing their loan portfolios may not be directly observable, our proposed measure serves as a proxy for estimating the average probability of default (PD) among borrowers within the bank's portfolio.

[5] For brevity, we use the label *Z-Score* in referring to the natural logarithm of the Z-Score.

3.4. Summary statistics

Table 1 presents summary statistics for our variables of interest over our sample period. The average bank reports 51 accounting items per time. *Frequency* shows that the average bank revises 0.75 percent of its accounting items. This implies that the average bank revises one accounting item in two to three months. The banks at the 95th and 99th percentile revise 4.2 percent and 17.2 percent of accounting statements per time, which make about two and nine accounting items, respectively. The bank at the maximum end of the distribution revises its accounting statement completely. The average bank's severity of revisions is about 4.6 percent of its total assets. Since our severity measure is computed using only the accounting items that are revised, the sample size is reduced. Turning to banks' risk characteristics, Table 1 shows that the average bank's *PD* is 0.067, the *CAMEL* rating 3.04, and the *Z-Score* 4.6.

Panel A of Table 2 reports the number and fraction of revisions. In our master dataset (item-bank-time level), the number of revised items is 54,416 which is 0.73 percent of total reported items of 7,438,180. In our aggregated dataset (bank-time level), there are 12,666 bank-time pairs with non-zero metrics of revisions. This makes about 8.65 percent of our aggregated data that have 146,442 observations. Panel B of Table 2 presents the timing of revisions with respect to the date on which the financial statements become public. Importantly, 78.5 percent of revisions in our sample take place before the financial information becomes public. This feature of our data makes our study the first of its kind.

4. Are revisions an early-warning indicator of bank risk?

4.1. Main results

We examine the relation between pre-publication revisions and bank risk using the following regression model:

$$Bank\ Risk_{bt-5:t} = \alpha_t + \alpha_b + \beta R_{bt-6} + \varepsilon \tag{3}$$

where $Bank\ Risk_{bt-5:t}$ denotes any of our three main indicators of bank risk: $PD_{bt-5:t}$, $CAMEL_{bt-5:t}$, or $Z-Score_{bt-5:t}$.[6] *Bank Risk* indicators are computed over a rolling window of six months (from *t*-5 to *t*). R_{bt-6} denotes any of our measures of revisions, the main ones being $Frequency_{bt-6}$ and $Severity\ to\ Assets_{bt-6}$. Importantly, we measure the characteristics of revisions strictly before the bank risk measures to avoid simultaneity. The parameter β is the coefficient of interest. We include time fixed effects (α_t) and bank fixed effects (α_b). Bank fixed effects control for any time-invariant unobserved heterogeneity across banks that affect *Bank Risk,* while time fixed effects (year-month level) control for particular changes over time. We cluster standard errors at the bank level because bank risk is likely to be correlated over time.

We investigate whether the banks that revise regulatory financial information are riskier. More specifically, we examine whether our metrics of revisions can serve as an early-warning indicator of bank risk. If this should be the case, estimations from equation (3) would return a positive sign on the coefficient β for the *PD* and a negative sign on the *CAMEL* rating and *Z-Score*. Such a finding would indicate that banks that revise more frequently and severely have higher average borrower *PDs* and lower *CAMEL* ratings and *Z-Scores*.

We start our analysis with a multivariate regression of the measures of bank risk on *Frequency*. Table 3 reports the results.[7] We find across all specifications that our frequency estimates are higher for riskier banks. The coefficient of *Frequency* is 0.021 in the *PD* regression in Column (1) and -0.324 in the *CAMEL* regression in Column (2). For example, the latter implies that a change of one standard deviation in *Frequency* accounts for an average *CAMEL* rating decrease of 10.7 percent of its unconditional mean. In Column (3), the corresponding decrease in the Z-Score is 6 percent.

[6] We omit the subscripts in the description below to facilitate exposition.

[7] Note that the number of observations in our specifications slightly differs because accounting items that need to be reported depend on the type of bank.

