Bank Accounting Discretion Over the Business Cycle*

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Abstract

This paper documents cross-sectional variation in how banks exercise accounting discretion over the business cycle, and it examines the effects of this behavior on banks' financial intermediation activities and financial stability. I show that while banks with substantial core deposit bases manage loan loss provisions to smooth earnings over the business cycle, consistent with prior literature, banks with limited core deposits exhibit the opposite behavior. Specifically, they understate provisions during economic upturns and thus overstate them during downturns. This pattern is driven by risk-taking incentives: banks with fewer core deposits reduce provisions in good times to attract wholesale funding, thereby increasing their lending capacity. Additionally, I find that this loan growth enhances these banks' ability to delay provisions, which in turn facilitates more wholesale funding and lending. This feedback mechanism interacts with the risk-taking channel, functioning as an "accounting accelerator." However, because wholesale funding is information sensitive and loan loss provisions cannot be delayed through bad times, the accounting-driven credit expansion in good times also exacerbates the severity of economic downturns, amplifying business cycle fluctuations and threatening financial stability.

*I greatly appreciate the guidance and support of my dissertation committee: Viral Acharya (Co-Chair), Mary Billings, Ilan Guttman, Stephen Ryan (Co-Chair). I thank Aleksander Aleszczyk, Jeremy Bertomeu, Gauri Bhat, Sandra Chamberlain, Christine Cuny, Yiwei Dou, Richard Frankel, Pingyang Gao, Zachary Kaplan, Chongho Kim, Seil Kim, Sehwa Kim, Pierre Liang, Yao Lu, Russell Lundholm, Xiumin Martin, Michael Minnis, Xiaojing Meng, Allison Nicoletti, Joshua Ronen, Yanting Shi, Hangyuan Shi, Gurpal Sran, Sorabh Tomar, Rajesh Vijayaraghavan, George Yang, Frank Zhou, as well as seminar participants at NYU Stern, UBC Sauder, WUSTL Olin, SMU Cox, SMU Singapore, HKU, HKUST, CUHK, CityU, and Renmin University for insightful comments. All remaining errors are my own.

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1 Introduction

The financial crisis sparked renewed debate about the stability of the financial system and especially about the desirability of banks' discretion in reporting loan losses (Acharya and Ryan, 2016; Beatty and Liao, 2014). Prior studies document that traditional depository banks smooth their earnings over the business cycle (Liu and Ryan, 1995, 2006; Greenawalt and Sinkey, 1988; Kanagaretnam et al., 2003, 2004). However, this literature leaves unanswered questions about why banks are frequently criticized for insufficient loss recognition before crises and the broader implications of their earnings management behavior. This paper addresses these issues by analyzing cross-sectional variation in how commercial banks manage earnings across the business cycle and analyzes how this variation affects their financial intermediation activities and financial stability.

Specifically, this paper focuses on banks' exercise of accounting discretion over loan loss provisions to manage earnings. Loan loss provisions are banks' initial estimates of future credit losses on new loans and estimated changes in future losses on preexisting loans. These provisions are the most important bank accruals, and research suggests that they are used by banks to manage earnings and regulatory capital (Beatty and Liao, 2014; Dechow et al., 2010). Prior studies show that *abnormal* loan loss provisions largely reflect banks' accounting discretion and are often used as a proxy for banks' financial reporting quality (Jiang et al., 2016; Yue et al., 2021). Following this literature, I measure accounting discretion using *abnormal* loan loss provisions, which are the estimated residuals from a model of nondiscretionary loan loss provisions. I interpret negative (positive) residuals as banks exercising accounting discretion to understate (overstate) loan loss provisions.

This paper examines banks' discretion over loan loss provisions through the lens of their liability structures. This liability-side perspective is motivated for several reasons. First, Beatty and Liao (2014) highlight in their review of the empirical literature on banks' financial reporting that prior research largely ignores liability-side information problems and their impact on earnings management.[1] Second, the collapse of Silicon Valley Bank (SVB) underscores the critical role of liability-side characteristics in triggering a self-fulfilling panic run in response to perceived bank losses (Jiang et al., 2024). Third, recent decades have witnessed a significant shift in bank funding structures, with banks increasingly relying on uninsured debt from institutional investors rather than traditional retail deposits. Given that different types of liabilities have varying sensitivities to financial information, understanding how liability structures influence banks' use of accounting discretion is of first-order significance for assessing its financial stability implications.

I begin by documenting how the time-series relationship between banks' abnormal loan loss provisions and the business cycle differs between banks with large and small core deposit

[1] Specifically, Beatty and Liao (2014) state that the "earnings smoothing objective is not well motivated in the banking literature and ignores how depositor information problems affect earnings and capital management, despite the importance of this information problem" (p. 378).

bases. Core deposits, which consist of retail checking, savings, and small time deposits, are regarded as the most stable and dependable source of funding for banks (Federal Deposit Insurance Corporation, 2011). Banks with a strong deposit franchise can raise core deposits to meet their lending needs. In contrast, banks with insufficient core deposits must rely on wholesale funding—sources outside of core deposits.[2] Unlike sticky core deposits, wholesale funding is typically uninsured, short-term, and highly sensitive to information (Pérignon et al., 2018), thereby increasing bank liquidity risks during market disruptions, as demonstrated by the failure of SVB (Jiang et al., 2024).

Figure 1 shows that banks with large core deposit bases exhibit a positive correlation between changes in their abnormal provisions and changes in industrial production, but this relationship is significantly negative for banks with smaller core deposits. Thus, while banks with substantial core deposits manage provisions to smooth earnings over the business cycle,[3] consistent with prior literature, those with limited core deposits behave oppositely. These contrasting patterns support the notion that a bank's funding structure (core deposits vs. wholesale funding) influences how it manages provisions and earnings. Additionally, this finding is evident in the cross-section. I estimate each bank's sensitivity of abnormal loan loss provisions to the business cycle and refer to this sensitivity as its "discretion beta." Figure 2 reveals a strong negative correlation between a bank's discretion beta and its reliance on wholesale funding, confirming that banks more dependent on wholesale funding are less likely to smooth earnings throughout the business cycle.

Motivated by this important yet understudied pattern, I develop a stylized model to generate empirical predictions in a setting where a bank privately observes its loan loss rate and makes reporting decisions in anticipation of business cycle fluctuations. In this framework, wholesale lenders impose limits on the bank's access to wholesale funding based on its reported earnings, which the bank can manipulate through discretion over loan loss provisions. Importantly, the model assumes that lenders' scrutiny of reported earnings is more intense during downturns than in booms.[4] Consequently, while earnings manipulation can be concealed during good times, it will be partially revealed during downturns. In equilibrium, the bank's optimal earnings manipulation balances the trade-off between the benefits of raising wholesale debt and extending loans during booms and the costs of losing wholesale funding and reducing lending during busts. This trade-off between *growth* and *stability* provides a key analytical insight into the findings presented in Figures 1 and 2. Banks with limited core

[2]Throughout the paper, wholesale funding refers to noncore liabilities, defined as total liabilities minus core deposits. It is a term that encompasses various funding sources, including large time deposits, repurchase agreements, commercial paper, Federal Home Loan Bank (FHLB) advances, and other financing instruments banks use to raise funds.

[3]Earnings are smoothed over the business cycle when loan loss provisions are overstated during good times and understated during bad times.

[4]This assumption is supported by extensive literature indicating that information production and revelation in credit markets is countercyclical (e.g., Gorton and Ordonez, 2014, 2020; Lisowsky et al., 2017; Weitzner and Howes, 2021).

deposits are more likely to understate loan loss provisions during booms to facilitate growth, leading to larger provisions being recorded during downturns. In contrast, banks with large core deposits face less pressure to manage provisions aggressively, allowing them to smooth earnings and maintain stability. This shift from earnings smoothing to risk-taking will become more pronounced as a bank's reliance on wholesale funding increases. And the incentive for risk taking grows when a bank's actual or unmanaged performance declines.

To test these predictions, I construct a data set of all FDIC-insured commercial banks in the U.S. between 1990 and 2019.[5] By exploiting cross-sectional variation in banks' reliance on wholesale funding, I find that the negative relationship between changes in banks' abnormal loan loss provisions and changes in industrial production indeed intensifies monotonically with this reliance. In other words, the more a bank relies on wholesale debt, the more it understates its loan loss provisions in good times and thus overstates them in bad times. I conduct a number of robustness tests to validate my findings. First, to address concerns that loan portfolio differences might explain the results, I examine provisioning behavior across banks grouped by loan composition and also analyze bank adequacy ratios. The results show that wholesale-reliant banks had lower adequacy ratios around the financial crisis, indicating understated loan losses rather than less risky portfolios. Second, I include extensive controls and fixed effects and restrict the sample to private banks to account for differences in regulatory and information environments. The results hold consistently across these tests, suggesting that the findings are unlikely driven by other confounding factors. Moreover, when partitioning banks based on their pre-provision performance, I find that the results monotonically strengthen as bank pre-provision performance deteriorates, consistent with banks' incentives to take risks increasing as their actual performance declines. Taken together, these cross-sectional results suggest that banks that rely on wholesale funding strategically exercise discretion over loan loss provisions to increase their earnings in good times.