We complement this analysis with evidence on the timing and complexity of revisions. Lagging all revisions per bank and month by six months, we create two proxies and report results in Table 4. The first one, *Delivery Delay,* equals the number of days between the actual delivery date and the submission deadline of the financial statement. In case of multiple revisions, we use the latest delivery date. We hypothesize that a delayed delivery of financial statements after the submission deadline (but before the publication date) already indicates a red flag. We find significant results across all bank risk measures in line with this reasoning (Panel A). For instance, the coefficient estimate for *PD* is 0.030 and significant at the 1% level. The other proxy is *Revision Time Span*, which equals the number of days between the last and the first delivery date (Panel B). This proxy also indicates more complex revisions. We find consistent evidence for all bank risk measures.

Our next analysis focuses on the intensity of revisions. We measure intensity at the bank-time level with *Severity to Assets* lagged by six months. Table 5 presents the results. The coefficient β carries the expected sign in all three models and shows that the intensity of revisions is significantly higher for riskier banks.

4.2. Revisions of accounting items and bank risk: a machine learning exercise

For the machine learning exercise, we replace the aggregated frequency measure with $Revision_{ibt}$, which is a condition testing if the final value of an accounting item *i* of bank *b* at time *t* is different than the initial value of the accounting item. Specifically, we use 155 financial statement *Revision* variables in addition to year-month and bank type dummies. According to Hastie et al. (2009), running an OLS model for such a dataset has two major disadvantages. First, OLS estimates often have low bias but large variance. Prediction accuracy can be improved for in case of a large set of predictors by shrinking some coefficients. By doing so, we under-proportionally increase the bias to reduce the variance of the predicted values. Second, with a large number of predictors, we often would like to determine a smaller subset that drives the forecasting power. Interpretation of the results is easier by focusing on these key results.

Shrinkage estimators such as RIDGE or LASSO are popular machine learning techniques to tackle both issues (Tibshirani, 1996).[8] We use the LASSO because compared to RIDGE, which shrinks coefficients to non-zero values according to their influence, it shrinks less important coefficients to zero, facilitating the interpretation for larger sets of predictors. Specifically, we use the extended Bayesian information criterion (BIC) to find the optimal degree of penalization, i.e., the tuning parameter lambda (Chen and Chen, 2008).

Panel A of Table 6 presents the revised accounting items selected in the LASSO regression and their importance for each of our bank risk variables, while Panel B lists the names of the corresponding accounting items[9]. The *CAMEL* rating appears to be more sensitive to revisions than the other bank risk measures since it is affected by 22 accounting item revisions.

The seven items selected by the LASSO analysis that affect the bank *PD* in Panel A of Table 6 are: *Credit operations with classification AA* (best loan rating) and *Credit operations with classification H* (worst loan rating) from the Compensation accounts, *Cash deposits* and *Miscellaneous items* at the liability side, *Accumulated profits or losses for credit unions f*rom the equity side, and *Provisions and equity adjustments* and *Income tax* from cost accounts. In case of the *Z-Score*, 12 items are picked up by the LASSO exercise.

[8] See, for example, Kozak et al. (2020), Feng et al. (2020), or Gu et al. (2020) for recent implementations of the LASSO.

[9] This exercise offer insight into the underlying channels influencing bank risk, particularly through pre-publication revisions at the account level. In this context, mechanical associations are not an issue as change in accounting variables serve to reinforce the validity of our findings, highlighting the direct impact of operational enhancements on mitigating risk within the bank's portfolio. Such associations underscore the practical implications for risk management strategies within financial institutions.

Table 6 highlights two aspects. First, the selected items and their importance are mixed across the bank risk measures. This is plausible because the dependent variables focus on different dimensions of bank risk (asset risk, capital structure, profitability, etc.). Second, the signs of the effects are almost all in the same direction for the *CAMEL* rating and the *Z-Score* and in the opposite direction for the *PD*. This finding confirms the expected sign of the effects in our previous analyses and suggests that revisions of several accounting items (possibly with a greater discretionary potential) may contain information that is useful for monitoring bank risk.

4.3. Robustness tests

We perform several robustness tests related to variable choice, variable measurement, model specifications and sample composition.

First, one concern could be that our results are sensitive to the choice of the lag length. To explore whether the lag length affects our results, we re-estimate equation (3) using lags of 12 months and 18 months of *Frequency*, respectively. The results are shown in the Online Appendix Table OA.2. They are qualitatively similar to the results of Table 3 although the size and the statistical significance of some estimates decrease with the increase in lag length up to 18 months. Such a decrease is as expected, given that more long-term forecasts are more difficult compared to less distant predictions as in our baseline analysis with six months.

Second, we consider an alternative time window for computing the measures of *Bank Risk*. Instead of using a 6-month rolling window (from t-5 to t), we compute the risk measures over 12-month (from t-11 to t) and 18-month (from t-17 to t) rolling windows. Computing risk measures in this manner implies that we need to lag the explanatory variables by 12 months (or 18 months) in order to avoid an overlap with the computation window of our risk measures.

The Online Appendix Table OA.3 shows the results. Overall, our results are robust to changing the time window over which the bank risk measures are computed.

Third, in further (unreported) tests, we consider additional bank risk measures. We take the standard deviations of the return on assets and the return on equity as measures of earning volatility. Moreover, we take the non-performing loan coverage and the liquidity coverage ratio. These measures are defined following the Central Bank of Brazil's supervisory manual. In all of these tests, the frequency of revisions, lagged by 6 months, is significantly related to future bank risk.

Fourth, we re-estimate the models from Table 3 excluding the 262 banks that were closed during our sample period. We report the results in Table OA.4. We find that *Frequency* is signed as expected and significant for all three bank risk measures, with slightly smaller economic significance. Overall, this test confirms our main result and shows that the predictive ability of pre-publication revisions is not driven by bank closures.

Fifth, the BCB, as the supervisor and regulator, may influence banks' revisions of financial reports. As explained in Section 2, the BCB performs post-processing checks on the financial reports submitted by the banks. The BCB then asks the banks for explanation and/or rectification if it observes any anomaly. To rule out the concern that revisions attributable to the BCB drive our results, we distinguish in an additional unreported analysis between the revisions (possibly) initiated by the BCB and the ones initiated by the banks themselves. We construct an alternative data sample which excludes any revisions initiated by the BCB. The remaining sample contains approximately 92 percent of our aggregated dataset used in Section 4.1. The coefficient estimates across all our specifications remain qualitatively unchanged. These results are available upon request from the authors.

5. Conclusions

We investigate whether pre-publication revisions of financial statements contain forward-looking information about bank risk. We use the average *PD* of a bank's individual borrowers, the *CAMEL* rating, and the *Z-Score* as measures of ex ante bank risk. Analyzing a unique dataset containing monthly financial reports of all Brazilian banks submitted to the Central Bank during 2007-2019, we show that the majority of all revisions occur before the publication of these reports. The frequency, missing of reporting deadlines, and severity of revisions are positively related to future bank risk. We further analyze how the revision of individual accounts affect bank risk using machine learning, which shows the mechanisms through which pre-publication revisions affect bank risk.

Overall, our findings have clear policy implications. They suggest that pre-publication revisions contain valuable information for monitoring financial institutions. Proactive regulatory actions help to promote safe and sound banking systems and the early-warning indications of our revision metrics lend them suitable for this purpose. Pre-publication revision activity of all banks should hence be regularly tracked and thoroughly analyzed by financial supervisors and regulators with a view to enhance financial stability. There are two main advantages of scrutinizing banks' pre-publication revision activity. First, it can be implemented for all banks, including small and unlisted banks, for which market monitoring is limited. Second, it can be done at an early stage, which in turn enables faster subsequent regulatory interventions if necessary. Timely actions from regulators and policymakers are critical to prevent systemic stress events like the Global Financial Crisis.

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Table 1: Summary statistics

This table presents summary statistics for our sample. The sample period is from January 2007 to March 2019. All variables are defined in the Online Appendix Table OA.1.