Next, I examine the real consequences of such risk-taking behavior. My model suggests that banks' inflated earnings through understated loan provisions increase wholesale lenders' willingness to lend and enable banks to expand lending during good times. This mechanism is empirically challenging to test because banks endogenously manage loan loss provisions. I address this challenge using an instrumental variable that is the interaction of the *macroeconomically driven* changes in industrial production with a *predetermined* measure of banks' wholesale funding reliance. This instrument provides plausibly exogenous cross-sectional variation in changes of banks' abnormal loan loss provisions. Consistent with the model, I find that the instrumented variation in banks' understated provisions is significantly positively associated with their inflow of wholesale debt and significantly negatively associated with their required interest rates and collateral postings, indicating a rightward shift in the wholesale debt supply curve. These results suggest that understatement of loan loss provisions enables

[5] My sample ends in 2019, because banks started to adopt the current expected credit loss (CECL) model in 2020, replacing the FAS 5's incurred loss model and shifting to a new accounting regime.

banks to expand their wholesale debt capacity, as reflected in loosened collateral requirements.

I then analyze the impact of the risk-taking behavior on bank lending. To ensure that banks face similar lending opportunities, I compare lending by different banks operating in the same county in the same year. I implement this within-county-year estimation using residential mortgage originations reported in the Home Mortgage Disclosure Act (HMDA) database. I focus on residential mortgages both because I can observe where individual mortgaged properties are located and because these mortgages account for a sizeable portion (over 20 percent) of bank loans (Gan and Riddiough, 2008; Mankart et al., 2020) and have a pivotal role in the economy (Mian and Sufi, 2009). I find that a one-standard-deviation decrease in banks' abnormal loan loss provisions is associated with a 25.27 percentage point increase in their mortgage acceptance rates. The differential lending behavior is also visible at the intensive margin. I find that banks with lower abnormal loan loss provisions extend more credit within a county than other banks in the area. They are also more likely to sell mortgages after origination, suggesting their volume-oriented business model. These results support the risk-taking channel and imply that banks' abnormal loan loss provisions shape their credit supply.

I also document *a feedback channel* in which increased loans, especially commercial loans for which private information about credit losses is significant, enhances banks' ability to exercise discretion over loan loss provisions. As Figure 3 shows, the feedback channel reinforces the risk-taking channel, generating persistent understatement of banks' loan loss provisions and increased bank lending during good times. Intuitively, the risk-taking channel increases banks' *willingness* to apply accounting discretion, whereas the feedback channel enhances their *ability* to do so. The interaction between the *willingness* and *ability* to exercise accounting discretion functions as an "*accounting accelerator*" that increases banks' credit supply during booms.

However, the accounting accelerator also yields costs for banks and the financial system in bad times, when banks' increased loan charge-offs induce other market participants to increase information search and thus discover the banks' understated loan losses (Rajan, 1994; Dang et al., 2017; Gorton and Ordonez, 2014, 2020). Via the risk-taking channel, banks that reveal their prior understated loan losses suffer sharp outflows of wholesale debt and reductions in lending capacity. Via the feedback channel, decreased bank lending then restricts banks' discretion to delay recognizing loan losses. These effects yield a persistent contraction of bank lending in bad times, exacerbating the severity of economic downturns, amplifying the business cycle, and possibly threatening financial stability.

This threat to financial stability can arise from both sides of bank balance sheets. On the liability side, wholesale funding is short-duration and information sensitive (Pérignon et al., 2018), so rollover risk increases as economic conditions worsen. On the asset side, continual growth in banks' loans may result from their relaxation of lending standards, yielding deterioration in loan quality and accumulation of loan credit risk over time (Jordà et al., 2013;

López-Salido et al., 2017). I find evidence of both risks using Call Report and Dealscan data. Specifically, I show that banks that understated loan loss provisions extended more credit to unproductive firms in the run-up to the 2008 financial crisis (i.e., the housing bubble period from 2004 to 2006), and that banks that relied heavily on wholesale funding were less able to roll over this funding or obtain new wholesale funding during the crisis. My findings imply that the accounting accelerator yields significant costs for the real economy through capital misallocation in exhausted booms and rollover risk in subsequent busts. Because these costs are not always fully internalized by individual banks, they can be socially excessive. As such, regulators face a challenging *intertemporal trade-off* between stimulating the economy today and building up financial risks for the future.

My analysis provides a number of results that are novel to the banking literature and contribute to the growing interest in the role of bank accounting in improving or deteriorating financial stability (Flannery et al., 2004, 2013; Dang et al., 2017; Chen et al., 2022; Gallemore, 2022). For example, my results on the cross-sectional variation in how banks manage loan loss provisions across business cycles help explain why risky banks are under-reserved before crises, while others record losses more promptly. My findings regarding the risk-taking channel and banks' reliance on wholesale funding are important for understanding the dynamic trade-off between short-run economic growth and long-run financial stability. Finally, the concept of the accounting accelerator highlights the importance of banks' accounting discretion in shaping their credit supply over the business cycle.

This paper also speaks to the controversy over whether banks' accounting discretion is a source of financial fragility (Ryan, 2008; Laux and Leuz, 2009; Khan, 2019; Plantin et al., 2008; Xie, 2016). While the existing literature on banks' financial reporting has illuminated the *average* implications of discretionary loan loss provisioning for financial stability (e.g., Beatty and Liao, 2014; Bushman, 2014), my results emphasize the importance of the *dynamic* implications of this provisioning for financial stability. This paper also provides a framework that clarifies the strategic incentives behind banks' use of provisions over time, aligning with the recommendations of Leuz (2009) and Acharya and Ryan (2016). It is important for policymakers to be aware of both types of implications to be prepared to make informed choices when the need arises. Moreover, the liability-side focus of this paper also offers valuable insights into the interaction between bank funding stability and accounting discretion, particularly in light of the recent SVB crisis (Granja et al., 2024). Therefore, my analysis is not only appealing from an academic perspective but also important from a practical regulatory angle.

The remainder of the paper is structured as follows. Section 2 discusses the related literature. Section 3 explains the measure of banks' discretion over loan loss provisions. Section 4 introduces the motivating evidence. Section 5 discusses the empirical predictions of a stylized model. Section 6 describes the data sources. Section 7 presents the baseline empirical results about how banks' discretion over loan loss provisions varies with the business cycle. Section 8 examines the real effects of this discretionary behavior. Section 9 discusses the implications of my findings for financial stability. Section 10 concludes.

2 Related Literature

This paper relates to three strands of literature. First, the longstanding literature on banks' earnings management posits and provides evidence that traditional depository banks smooth earnings. That is, banks save potential current earnings for future periods when performance is good and borrow potential earnings from future periods when performance is bad (Greenawalt and Sinkey, 1988; Collins et al., 1995; Liu and Ryan, 2006). Banks have incentives to follow this pattern to smooth earnings to meet analyst forecasts or circumvent capital requirements (Galai et al., 2012), to reduce earnings variability and lower risk premiums (Trueman and Titman, 1988; Dantas et al., 2022), and to maintain managers' reputations and improve their job security (Fudenberg and Tirole, 1995; DeFond and Park, 1997). This paper contributes to this stream of research by exploring cross-sectional variation in commercial banks' earnings management, demonstrating that incentives to smooth income over the business cycle vary across banks and showing that banks' liability structures influence this variation. My paper also comports with several studies showing that banks exercise accounting discretion differently. For instance, Beatty et al. (2002) find that public banks delay recognizing more loan losses to achieve earnings targets than private banks. Liu and Ryan (2006) argue that banks that record higher losses are likely to have fewer financial constraints and more profitable. Relative to the existing research, this paper provides both theoretical and empirical evidence on how different banks manage earnings over the business cycle and discusses their short-run and long-run economic implications.

Second, this paper speaks to a large literature examining the relationship between bank financial reporting and financial stability. Much of this literature focuses on loan loss provisions, which are the most important accounting accruals for banks and reflect banks' judgments about future loan losses.[6] Many studies analyze the discretionary nature of loan loss provisions and discuss their importance for financial stability and credit availability (Acharya and Ryan, 2016; Beatty and Liao, 2011, 2014; Bushman, 2014; Bushman and Williams, 2012, 2015; Corona et al., 2019; Huizinga and Laeven, 2012; Laux and Leuz, 2009; Laeven and

[6]Prior to 2020, banks estimated loan loss provisions using the FAS 5's incurred loss model. This model requires banks to accrue for credit losses only if those losses are incurred, probable of being realized, and capable of reasonable estimation based on current information. After 2020, the FASB replaced the incurred loss model with the current expected credit loss (CECL) model that requires accruing of all expected loan losses based on reasonable and supportable forecasts. CECL was initially set to take effect on January 1, 2020, for entities that are SEC filers but are not designated as smaller reporting companies (SRCs). However, because of the COVID-19 pandemic, the CARES Act allows those entities to delay the CECL adoption until the earlier of (1) the first day of an eligible financial institution's fiscal year that begins after the end of the COVID-19 national emergency, or (2) January 1, 2022. For SRCs, the effective date of CECL is postponed to January 2023.

Majnoni, 2003; Akins et al., 2017; Kim, 2021). For instance, Beatty and Liao (2011) show that banks with delayed loan loss provisions have larger contractions in bank lending during recessions. Bushman and Williams (2012, 2015) find that delayed loan loss provisioning is positively associated with bank risk-taking. Despite much empirical research, it remains puzzling why banks' loan loss allowances[7] can have a significant economic impact on financial stability, given that these allowances on average are only about 1% of banks' total assets (Ryan, 2017). This paper takes an important step toward answering this question. My results suggest that banks exercise discretion over loan loss provisions to strategically manage funding by shaping outsiders' beliefs of the banks' fundamentals, thereby impacting financial stability and economic growth. More importantly, unlike the traditional credit crunch channel, this paper emphasizes that the composition of liabilities—particularly core deposits versus wholesale funding—matters due to their differing information sensitivity, not merely the total liabilities affecting regulatory capital ratios. Furthermore, this study contributes to the discussion about the possible connection between bank accounting and financial crises (Ryan, 2008; Laux and Leuz, 2009; Khan, 2019; Plantin et al., 2008; Xie, 2016) by pointing out an accounting acceleration mechanism through manipulating earnings in bank financial reporting.

Third, this paper adds to a growing literature on studying the role and consequences of credit supply during business cycles (Rajan, 1994; Borio and White, 2004). This literature became more prominent following the Global Financial Crisis. Several papers explore the origins of credit cycles (e.g. Schularick and Taylor, 2012; Gilchrist and Zakrajšek, 2012). Some have emphasized how financial frictions and investor sentiment serve as key channels in intensifying both booms and the subsequent busts (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014; López-Salido et al., 2017; Bordalo et al., 2018). Extending this literature, this paper presents evidence as to how certain banks' accounting discretion amplifies business cycles. Specifically, I find that the abnormal loan loss provisions are procyclical (countercyclical) for banks with a low (high) reliance on wholesale funding. This finding suggests that it is crucial to consider the heterogeneity of banks and pay attention to their accounting opportunism. Although other channels are likely at work, the bank accounting channel documented here is a distinctive additional driver of bank credit supply over the business cycle.

My results also have several policy implications. First, they provide new insights into the relationship between credit supply and financial stability by considering bank accounting discretion over the business cycle, an area largely unexplored in prior finance and economics literature (e.g., Diamond and Dybvig, 1983; Allen and Gale, 1998; Holmström and Tirole,

[7]Under the incurred loss model, when a credit loss event occurs and the loss amount can be reasonably estimated, bank managers should estimate and present the loan loss provisions in their income statement for the current period. Loan loss reserves or allowances are a contra asset account that represents the *cumulative* estimated amount of loan losses. Upon confirmation of the losses, charge-offs will be recorded, and the loan loss reserve and outstanding loans will be reduced by the uncollectible amount.

1998). Second, they indicate that banks can exercise discretion over loan loss provisions to facilitate risk-taking activities, highlighting the importance of bank accounting and disclosure regulations. My findings support the view that "countercyclically transparent" disclosure requirements are valuable, since bank regulators can detect early warnings before aggregate risk exposures pose serious threats to stability (Acharya and Ryan, 2016; Leuz, 2009). Third, my results suggest that expansionary credit fueled by wholesale funding during good times might jeopardize the financial system and suppress economic growth during bad times. A central bank that implements policy measures that escalate wholesale debt in the banking sector with the objective of restoring lending and growth thus might end up working against its own objectives.

3 Measurement of Bank Accounting Discretion

In this paper, accounting discretion refers to the extent to which a bank exercises its discretion over loan loss provisions to manage earnings. Loan loss provisions are accounting estimates of future loan losses. They are the most important bank accruals.[8] As shown in prior research, bank managers can strategically manipulate earnings and circumvent capital requirements through exercise of discretion over provisions for loan losses (Beatty and Liao, 2014). In turn, the discretion in loan loss provisions significantly influences the financial reporting quality of banks and thus the flow of information between insiders and outsiders (Acharya and Ryan, 2016). Based on previous banking literature (e.g., Jiang et al., 2016; Yue et al., 2021; Beatty and Liao, 2014), I measure accounting discretion using *abnormal* loan loss provisions. Specifically, I estimate the following loan loss provision model and use the residuals to construct proxies for bank accounting discretion:

$$\begin{aligned} LLP_{i,t} = {} & \beta_{1,t}\triangle NPL_{i,t+1} + \beta_{2,t}\triangle NPL_{i,t} + \beta_{3,t}\triangle NPL_{i,t-1} + \beta_{4,t}\triangle NPL_{i,t-2} \\ & + \beta_{5,t}Size_{i,t-1} + \beta_{6,t}\triangle Loan_{i,t} + \beta_{7,t}CO_{i,t} + \gamma_t LoanComp_{i,t-1} \\ & + \delta_{1,t}LoanComp_{i,t-1} \times \triangle NPL_{i,t+1} + \delta_{2,t}LoanComp_{i,t-1} \times \triangle NPL_{i,t} \\ & + \delta_{3,t}LoanComp_{i,t-1} \times \triangle NPL_{i,t-1} + \delta_{4,t}LoanComp_{i,t-1} \times \triangle NPL_{i,t-2} + \alpha_i + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where i and t index banks and quarters, respectively. The variable $LLP_{i,t}$ is bank i's loan loss provision in quarter t scaled by lagged total loans, and $\triangle NPL_{i,t}$ is bank i's change in nonperforming loans from quarter $t-1$ to quarter t scaled by lagged total loans. As noted by Liu and Ryan (2006), $\triangle NPL_{i,t}$ represents relatively nondiscretionary indicators of future credit losses. The model above also includes $\triangle NPL_{i,t+1}$, the next year's change in nonperforming loans scaled by lagged total loans, as well as $\triangle NPL_{i,t-1}$ and $\triangle NPL_{i,t-2}$, the prior two years' changes in nonperforming loans scaled by lagged total loans. The logic is that banks likely

[8] With the exception of fair value estimates for very large trading-oriented banks, loan loss accruals are banks' largest accounting estimates (Acharya and Ryan, 2016).

determine loss provisions using historical, current, and forward-looking nonperforming loan information (Bushman and Williams, 2012). The variable $Size_{i,t-1}$ represents the natural logarithm of lagged bank total assets, and $\triangle Loan_{i,t}$ denotes bank i's loan growth rate in quarter t.

Following Basu et al. (2020), I include net loan charge-offs ($CO_{i,t}$) to address the concern that loan loss provisions may not be a linear function of nonperforming loan changes.[9] I also control for banks' loan portfolio composition ($LoanComposition_{i,t-1}$) since it varies considerably among banks and is strongly correlated with the timeliness and amount of banks' loan loss accruals (Ryan and Keeley, 2013; Bhat et al., 2021). Specifically, I consider banks' shares of real estate loans, commercial and industrial loans, and consumer loans as percentages of total loans. I also interact those shares with the historical, current, and future changes in nonperforming loans (i.e., $\triangle NPL_{i,t-2}$, $\triangle NPL_{i,t-1}$, $\triangle NPL_{i,t}$, and $\triangle NPL_{i,t+1}$) to account for differences in loan originations and delinquencies across different types of loans (Acharya and Ryan, 2016).

Additionally, I include bank fixed effects (α_i) to absorb time-invariant differences in loan loss provisions across banks. Bank fixed effects are important in this earnings management context because they eliminate confounding, bank-specific traits that are unrelated to managerial discretion. Additionally, they ensure that the average residual for a given bank across years equals zero, allowing a clearer assessment of discretionary provision behavior.

To better answer my research question, equation (1) deviates in two ways from the loan loss provision models used in previous studies (e.g., Jiang et al., 2016; Yue et al., 2021). First, the model allows the coefficients of all explanatory variables to vary over time. This incorporates dynamic economic uncertainty into banks' nondiscretionary estimation of loan losses, thus significantly reducing model estimation errors. Second, the model does not include time fixed effects or macroeconomic factors, which allows me to examine how banks exercise discretion in estimating loan losses over the business cycle.

According to Beatty and Liao (2014), the fitted values in equation (1) represent the normal or nondiscretionary component of LLP, and the residuals represent the abnormal or discretionary component. Following prior studies, I use the signed residuals to proxy for banks' exercise of accounting discretion. While absolute residual values measure overall provision quality (Beatty and Liao, 2014), signed residuals provide more insight into how and why provision manipulation occurs (Kanagaretnam et al., 2009). Negative residuals capture income-increasing earnings management and positive residuals capture income-decreasing earnings management. This distinction is useful for gaining a better understanding of how banks man-

[9] Basu et al. (2020) argue that loan charge-offs should also be included in the linear model of LLP after comparing four potential models proposed by Beatty and Liao (2014). They find that loan charge-offs are associated with both declines in nonperforming loans and increases in LLP, resulting in a V-shaped, rather than linear, relationship between LLP and change in nonperforming loans. However, note that net loan charge-offs may be managed by banks and in principle are recorded after banks estimate their loan loss provisions (Liu and Ryan, 2006). Nevertheless, my results are robust if I do not include net loan charge-offs in the LLP estimation model.

age earnings over the business cycle. As a robustness check, I also use each bank's residuals divided by the standard deviation of its residuals as an alternative measure of bank discretion. The standardized residuals, which I refer to as "*Discretion (standardized)*," mitigate the concern that risker banks' residuals have inherently higher variance and thus bias the results.[10]

Using signed residuals to measure bank accounting discretion has both conceptual and statistical advantages. First, loan loss provisions have been extensively studied and their determinants are well understood in the accounting literature (Beatty and Liao, 2014; Acharya and Ryan, 2016). Thus, the residuals from the estimation of model (1) likely capture banks' earnings management rather than merely estimation noise.[11] Second, compared to other proxies, such as delayed expected loss recognition used in Bushman and Williams (2015),[12] estimating model (1) with panel data provides a more timely and accurate estimation of accounting discretion for each bank in each quarter. Finally, this method requires only banks' financial reporting data, not market data. Thus, it helps increase sample coverage since most U.S. commercial banks are not publicly traded.