	(1) Number of obs.	(2) Mean	(3) SD	(4) p5	(5) Median	(6) p95
Risk indicators						
$PD_{bt-5:t}$	139,856	0.0672	0.1236	0.0050	0.0365	0.2019
$CAMEL_{bt-5:t}$	146,442	3.0388	0.9258	1.6250	2.9333	4.7500
$Z\text{-}Score_{bt-5:t}$	144,216	4.5972	0.9620	3.6611	4.3944	6.3822
Explanatory variables						
$Revision_{ibt}$	7,438,180	0.0073	0.0852	0	0	0
$Accounting\ Items\ Reported_{bt}$	146,442	50.7927	17.8663	25	51	83
$Frequency_{bt}$	146,442	0.0075	0.0397	0.0000	0.0000	0.0417
$Severity\ to\ Assets_{bt}$	12,378	0.0460	0.1084	0.0000	0.0067	0.2152
$Delivery\ Delay_{bt}$	146,390	1.6723	21.6514	-12	-3	28
$Revision\ Time\ Span_{bt}$	146,390	3.9602	15.4728	0	0	21

Table 2: Number and timing of revisions

This table reports the number of financial statement revisions in Panel A and the timing of the revisions in Panel B.

Panel A: Number of revisions

	$Revisions_{ibt}$ item-bank-time level		Revisions bank-time level	
	Number of obs.	%	Number of obs.	%
No	7,383,764	99.27	133,776	91.35
Yes	54,416	0.73	12,666	8.65
Total	7,438,180	100	146,442	100

Panel B: Timing of revisions

	$Revisions_{ibt}$	
	Number of obs.	%
Before publishing date	42,716	78.50
On publishing date	141	0.26
After publishing date	11,559	21.24
Total	54,416	100

Table 3: Frequency of revisions and bank risk

This table estimates the relationship between frequency of revisions and bank risk. Panel A reports OLS regression results of dependent variables of $PD_{bt\text{-}5:t}$, $CAMEL_{bt\text{-}5:t}$, and $Z\text{-}Score_{bt\text{-}5:t}$ on $Frequency_{bt\text{-}6}$. All explanatory variables are lagged by six months. All variables are defined in the Online Appendix Table OA.1. Standard errors appear in parentheses and are clustered at the bank level. *, **, and *** indicate significance levels at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
	PD	*CAMEL*	*Z-Score*
Expected sign	(+)	(-)	(-)
$Frequency_{bt\text{-}6}$	0.021**	-0.324***	-0.277***
	(0.011)	(0.063)	(0.068)
Bank & Time FE	Yes	Yes	Yes
Number of observations	125,795	131,348	131,256
Adjusted R^2	0.676	0.758	0.568

Table 4: Revision speed, complexity and bank risk

This table examines whether speed and complexity of revisions are related to bank risk. We report OLS regression results of dependent variables of $PD_{bt-5:t}$, $CAMEL_{bt-5:t}$, and $Z\text{-}Score_{bt-5:t}$ on two proxies for revision speed and complexity: $Delivery\ Delay_{bt-6}$ (Panel A) and $Revision\ Time\ Span_{bt-6}$ (Panel B). *Delivery Delay* equals the number of days between the actual delivery date and the submission deadline of the financial statement. In case of multiple revisions, we use the latest delivery date. *Revision Time Span* equals the number of days between the last and first delivery date. All explanatory variables are lagged by six months. All variables are defined in Online Appendix Table OA.1. Standard errors appear in parentheses and are clustered at the bank level. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	(1)	(2)	(3)
	PD	*CAMEL*	*Z-Score*
Expected sign	(+)	(-)	(-)
Panel A: Delivery Delay			
$Delivery\ Delay_{bt-6}$	0.030***	-0.137***	-0.175***
	(0.006)	(0.018)	(0.024)
Bank & Time FE	Yes	Yes	Yes
Number of observations	125,785	131,337	131,245
Adjusted R^2	0.678	0.759	0.569
Panel B: Revision Time Span			
$Revision\ Time\ Span_{bt-6}$	0.007**	-0.099***	-0.090***
	(0.003)	(0.017)	(0.017)
Bank & Time FE	Yes	Yes	Yes
Number of observations	125,785	131,337	131,245
Adjusted R^2	0.676	0.758	0.568

Table 5: Severity of revisions and bank risk

This table presents estimates for the relationship between severity of revisions and bank risk. We show OLS regression results of $PD_{bt-5:t}$, $CAMEL_{bt-5:t,}$, and $Z\text{-}Score_{bt-5:t}$ on *Severity to Assets*$_{bt-6}$. All variables are defined in Online Appendix Table OA.1. Standard errors appear in parentheses and are clustered at the bank level. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	(1)	(2)	(3)
	PD	*CAMEL*	*Z-Score*
Expected sign	(+)	(-)	(-)
Severity to Assets$_{bt-6}$	0.025**	-0.097*	-0.159**
	(0.012)	(0.059)	(0.067)
Bank & Time FE	Yes	Yes	Yes
Number of observations	10,852	11,176	11,176
Adjusted R^2	0.574	0.794	0.551

Table 6: Machine learning analysis of revised accounting items and bank risk

This table reports the importance of the selected accounting items by the LASSO regression to each of the dependent variables $PD_{bt\text{-}5:t}$, $CAMEL_{bt\text{-}5:t}$, and $Z\text{-}Score_{bt\text{-}5:t}$. All regressions also include time and bank type fixed effects. We use the extended Bayesian information criterion (BIC) to find the optimal degree of penalization.

Panel A: LASSO regression

Assets

Predictors	***PD***	***CAMEL***	***Z-Score***
Liquid and long-term assets			
11200002		0.033	
12500000		0.244	
14100006		-0.030	
16100004		0.049	
16300000		-0.017	
16900008			-0.042
18300008		-0.024	
18800003		-0.019	
19800002		-0.195	
Permanent			
21200009			-0.023
Compensation accounts			
30900008		-0.056	-0.011
31100003	-0.002		
31300009		-0.051	
31500005		-0.026	
31600008		-0.069	
31700001		-0.016	
31900007	0.012		-0.029

Liabilities

Predictors	***PD***	***CAMEL***	***Z-Score***
Liquid and long-term liabilities			
41100000	0.003	-0.276	-0.116
41500002			-0.026
44500009		-0.061	0.442
49300008		0.131	
49800003	0.464	-0.915	-1.269
49900006		-0.016	
Equity			
61100004		0.032	
61700002	0.009	-0.081	-0.050
61800005		-0.172	-0.068
Costs			
81600003			-0.007
81800009	0.002		-0.016
89400009	-0.012		
Compensation accounts			
90900000		-0.061	-0.042

Panel B: List of the accounting items selected by the LASSO regression

Assets	
Liquid and long term assets	
11200002	Banking deposits
12500000	Savings deposits
14100006	Rights with participants of the settlement/payment systems
16100004	Discounted loans and credit rights
16300000	Rural loans
16900008	Provisions for credit operations
18300008	Income receivable
18800003	Miscellaneous items
19800002	Other values and assets
Permanent	
21200009	Investment in affiliates and subsidiaries in the country
Compensation accounts	
30900008	Compensation control
31100003	Credit operations with classification AA
31300009	Credit operations with classification B
31500005	Credit operations with classification D
31600008	Credit operations with classification E
31700001	Credit operations with classification F
31900007	Credit operations with classification H

Liabilities	
Liquid and long-term liabilities	
41100000	Cash deposits
41500002	Time deposits
44500009	Resources received from affiliated cooperatives
49300008	Other social and statutory obligations
49800003	Miscellaneous items
49900006	Miscellaneous items
Equity	
61100004	Social capital
61700002	Accumulated profits or losses for credit unions
61800005	Accumulated profits or losses for banks
Costs	
81600003	Expenses with affiliations
81800009	Provisions and equity adjustments
89400009	Income tax
Compensation accounts	
90900000	Compensation control

Online Appendix

Pre-Publication Revisions of Bank Financial Statements: A Novel Way to Monitor Banks?