Admittedly, accounting discretion is challenging to measure empirically. To assess the validity of my measures, I present additional analyses in the Appendix. I first examine whether the residuals in equation (1) predict banks' restatements, provided that restatements capture the most egregious provision manipulations and are a result of opportunistic reporting (Costello et al., 2019). Following Beatty and Liao (2014), Figure 5 shows that the residuals are indeed strongly correlated with both the likelihood and the amount of future restatements. Moreover, I analyze the properties of the residuals. Figure 6a shows that the residuals vary with changes in nonperforming loans, consistent with banks retaining discretion over both increases and decreases in loan performance. Figure 6b plots the kernel density of the coefficients in an AR(1) process of the residuals for each bank. While the AR(1) estimates exhibit wide dispersion, a substantial mass is concentrated around zero. The average AR(1) estimate is demarcated by the dashed red line at 0.08. This estimate suggests that residuals have low persistence and are unlikely to be forecasted by the market based on their past realizations. Taken together, these results show that the residuals in equation (1) reasonably reflect the earnings quality of banks and likely capture banks' strategic accounting behavior that is opaque to outsiders.

[10] Figure 7 in the Appendix displays the distributions of residuals and standardized residuals.

[11] The adjusted R-squared for the model estimation in my sample is 0.5346, indicating a reasonably high level of explanatory power.

[12] Bushman and Williams (2015) estimate two models of loan loss provisions (one with and one without $\triangle NPL_{i,t}$ and $\triangle NPL_{i,t+1}$) for each bank on a three-year rolling window. They measure "delayed expected loss recognition" based on the difference in the adjusted R^2 between these two models.

4 Motivating Evidence

This section presents some stylized facts that motivate this paper. I start by analyzing the aggregate time-series correlation between bank accounting discretion and the business cycle. Then, I provide cross-sectional evidence as to how the correlation varies with bank liability structures. Lastly, I present descriptive evidence on the characteristics of banks with different liability structures.

4.1 Time-Series Evidence

Figure 1 plots the evolution of the average accounting discretion across banks over the business cycle in the U.S. from 1990 to 2019. Accounting discretion is measured by abnormal loan loss provisions (i.e., residuals from the estimation of equation (1)). I proxy for business cycles using changes in the natural logarithm of industrial production.

In light of Beatty and Liao's (2014) argument that the deposit-side information problem has been largely ignored in the literature on banks' earnings management, Figure 1 displays results for banks grouped by whether their core deposits, as a percentage of total liabilities, are above or below the sample median. For banks with large core deposit bases (i.e., above-median group), their changes in abnormal loan loss provisions are positively associated with changes in industrial production (the correlation is 36% in Figure 1a). However, for banks with limited core deposits (i.e., below-median group), their abnormal loan loss provisions change negatively with industrial production (the correlation is −46% in Figure 1b). The difference is particularly pronounced during recessions, such as the Great Recession of 2008. Moreover, Appendix Figure 8 shows that the time-series patterns of loan loss provisions, which include both discretionary and nondiscretionary components, are remarkably similar across these two groups of banks. This implies that the difference in Figure 1 is likely caused by the way banks exercise accounting discretion. These results collectively indicate the importance of banks' liability structures in explaining variation in their management of loan loss provisions and earnings over the business cycle.

4.2 Cross-Sectional Evidence

The time-series evidence can be biased toward small banks and provides less information about distributional influences. To mitigate this concern, I explore cross-sectional variation in banks' exercise of their accounting discretion over the business cycle. I do so by estimating the following time-series regression for each bank:

$$\triangle Discretion_{i,t} = \alpha_i + \beta_i \triangle IP_t + \varepsilon_{i,t}, \tag{2}$$

where $\triangle Discretion_{i,t}$ is the year-over-year change (i.e., from quarter $t-4$ to t) in bank i's abnormal loan loss provisions. $\triangle IP_t$ is the year-over-year change in the natural logarithm of industrial production. The year-over-year changes are conducted to account for seasonality. Following the asset pricing literature, I restrict the sample to banks that have at least 40 quarterly observations between 1990 and 2019 to estimate β_i with reasonable precision.

The coefficient of interest, β_i, captures the sensitivity of bank accounting discretion to business cycle fluctuations. I refer to β_i as the discretion beta of bank i. Positive beta implies that banks exercise discretion over loan loss provisions to smooth earnings. In contrast, negative beta indicates that loan loss provisions are understated during good times and overstated during bad times, which is the opposite of earnings smoothing.

I then relate these discretion betas to bank liability structures. In particular, I focus on wholesale funding reliance—defined as the ratio of noncore liabilities to total liabilities, representing the share of funding sourced outside core deposits. In Figure 2, I illustrate the relationship between discretion betas and wholesale funding reliance by using binned scatter plots. I first sort banks into 20 bins based on their wholesale funding reliance and then plot the average discretion betas within each bin. As shown in Figure 2, the relationship is strongly negative and fairly tight around the line of best fit. Discretion betas decrease with the extent to which a bank relies on wholesale funding. A bank with low (high) wholesale funding typically has a positive (negative) discretion beta. Moreover, the results remain consistent even after controlling for bank loan composition, alleviating concerns that the negative relationship is driven by differences in bank assets rather than their liability structures. Overall, the results in Figure 2 are consistent with the time-series observations in Figure 1 and suggest that banks that rely on wholesale or noncore funding tend to understate loan losses in good times and overstate them in bad times rather than smoothing their earnings over the business cycle.

4.3 Descriptive Evidence

Given the importance of wholesale funding, Tables 9 and 10 in the Appendix provide the characteristics and examples of banks with high and low reliance on wholesale funding, respectively. As expected, the extent of reliance on wholesale funding reflects distinct banking business models.

Banks with low wholesale funding resemble traditional depository institutions. These are typically community banks with strong deposit franchises, serving the personal and commercial banking needs of local residents and small businesses through traditional banking services. These banks operate within smaller geographic regions and are less likely to be publicly traded, with a focus on serving and supporting their local communities.

In contrast, banks with high wholesale funding tend to be larger, more diversified institutions offering a broad range of financial services. Some are U.S. commercial banks with global operations, serving both individual and institutional clients, while others specialize in certain sectors, such as providing services to high-net-worth individuals or focusing on the real estate industry. These banks are generally more volume-driven, as evidenced by their lower profitability per loan and lower capital ratios. It is important to note that some of these banks faced significant challenges during the 2008 financial crisis, resulting in regulatory intervention, closures, or acquisitions by larger institutions. Despite these events, many have played significant roles in the U.S. financial system.

5 Empirical Predictions

This section provides a theoretical interpretation of the novel empirical findings in Section 4 and outlines the intuition behind the empirical predictions tested in the paper. A stylized model formalizing this intuition is presented in the Appendix.

Consider an economy with two periods. In the first period, a bank is endowed with an initial balance sheet, privately observes its loan loss rate, and exercises discretion over reporting its earnings through loan loss provisions. In the second period, the economy may either enter a boom or a bust with some probability. The bank's profits are determined after the revelation of the economic state.

The bank funds its loans with a combination of risk-free core deposits and risky wholesale debt. Unlike sticky core deposits, wholesale debt has an information-sensitive and elastic supply. While wholesale lenders can't directly assess the bank's loan quality or financial health, they base their lending decisions on the bank's reported earnings. However, during a bust, an additional unbiased signal about the bank's loan quality becomes visible, which can partially reveal the bank's earnings manipulation. When wholesale lenders observe this signal, they revise their beliefs based on this new information, leading to significant withdrawals or inflows of wholesale debt, depending on whether their perception of the bank quality deteriorates or improves.

The bank's reporting decision is made to maximize its expected profits, taking into account economic uncertainty and the behavior of wholesale lenders. On one hand, the need to attract wholesale funding incentivizes the bank to understate loan loss provisions, inflating reported earnings and boosting its credibility to expand lending capacity during good times. On the other hand, this strategy can backfire during downturns, when earnings manipulation is revealed, triggering large withdrawals by wholesale lenders and forcing the bank to scale back its intermediation activities. Thus, the bank faces a trade-off between the benefits of increased funding in good times and the risks of liquidity shortfalls and penalties for misreporting in bad times.

This trade-off is particularly pronounced for banks that rely heavily on wholesale funding. These banks are under greater pressure to signal financial strength to attract wholesale debt, driving more aggressive management of loan loss provisions. In contrast, banks with substantial core deposits face less pressure to engage in such behavior due to their lower dependence on wholesale funding. This difference in funding structure explains why banks with limited core deposits are more likely to manipulate provisions as part of their risk-taking behavior.