Table OA.1: Variable definitions

Variable	Definition
Risk indicators	
$PD_{bt-5:t}$	Defined as $\frac{\sum_{r=Aa,A,B,C,D,E,F,G,H}(Loans\ Rated\ r\ x\ Probability\ of\ Default\ of\ Loans\ Rated\ r)_{bt}}{Total\ Laons_{bt}}$, where $Loans\ Rated\ r$ represent loans of bank *b* at time *t* in each rating category $r = Aa, A, B, C, D, E, F, G$, and H with *Probability of Default* of 0%, 0.5%, 1%, 3%, 10%, 30%, 50%, 70%, and 100% respectively, computed over a rolling window of six months, *t*-5 to *t*, winsorized at 1%/99% level. $Total\ Loans_{bt}$ are the total loans of bank *b* at time *t*. The ratio is winsorized at 1%/99% level.
$CAMEL_{bt-5:t}$	Average rating of $Capital_{bt}$, $Asset\ quality_{bt}$, $Management_{bt}$, $Earnings_{bt}$ and $Liquidity_{bt}$ of bank *b* at time *t*, computed as an average rating over six months, *t*-5 to *t*. It takes values from 1 to 5 where 5 is the best. $Capital_{bt}$ is the ratio of shareholders' equity to total assets of bank *b* at time *t*. $Asset\ quality_{bt}$ is the ratio of mandatory regulatory provisions to gross loans of bank *b* at time *t*. $Management_{bt}$ is the ratio of operating expenses to net operating income of bank *b* at time *t*. $Earnings_{bt}$ is the rate of return on assets of bank *b* at time *t*. $Liquidity_{b}$ is the natural logarithm of the ratio of liquid assets to deposits and short-term funding of bank *b* at time *t*. All variables are winsorized at 1%/99% level.
$Z\text{-}Score_{bt-5:t}$	Defined as natural logarithm of $(ROA_{bt} + Equity\ Ratio_{bt})/SD\ ROA_{bt-5:t}$, where ROA_{bt} is the rate of return on assets of bank *b* at time *t* and $Equity\ Ratio_{bt}$ is the ratio of shareholders' equity to total assets of bank *b* at time *t,* both winsorized at 1%/99% level. $SD\ ROA_{bt-5:t}$ is the standard deviation of the rate of return on assets of bank *b* at time *t*, computed over a rolling window of six months, *t*-5 to *t*, winsorized at 1%/99% level. Z-Score is rescaled to a positive number before taking the log.
Explanatory variables	
$Revision_{ibt}$	A dummy variable which is 1 if the final value of an accounting item *i* of bank *b* at time *t* is different than the initial value of the item *i*, and 0 otherwise.
$Frequency_{bt}$	Defined as $\frac{\sum_{i=1}^{I} Count_{\{Revision_{ibt} \neq 0\}}}{Total\ Items_{bt}}$, where the numerator counts the non-zero values of $Revision_{ibt}$ of bank *b* at time *t* and $Total\ Items_{bt}$ is the total number of observations of bank *b* at time *t.*
Severity to $Assets_{bt}$	Defined as $\frac{\sum_{i=1}^{l} \lvert Item\ Post_{ibt} - Item\ Pre_{ibt} \rvert}{Total\ Assets_{bt}}$, where $Item\ Post_{ibt}$ is the value of an item *i* of bank *b* at time *t* after revision, $Item\ Pre_{ibt}$ is the value of an item *i* of bank *b* at time *t* before revision, and $Total\ Assets_{bt}$ are the total assets of bank *b* at time *t*. The ratio is capped at 1 and it is computed only for the items for which $Revision_{ibt}$ equals 1.
Delivery $Delay_{bt}$	The number of days between the delivery date of financial statements of bank *b* for reporting month *t* and the submission deadline for month *t*, computed as: delivery $date_{bt}$ - $deadline_{t}$. In case of multiple revisions, we use the latest delivery date.
Revision Time $Span_{bt}$	The number of days between the last and first delivery date of bank *b* for reporting month *t*, computed as: last delivery $date_{bt}$ – first delivery $date_{bt}$.