PREDICTION 1: *Banks with limited core deposits are more likely to understate loan loss provisions during economic booms to facilitate growth, leading to larger provisions being revealed during downturns. This risk-taking behavior intensifies as the bank's reliance on wholesale funding increases.*

Because the loan loss rate is privately observed by the bank and wholesale lenders infer it from reported earnings, the incentive to inflate earnings and attract wholesale funding becomes stronger when the bank incurs larger loan losses. Therefore, the risk-taking behavior is more pronounced when the bank's pre-provision performance deteriorates.

PREDICTION 2: *Banks with lower pre-provision profitability are more likely to understate loan loss provisions to engage in risk-taking during economic booms, leading to larger provisions during economic downturns.*

This framework assumes that wholesale lenders become more cautious about earnings manipulation during downturns than during upturns. This variation in information sensitivity is recognized for two reasons. First, in good times, lenders perceive a relatively low likelihood of default and rely on publicly disclosed earnings because the marginal benefit of acquiring additional information is small. In contrast, during downturns, lenders grow more skeptical of earnings quality and invest in information acquisition to reassess the bank's fundamentals. This aligns with the arguments of Dang et al. (2017), Lisowsky et al. (2017), and Diamond et al. (2020) that information production increases when economic conditions worsen. Second, during normal times, lenders may rely on regulatory oversight, reducing their need for independent monitoring. However, during a recession or financial crisis, when regulatory effectiveness is questioned, lenders increase their own scrutiny of bank financial reporting. It is consistent with evidence from Acharya et al. (2016) that market discipline may fail when investors anticipate government guarantees on the unsecured debt of large financial institutions.

Earnings manipulation in this context is achieved through loan loss provisions. Thus, another related assumption is that wholesale lending decisions are influenced by provisions. This is a relatively weak assumption given that loan loss provisions are typically the largest and most forward-looking bank accruals. Provisions can increase the availability of wholesale funding directly by relaxing collateral constraints,[13] especially for wholesale funding such as FHLB advances, which use bank loans as collateral. Indirectly, provisions can influence wholesale lenders' willingness to lend by acting as early signals of deteriorating bank fundamentals.

[13] While certain types of wholesale debt are uncollateralized (e.g., federal funds), some are collateralized, and the assumption that wholesale debt requires collateral is standard in the banking literature. This assumption is based on the fact that wholesale debt is not insured by the government (Kashyap and Stein, 2000) and banks have limited commitment to repay debt (Stein, 2012).

Higher provisions indicate a weakening loan portfolio and rising credit risk. For example, during the 2008 financial crisis, Countrywide Bank faced a freeze in wholesale funding, triggered by elevated loan loss provisions and subsequent earnings losses.

It is important to note that the predictions discussed above are derived within a rational expectation framework, where banks optimize their behavior by weighing the trade-offs between pursuing aggressive growth in good times and managing heightened vulnerability in downturns. Wholesale lenders, in turn, behave rationally, becoming more cautious in bad times than in good times. However, behavioral explanations such as diagnostic expectations and short-termism may also account for why banks with limited core deposits engage in accounting discretion to facilitate risk-taking. While these behavioral factors are not central to this paper, they offer additional support for the empirical predictions.

6 Data

This section describes different data sources and how the main variables were constructed for this study. Table 1 reports related summary statistics.

Bank data. The bank financial data are from the U.S. Call Reports provided by the Federal Reserve Bank of Chicago and the Federal Financial Institutions Examination Council (FFIEC). The data contain detailed quarterly income statements and balance sheets for each U.S. bank. To facilitate comparison and interpretation of my results, I restrict the sample to all FDIC-insured commercial banks located within the 50 states and the District of Columbia over the period from 1990Q1 to 2019Q4. Following the literature, I also exclude observations with quarterly asset growth greater than 10% to avoid the impact of mergers and acquisitions (Acharya and Mora, 2015; Gatev and Strahan, 2006).

Business cycle data. The data used to measure business cycles are the changes in the natural logarithm of the U.S. industrial production (IP) index. The index measures the real output of the manufacturing, mining, and electric and gas utilities industries. It illuminates fluctuations in overall economic activity and thus serves as an indicator of business cycle movement (e.g. Creal et al., 2010; Scotti, 2016).[14] The index data is obtained from the Federal Reserve Economic Data (FRED) and available at the monthly frequency. I convert the data to quarterly frequency by taking the average value within each quarter.

Mortgage loan data. I collect data on residential mortgage loan originations from the Home Mortgage Disclosure Act (HMDA) dataset. It contains detailed loan-level information on residential mortgages originated or purchased by most mortgage lending institutions in

[14] My results are robust to alternative measures of the business cycle, such as real GDP growth rates (e.g., Stock and Watson, 2014).

the U.S. on an annual basis. The dataset is unique in its comprehensiveness and granularity, notably in terms of the geographic location of borrowers.[15] Particularly, it reports the total number of mortgage loans issued by a financial institution in a given county in a given year. My data sample covers from 1990 to 2019. To ensure that banks are exposed to the credit risk of the mortgages, my sample excludes GSE loans, i.e. the mortgages subsidized by the Federal Housing Authority, the U.S. Department of Veterans Affairs, or other government agencies. I use banks' RSSD identifiers to merge their home mortgage loan and Call Report data.

TFP data. I measure firm-level total factor productivity (TFP) based on İmrohoroğlu and Tüzel (2014). The data is available at an annual frequency from 1963 to 2019.[16] They estimate TFP using firm-level data on sales, operating income, and number of employees from Compustat, output and investment deflators from the Bureau of Economic Analysis, and wage data from the Social Security Administration. This estimation approach has the advantage of adjusting for selection and simultaneity bias and addressing within-firm correlations in productivity.

Syndicated loan data. I use data on syndicated loans from Thomson Reuters Dealscan database. It contains information on loan size, pricing, maturity, type, collateral, covenants, and lenders. The unit of observation in the database is a facility. A syndicated loan package typically consists of multiple different facilities initiated at the same time. For my analysis, I select all loans originated by U.S. banks and sum loan volumes to the bank-firm-year level. I rely on the mapping file[17] used in Chakraborty et al. (2020) to match lenders in Dealscan to Call Reports. I use the Dealscan-Compustat linking table[18] provided by Chava and Roberts (2008) to collect financial information for each borrower from Compustat.

7 Accounting Discretion and Business Cycle

This section presents a formal empirical analysis of how bank accounting discretion varies over the business cycle. The analysis begins by documenting the impact of wholesale funding and then examines whether it relates to banks' risk-taking incentives, as suggested by my empirical predictions.

[15]Only the data for residential mortgage loans (from HMDA) and small business loans (from Community Reinvestment Act, CRA) are publicly available at the bank-county-year level. I use the mortgage loan data instead of small business loan data for two reasons. First, mortgage loans account for the most substantial part of bank loans, while the share of small business loans is small (Mankart et al., 2020). The second reason is that the number of banks reporting CRA data is smaller than that of HMDA-reporting banks. To increase my data coverage and capture the substantial part of bank lending decisions, I decide to use HMDA in this paper.

[16]The TFP data is available in Selale Tuzel's website (https://sites.google.com/usc.edu/selale-tuzel/home?authuser=2).

[17]Thanks to Indraneel Chakraborty, Itay Goldstein, and Andrew MacKinlay for sharing the mapping file.

[18]I am grateful to Sudheer Chava and Michael Roberts for making the linking table publicly available.

7.1 Role of Wholesale Funding

To formally examine the role of wholesale funding on banks' exercise of accounting discretion over cycles, I exploit cross-sectional variation in bank liability structures and estimate the following regression:

$$\triangle Discretion_{i,t} = \beta_0 \triangle IP_t + \beta_1 \triangle IP_t \times WFR_{i,t-5} + \beta_2 WFR_{i,t-5} + \gamma X_{i,t-4} + \varepsilon_{i,t}. \quad (3)$$

The dependent variable $\triangle Discretion_{i,t}$ is the change in bank i's accounting discretion from quarter $t-4$ to t. As discussed earlier, accounting discretion is proxied by abnormal loan loss provisions (i.e., either the residuals or standardized residuals in equation (1)). I use the year-over-year change in accounting discretion to remove the seasonality in bank loan loss provisions.[19]

The independent variable $\triangle IP_t$ is the year-over-year change (from quarter $t-4$ to t) in the natural logarithm of industrial production, a commonly used proxy for the business cycle. $WFR_{i,t-5}$ is a vector of dummy variables that indicate the quartile rank of bank i's wholesale funding reliance in quarter $t-5$.[20] Wholesale funding reliance is defined as the ratio of a bank's noncore liabilities to total liabilities. I use wholesale funding reliance in quarter $t-5$ to ensure that it is predetermined and unaffected by $\triangle IP_t$.[21] The coefficient of interest is β_1, which represents the sensitivity of changes in banks' abnormal loan loss provisions to changes in industrial production, given an increase in wholesale funding reliance.

$X_{i,t-4}$ is a vector of important bank characteristics that include size (log of total assets), capital ratio (Tier 1 leverage ratio), ROE (net income to total equity), loan portfolio composition (the shares of real estate loans, commercial and industrial loans, and consumer loans), audit quality (a dummy variable for receiving an independent audit), and bank diversification (log of one plus the number of deposit branches). In some specifications, I also include bank fixed effects to absorb persistent differences in risk assessment models across banks and quarter time fixed effects to control for the impact of changes in the regulatory environment, overall economic conditions, and other time-specific factors that might affect the estimation of loan loss provision. The standard errors are clustered at the bank level.[22]

The results are reported in Table 2. Column 1 shows the baseline result, where I interact the quartile indicators of wholesale funding reliance with changes in industrial production. I find that the direct effect of $\triangle IP_t$ is significantly positive, consistent with prior literature on bank income smoothing. More importantly, the specification in column 1 shows that the relationship between banks' abnormal loan loss provisions and industrial production decreases

[19] Banks tend to manage provisions for loan losses to a greater extent in the last quarter of a year.

[20] I split banks into quartiles based on their $WFR_{i,t-5}$. I use the lowest quartile as a benchmark and refer to the remaining 2^{nd}, 3^{rd}, and 4^{th} quartiles as Q2 WFR, Q3 WFR, and Q4 WFR, respectively. Untabulated results indicate that WFR quartile rankings remain fairly stable across banks over time.

[21] Inferences are not affected if WFR is measured in quarter $t-4$.

[22] The results are robust when applying bootstrap to correct standard errors.

monotonically with wholesale funding reliance (i.e., $\beta_1 < 0$), consistent with the Prediction 1 in Section 5. The difference in β_1 estimates across WFR quartiles is also large and statistically significant. This finding is unaffected by including bank fixed effects and quarter fixed effects. In the specification with the richest controls in column 3, the accounting discretion of fourth-quartile-WFR banks responds about four times more negatively to variation in industrial production as does the accounting discretion of second-quartile-WFR banks. Columns 4 to 6 use standardized discretion as the dependent variable and display similar coefficient estimates. As a robustness check, I also conduct the analysis using a sample that excludes NBER-defined recession periods.[23] Results are presented in Appendix Table 11. Although the coefficient magnitude decreases, the β_1 estimates remain negative and statistically significant for banks that rely heavily on wholesale funding, confirming that the prior findings are not solely driven by severe crises.

There are two main challenges to my identification of wholesale funding reliance. First, one might be concerned that the results can be explained by differences in loan portfolios across banks. If banks with varying levels of wholesale funding have distinct loan compositions, they may adopt different loan loss provisioning practices, independent of any discretionary differences. Second, even without significant portfolio differences, attributing discretionary loan loss provisions specifically to wholesale funding reliance is challenging, as reliance on wholesale funding may be endogenously correlated with other bank characteristics.

To address the first challenge, I show that the findings hold when examining accounting discretion across bank groups categorized by loan composition (see Appendix Table 13).[24] This approach reduces loan-type-related measurement error, helping to isolate the discretionary component of loan loss provisions from the nondiscretionary component. Additionally, to account for unobservable factors, such as loan quality known privately to banks, I examine their adequacy ratios, defined as the ratio of loan loss allowance to nonperforming loans. If wholesale-reliant banks had lower provisions due to holding less risky loans, they would display higher adequacy ratios around the crisis. However, as shown in Appendix Table 15, these banks exhibit significantly lower adequacy ratios, indicating insufficient loan loss reserves from understated provisions and suggesting that their loan portfolios are, in fact, risky.

To mitigate the second challenge, I ensure my results are robust to other potentially confounding bank characteristics. First, I control for interactions between changes in industrial production and key bank characteristics (see Appendix Table 12), showing that the results hold across these stringent specifications. Second, I limit the sample to private banks to mitigate concerns about differing information and regulatory environments between public and private banks. Appendix Table 14 confirms that the results remain consistent within this

[23] My sample period includes three NBER-defined recessions 1990/08–1991/03, 2001/04–2001/11, and 2008/01–2009/06.

[24] I separate banks into three groups by their dominant loan types (i.e., real estate loans, commercial and industrial loans, and consumer loans) and then estimate equation (1) separately for each group.

restricted sample, indicating that the observed relationship is not driven by these factors.

Taken together, these results are consistent with the graphical evidence in Figures 1 and 2, provide support for Prediction 1, and confirm the importance of wholesale funding reliance in explaining bank discretionary accounting behavior across business cycles.

7.2 Channel

A key takeaway from the previous analysis is that banks that rely on wholesale funding understate loan loss provisions in good times and thus record larger provisions in bad times. This raises the question of why these banks behave in this way. My model suggests that it is primarily a result of banks exercising their accounting discretion to facilitate risky growth (i.e., *the risk-taking channel*). In particular, banks with limited core deposits seek to prop up their reporting earnings by delaying the recognition of loan losses in order to attract funding from wholesale market during expansions, although they bear the consequences of accelerating loan losses during recessions.

To provide further evidence for the risk-taking channel, I test the Prediction 2 (see Section 5) by estimating equation (3) for banks partitioned into low, medium, and high terciles each year based on their pre-provision profitability. If banks exercise discretion over provisions for loan losses in an effort to boost earnings and attract wholesale funding, their incentives to manage provisions downward strengthen as their actual or unmanaged performance deteriorates because wholesale funding is unstable and attentive to changes in bank financial performance (Pérignon et al., 2018; Chen et al., 2022).

Panel A of Table 3 displays the partition results. As expected, for a given level of wholesale funding reliance, the negative correlation between changes in industrial production and changes in banks' abnormal loan loss provisions strengthens monotonically as their actual performance declines. For example, the coefficient on $\triangle IP \times$Q3 WFR is highly significant for the low pre-provision ROE subsample reported in column 1 and is insignificant for the high pre-provision ROE subsample reported in column 3. Column 4 reports the magnitude and significance of coefficient differences for the high versus low pre-provision ROE partitions. It shows that all of these differences are negative and generally increase in magnitude and significance with wholesale funding reliance. For instance, the difference of the coefficients on $\triangle IP \times$Q3 WFR is highly significantly negative at -1.0686, whereas the difference of the coefficients on $\triangle IP \times$Q2 WFR is insignificant at -0.4698. The results are robust to controlling for other bank characteristics and the inclusion of bank fixed effects and quarter fixed effects.

In Panel B of Table 3, I report the same tests with standardized discretion as the dependent variable. As before, Panel B shows that the banks with lower past performance are more likely to understate provisions in good times, more so when they rely more on wholesale funding. Specifically, the strongest result is obtained for banks with low pre-provision ROE and Q4 WFR, for which the coefficient of the interaction term (i.e., β_1) is negative and highly significant (-1.2988, $t = -4.77$). In contrast, the β_1 estimate is positive and insignificant for banks with high pre-provision ROE and Q2 WFR (0.0886, $t = 0.35$). This sizable coefficient difference suggests that banks with higher risk-taking incentives indeed manage their loan loss provisions downward more to display favorable performance to outsiders.

Overall, the cross-sectional results in Table 3 indicate that understatement of loan loss provisions is a manifestation of bank risk-taking through wholesale funding. This is consistent with my empirical predictions that banks with limited core deposits strategically manage their earnings to attract wholesale funding and facilitate their risky growth.

8 Real Effects of Accounting Discretion

Thus far, I have provided evidence that banks exercise accounting discretion to inflate earnings when their incentives to attract wholesale funding are higher. However, my results have not yet spoken to whether this accounting discretion directly affects banks' wholesale debt capacity and credit supply. As these real consequences are embedded in my empirical predictions, I examine them in this section to further demonstrate the risk-taking channel.

8.1 Effects on Wholesale Debt Capacity

My model suggests that banks inflate earnings in good times to expand their wholesale debt and consequently make more loans. The key assumption here is that core deposits are a scarce funding source for banks. Banks with insufficient core deposits resort to the wholesale market to achieve growth during booms. Under this condition, these banks exercise their accounting discretion to attract more wholesale funding.

However, proving such a relationship empirically is challenging because banks endogenously determine their accounting discretion. This endogeneity problem inhibits the identification of the real effects of accounting discretion. I address this identification challenge by exploiting cross-sectional variation in banks' accounting discretion over the business cycle. Specifically, I employ an instrumental variable (IV) approach in estimating the following regression:

$$\triangle Wholesale_{i,t+1} = \beta \triangle \widehat{Discretion}_{i,t} + \gamma X_{i,t-4} + \theta_i + \psi_t + \varepsilon_{i,t}. \tag{4}$$

The dependent variable $\triangle Wholesale_{i,t+1}$ represents the log change in bank i's noncore liabilities from quarter $t-4$ to $t+1$. Noncore liabilities refer to total liabilities less core deposits. As discussed earlier, they are often used in the literature to describe a broader category of bank funding originating from sources other than core deposits (Hanson et al., 2015). The independent variable $\triangle \widehat{Discretion}_{i,t}$ is the instrumented change in bank i's accounting discretion from quarter $t-4$ to t. I use $\triangle IP_t \times WFR_{i,t-5}$ (i.e., the product of a bank-specific *predetermined* wholesale funding reliance and the change in industrial production) as the instrument to estimate $\triangle \widehat{Discretion}_{i,t}$.

As already shown in Section 7, wholesale funding reliance strongly affects how banks exercise accounting discretion over the business cycle. This implies a strong correlation between the instrument and the change in accounting discretion. The instrument therefore identifies *plausible exogenous* macro-driven variation in bank-level accounting discretion. Thus, the relevant exclusion restriction is satisfied if an individual bank's wholesale funding reliance (and any unobserved bank-level characteristics that are correlated with this reliance) has no effect on the passthrough of the business cycle to variables other than accounting discretion that influence bank noncore liabilities. In other words, any factors that might violate the exclusion restriction in my identification strategy would also need to vary with wholesale funding reliance, which substantially narrows down the list of potential concerns.