Table OA.2: Frequency of revisions lagged by 12 and 18 months

This table examines the robustness of the main findings in Table 3. It reports OLS regression results of dependent variables of $PD_{bt-5:t}$, $CAMEL_{bt-5:t}$, and $Z\text{-}Score_{bt-5:t}$ on $Frequency_{bt-p}$. The explanatory variables are lagged by p = 12 months in Columns (1)-(3) and by p = 18 months in Columns (4)-(6). All variables are defined in Online Appendix Table OA.1. Standard errors appear in parentheses and are clustered at the bank level. *, **, and *** indicate significance levels at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	PD	*CAMEL*	*Z-Score*	*PD*	*CAMEL*	*Z-Score*
Expected sign	(+)	(-)	(-)	(+)	(-)	(-)
Lag length		p = 12			p = 18	
$Frequency_{bt-p}$	0.020*	-0.280***	-0.353***	0.023*	-0.179***	-0.245***
	(0.011)	(0.056)	(0.063)	(0.012)	(0.059)	(0.078)
Bank & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	111,657	116,684	116,643	97,845	102,477	102,445
Adjusted R^2	0.678	0.762	0.564	0.678	0.765	0.561

Table OA.3: Bank risk measures over a longer rolling window

This table examines the robustness of the findings in Table 3 using bank risk measures over longer rolling windows. Panel A uses a 12-month window by regressing the bank risk measures $PD_{bt\text{-}11:t}$, $CAMEL_{bt\text{-}11:t}$, and $Z\text{-}Score_{bt\text{-}11:t}$ on $Frequency_{bt\text{-}12}$. Panel B uses an 18-month window by regressing the bank risk measures $PD_{bt\text{-}17:t}$, $CAMEL_{bt\text{-}17:t}$, and $Z\text{-}Score_{bt\text{-}17:t}$ on $Frequency_{bt\text{-}18}$. All variables are defined in Online Appendix Table OA.1. Standard errors appear in parentheses and are clustered at the bank level. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	(1) *PD*	(2) *CAMEL*	(3) *Z-Score*
Expected sign	(+)	(-)	(-)
Panel A: 12-month lag			
$Frequency_{bt\text{-}12}$	0.018*	-0.317***	-0.234***
	(0.010)	(0.063)	(0.043)
Bank & Time FE	Yes	Yes	Yes
Number of observations	112,279	116,684	116,668
Adjusted R^2	0.720	0.796	0.674
Panel B: 18-month lag			
$Frequency_{bt\text{-}18}$	0.022**	-0.283***	-0.202***
	(0.011)	(0.055)	(0.052)
Bank & Time FE	Yes	Yes	Yes
Number of observations	98,426	102,477	102,464
Adjusted R^2	0.722	0.801	0.671

Table OA.4: Frequency of revisions excluding bank defaults

This table examines the robustness of the findings in Table 3. We exclude 262 banks that were closed during our sample period. We regress the bank risk measures $PD_{bt\text{-}5:t}$, $CAMEL_{bt\text{-}5:t}$, $Z\text{-}Score_{bt\text{-}5:t}$ on $Frequency_{bt\text{-}6}$. All explanatory variables are lagged by six months. All variables are defined in the Online Appendix Table OA.1. Standard errors appear in parentheses and are clustered at the bank level. *, **, and *** denote 10%, 5%, and 1% significance, respectively.

	(1)	(2)	(3)
	PD	*CAMEL*	*Z-Score*
Expected sign	(+)	(-)	(-)
$Frequency_{bt\text{-}6}$	0.019*	-0.297***	-0.276***
	(0.010)	(0.065)	(0.070)
Bank & Time FE	Yes	Yes	Yes
Number of observations	117,968	122,455	122,434
Adjusted R^2	0.658	0.752	0.552

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