To make the exclusion restriction reasonable, I control for a set of important bank characteristics $X_{i,t-4}$ that, according to prior studies, influence changes in bank wholesale debt. Besides taking into account bank size, capital ratio, ROE, loan composition, audit quality, and bank diversification, I also control for the average interest rate, collateral ratio, and maturity of wholesale debt (Danisewicz et al., 2021; Manove et al., 2001). In some specifications, I also interact $X_{i,t-4}$ with $\triangle IP_t$ to further control for these key determinants of bank noncore liabilities over the business cycle. I also include bank fixed effects (θ_i) and year fixed effects (ψ_t) to absorb time-invariant bank characteristics and market-wide shocks, respectively.

Table 4 presents the estimation results. Column 1 in Panel A shows a negative and highly significant β coefficient, consistent with my empirical prediction that understated loan loss provisions increase wholesale funding quantities. In Column 2, adding interactions between changes in industrial production and other bank controls slightly increases the magnitude of the estimate, which remains statistically significant.

Columns 3-4 examine changes in wholesale debt interest rates, while Columns 4-6 focus on changes in collateral requirements. The results indicate that understated provisions also reduce the interest rate (price) and the collateral postings required, suggesting a rightward shift in the wholesale debt supply curve. This relaxed collateral constraint aligns with an increase in bank debt capacity. As shown in Panel B of Table 4, the findings remain robust when using standardized discretion as the dependent variable. Moreover, the Cragg-Donald F-statistic for the first stage is consistently highly significant and sufficiently large across all specifications, confirming the strength of the instrument.

Taken together, these results provide further evidence for the risk-taking channel, showing that banks with limited core deposits manage earnings upwards to expand their wholesale debt capacity, evident in relaxed collateral constraints.

8.2 Effects on Bank Lending

To examine the implication of bank accounting discretion on lending, I need to rule out alternative explanations that lending opportunities or local economic conditions could influence bank lending decisions. To do so, I use the mortgage data from HMDA, which provides information on both the amount and the location of mortgage loans issued by financial institutions each year. This data allows me to track banks' mortgage originations over time and across counties. By exploiting a more granular cross-section at the bank-county-year level, I can largely control for factors related to local lending opportunities. Specifically, I estimate the following regression:

$$y_{i,c,t} = \beta \triangle \widehat{Discretion}_{i,t} + \gamma X_{i,t-1} + \theta_i + \delta_{c,t} + \varepsilon_{i,c,t}, \tag{5}$$

where $y_{i,c,t}$ is the acceptance rate for mortgage applications, the log of mortgage originations, the percentage of mortgage originations that are sold by bank i in county c from year $t-1$ to t. $\triangle \widehat{Discretion}_{i,t}$ is the change in bank i's accounting discretion from year $t-1$ to t, and it is instrumented with the interaction term $\triangle IP_t \times WFR_{i,t-1}$. Under the identification assumptions discussed in the previous section, the variation in $\triangle \widehat{Discretion}_{i,t}$ can be considered as the *plausible exogenous* cross-sectional variation in banks' accounting discretion that is driven by business cycle fluctuations.

$X_{i,t-1}$ is a set of bank-level controls, including bank size, capital ratio, ROE, loan composition, audit quality, and bank diversification. θ_i is bank fixed effects to control for time invariant differences across banks. Importantly, I include county $\times$ year fixed effects, $\delta_{c,t}$, to control for county-level changes in credit growth and absorb any time-variation induced for example by seasonality or economic trends. In a similar spirit as Khwaja and Mian (2008), I directly compare the lending behavior of banks with distinct accounting discretion in the same county in the same year. This within-county-year estimation requires counties to have multiple lending relationships in a year, which is true for most counties in my sample. I cluster standard errors at the county level.

The results are presented in Table 5. Column 1 shows that the acceptance rates for mortgages are higher among banks understating loan loss provisions. The effect is sizable and highly statistically significant. For mortgage applications in my sample, the likelihood of approval increases by 25.27 percentage points (equivalent to a 0.83 standard deviation increase) when banks' abnormal loan loss provisions decrease by one standard deviation. In addition to this extensive margin effect, column 2 shows that those underreported banks also significantly increase the dollar amount of mortgage originations. Furthermore, column 3 indicates that these banks sell a larger proportion of mortgages, reflecting their volume-oriented business model focused on originate-to-distribute activities. As a robustness check, I show very similar results with standardized discretion as the independent variable in columns 4 to 6.

Overall, these results suggest that understated loan loss provisions facilitate banks' credit supply at both intensive and extensive margins. The credit expansion aligns with these banks' volume-focused or growth-driven strategy.

9 Financial Stability

In the previous section, I establish that understated loan loss provisions facilitate banks' ability to obtain wholesale funding and expand their lending. I next discuss how this effect could function as a double-edged sword that affects the financial stability and real economy. I first document that the linkage between bank accounting discretion and credit supply can be explained within the framework of an accounting accelerator. Then I show that in the absence of appropriate regulations, accounting-driven credit expansion can lead to substantial economic costs over time by increasing rollover risk, capital misallocation, or both. More importantly, these costs are not always fully internalized by individual banks when they take on additional risk. As a result, there can be socially excessive risk posed by these banks.

9.1 Accounting Accelerator

To fully understand the role of bank accounting discretion over the business cycle, I start by outlining two channels in partial equilibrium after an expansionary economic shock. Figure 3 portrays these two channels. The first is *the risk-taking channel* already established: by exercising discretion to understate loan loss provisions, banks display more favorable performance and thus increase their debt capacity for wholesale funding. This debt expansion increases the supply of credit in the economy. The second channel is *the feedback channel* under which increased loans (or opaque assets in general) provide banks with greater flexibility to obscure and maintain their discretionary accounting behavior because there is considerable information asymmetry regarding the quality of their loan portfolios (Rajan, 1994; Diamond, 1984; Morgan, 2002).[25] This positive dynamic feedback generates endogenous persistence of bank accounting discretion and lending growth.

Intuitively, the risk-taking channel reflects banks' *willingness* to exercise accounting discretion, while the feedback channel reveals their *ability* to do so. As shown in Figure 3, these two channels reinforce each other and lead to a self-fulfilling equilibrium. As such, a kind of *accounting accelerator* effect emerges, accelerating the credit expansion in boom periods.

To identify the feedback channel and verify the accounting accelerator, I exploit the differences in how loan loss provisions are determined for different types of loans under Generally Accepted Accounting Principles and related accounting practices. Prior accounting research

[25] The feedback channel also operates as increased loans make the bank's loan portfolio more dynamic. Banks inherently can manage an open portfolio more flexibly than a closed one and handle new loans more discretionarily than older ones, as they are further from default. Since this mechanism is straightforward and potentially less interesting, it is not the focus of this paper.

has shown that banks' discretion over provisions varies significantly between heterogeneous and homogeneous loans due to differences in loan complicity and information opacity (see, e.g., Bhat et al., 2019, 2021). For homogeneous loans, such as consumer loans, banks estimate loss provisions primarily at the portfolio level based on historical loss statistics. For heterogeneous loans, for instance commercial and industrial (C&I) loans, their loss provisions are primarily estimated at the individual loan level based on the judgment of loan officers. Based on these differences, the feedback channel should operate more strongly for banks holding more heterogeneous loans, since accrual estimations for those opaque loans contain a larger scope for managerial discretion.

To explore these differences, I distinguish banks based on the proportion of their total assets made up of heterogeneous loans, referred to as the "opacity share." These heterogeneous loans include both commercial and industrial loans as well as commercial real estate loans. I then re-estimate equation (3) for banks divided into high and low opacity share groups. The results are shown in Table 6. Columns 1 and 2 report estimations for subsamples with above- and below-median opacity shares, respectively. Column 3 reports tests of the differences of the coefficients on $\triangle IP \times$WFR across these two subsamples. As expected, the effect of wholesale funding reliance on the sensitivity of accounting discretion to industrial production is significantly stronger for banks with higher opacity shares. For example, the coefficient on $\triangle IP \times$Q2 WFR for above-median group is about twice as large as that for below-median group. The difference is also statistically significant. Columns 4 to 6 report the same analyses by using standardized discretion as the dependent variable. The results are very similar, supporting the presence of the feedback channel.

Thus far, this paper has focused on the bright side of the accounting accelerator when times are good. However, the accelerator has downsides as well. When economic fundamentals deteriorate, banks' prior understatements of loan loss provisions likely come to light because of their increased loan charge-offs (Myers et al., 2007) and other market participants' increased information search and discovery (Rajan, 1994; Dang et al., 2017). This will lead to large loss revelation and loan reduction, escalating the severity of economic downturns and threatening financial stability. I provide concrete evidence of these negative consequences in the following sections.

9.2 Rollover Risk

When banks rely on wholesale funding to expand lending, this dependence on unstable wholesale funding could build up the liability-side risk on bank balance sheets over time. The prevailing view is that wholesale funding is vulnerable to sudden seizures during periods of market stress (Pérignon et al., 2018). This rollover risk can cause banks, especially those with deteriorating performance, to suddenly lose funding in the wholesale market. Such breakdowns can trigger widespread panic in the financial market and force many other banks to cut lending, further exacerbating the severity of the downturn and eroding the foundation for future growth (Iyer et al., 2014; Chodorow-Reich, 2014).

Similar to Chen et al. (2022), I use the Call Report data and estimate the following regression to examine whether the rollover risk was more salient for banks with high wholesale funding reliance during the 2008 financial crisis:

$$\triangle y_{i,t+1} = \beta_0 ROE_{i,t} + \beta_1 ROE_{i,t} \times WFR_{i,2006Q4} + \beta_2 WFR_{i,2006Q4} + \gamma X_{i,t} + \theta_i + \psi_t + \varepsilon_{i,t}, \quad (6)$$

where $\triangle y_{i,t+1}$ represents the change of uninsured liabilities, insured deposits, or total liabilities of bank i from quarter t to $t+1$. $ROE_{i,t}$ is the bank i's return on equity during the quarter t. $WFR_{i,2006Q4}$ is bank i's wholesale funding reliance during the fourth quarter of 2006. θ_i is bank fixed effects, and ψ_t is quarter fixed effects. $X_{i,t}$ is a set of bank-level factors that could affect the changes in bank liability structure, including bank size, capital ratio, loan composition, audit quality, bank diversification, core deposit rate, and wholesale interest rate.

As discussed in Chen et al. (2022), the coefficient on $ROE_{i,t}$ (i.e., β_0 in equation (6)) captures whether a bank' ability to rollover debt depends on its performance fluctuations (i.e., flow-to-performance sensitivity). To facilitate interpretation, I standardize the variable $WFR_{i,2006Q4}$ so that it has a mean 0 and standard deviation of 1. With this adjustment, β_0 measures the flow-to-performance sensitivity for the bank with average pre-crisis wholesale funding reliance. The coefficient on the interaction term between $WFR_{i,2006Q4}$ and $ROE_{i,t}$ (i.e., β_1 in equation (6)) measures the change in flow-to-performance sensitivity for one standard deviation from the average wholesale funding reliance.

Table 7 presents the estimation results around the financial crisis (from 2007Q1 to 2008Q4). Columns 1 and 2 report the estimates for bank uninsured liabilities. The coefficient on ROE is positive and statistically significant, suggesting that, on average, the flow of uninsured liabilities is sensitive to bank performance. More importantly, the coefficient on the interaction term between ROE and WFR is positive and highly significant, implying that the flow-to-performance sensitivity is amplified among banks with high wholesale funding reliance. The economic magnitude of the amplification is quite large. For instance, in the specification with the most extensive controls (column 2), a one-standard-deviation increase in wholesale funding reliance amplifies the average sensitivity by about 60% (= 0.0210/0.0348). In contrast, wholesale funding reliance does not have a significant impact on the flow of insured deposits, as illustrated in columns 3 and 4. These results are consistent with the fact that insured deposits are risk-free and less prone to sudden withdrawals. Consequently, columns 5 and 6 show that banks' total liabilities exhibit similar patterns as uninsured liabilities and become more information sensitive during the crisis with wholesale funding reliance. The magnitude of the effect is also economically meaningful: a one-standard-deviation increase in wholesale funding reliance increases the average liability sensitivity by about 76% (= 0.0325/0.0423).

Taken together, the findings in Table 7 are consistent with the notion that increased wholesale debt exposes banks to greater rollover risk, which could lead to large withdrawals once bank performance deteriorates. Since information asymmetry is particularly pronounced in times of market stress (e.g., the 2008 financial crisis), this can further increase wholesale debt information sensitivity and inevitably make bank total liabilities "flighty" (Pérignon et al., 2018; Chen et al., 2022).

These results, together with findings in prior sections, support the argument that bank accounting discretion is a double-edged sword to financial stability: although bank discretion can facilitate financial intermediation in good times, it can distort investors' beliefs and exacerbate information asymmetry problems during bad times, making bank liabilities unstable and impairing financial stability.

9.3 Credit Misallocation

Building on the accounting accelerator mechanism, another question arises about whether the process will repeat itself and lead to aggressive lending. Such excessive risk-taking can occur via a relaxation of lending standards, resulting in capital misallocation and eventually slowing down economic growth. There is ample evidence that credit booms driven by a cheap supply of credit yield a proliferation of unproductive economic activities and a deterioration of loan quality (Jordà et al., 2013; Mian et al., 2017; López-Salido et al., 2017; Krishnamurthy and Muir, 2017).

To assess this concern, I examine whether the risk-taking channel fosters capital misallocation in the real economy. I use data on syndicated loans from Thomson Reuters Dealscan database, which enables me to investigate the lending relationships between banks and corporate borrowers at a granular level. Specifically, I estimate the following model:

$$\begin{aligned} Lending_{i,j,t} = {} & \beta_0 TFP_{i,t-1} + \beta_1 TFP_{i,t-1} \times Hiding\ Loss_{j,t-1} + \beta_2 Hiding\ Loss_{j,t-1} \\ & + \gamma X_{j,t-1} + \theta_j + \psi_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where $Lending_{i,j,t}$ is the log of loans extended by bank j to firm i in year t, $TFP_{i,t-1}$ is firm i's total factor productivity in year $t-1$, $Hiding\ Loss_{j,t-1}$ is an indicator variable that equals one if bank j recorded negative abnormal loan loss provisions in year $t-1$, and $X_{j,t-1}$ is a set of bank-level controls including bank size, capital ratio, ROE, loan composition, audit quality, and bank diversification.

Following Khwaja and Mian (2008), I exploit the fact that some firms borrow from more than one bank in a given year and use a within-firm estimator to disentangle banks' loan supply from borrowers' loan demand. I use firm × year fixed effects $\psi_{i,t}$ to control for observable and unobservable firm characteristics that may affect firms' time-varying credit demand. I also include bank fixed effects θ_j to ensure that my results are not driven by persistent differences across banks, such as reputation and loan screening technology.

The coefficient of interest β_1 captures whether a bank's loss-hiding behavior correlates with its inefficient allocation of credit to unproductive firms. On the one hand, hiding losses can help banks maintain and attract wholesale funding, which enables them to lend more to productive firms. On the other hand, increased wholesale funding may induce those banks to take excessive risks, which may not be socially optimal and lead to credit misallocation. This boils down to an empirical issue of which possibility dominates and under what conditions.

To do so, I focus on two subperiods: the bubble period (2004−2006, i.e., three years leading up to the financial crisis) and the non-bubble period (2010−2012, i.e., three years after the financial crisis), and estimate equation (7) separately for each subperiod. The results are presented in Table 8. The β_1 coefficients in columns 1 to 3 are negative and significant, highlighting that loss-hiding banks extended less credit to productive firms during the bubble period than other banks. The results are robust even after including firm × year fixed effects in column 3 to further control for firm-year level changes in credit demand. However, I find that the coefficients on the interaction of TFP and the Hiding Loss indicator are positive and significant in column 6, indicating that firms with high productivity do receive more credit from loss-hiding banks during the non-bubble period.

Taken together, the results in Table 8 suggest that while banks' exercise of accounting discretion could facilitate capital allocation in normal times, it may foster credit misallocation when the economy is overheated. This could result in excessive risk-taking and a buildup of asset-side risk on bank balance sheets that ultimately trigger a recession, reminiscent of the financial crisis of 2008. These results also comport with recent empirical evidence, which suggests that periods of rapid credit growth fueled by prolonged expansionary monetary policies are typically associated with low aggregate productivity growth and low economic efficiency (Gopinath et al., 2017; García-Santana et al., 2020).

In summary, the findings in this section suggest that bank discretionary accounting decisions can have unintended consequences for the real economy in the long run since they impact banks' debt information sensitivity and their capital allocation decisions with implications for stability and growth. Thus, regulators face a challenging *intertemporal trade-off* between stimulating the economy today and building up financial risks in the future.

10 Conclusion

This paper documents a novel fact: banks with limited core deposits tend to understate loan loss provisions in good times and thus overstate them in bad times. This is at odds with the conventional wisdom that banks generally smooth their earnings over the business cycle. I show both theoretically and empirically that this fact can be explained by a risk-taking channel. That is, banks facing core deposit constraints inflate earnings to attract wholesale funding and expand lending during good times, although they then suffer from losing wholesale funding and reducing lending during bad times. Moreover, I show that the risk-taking channel can be considered within the framework of an accounting accelerator, where bank accounting discretion and lending reinforce each other, magnifying business cycle fluctuations. I also document that this process may impose significant costs on the financial system, due to an increased rollover risk in wholesale funding and capital misallocation risk in bank lending.

This paper highlights the importance of discretionary accounting in the banking system. My results suggest that the practice of accounting discretion provides an effective way for certain banks to attract wholesale funding and facilitate risk-taking. In this sense, accounting discretion is not merely a regulatory arbitrage to avoid capital requirements. It creates economic value by changing the quality of bank financial reporting, adjusting the availability of wholesale funding, and making the banking system more responsive to changes in business cycles.

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Figure 1: Bank Accounting Discretion and Business Cycles

This figure plots year-over-year changes in log industrial production (blue dashed line) against year-over-year changes in the average bank accounting discretion (green solid line in Panel (a); red solid line in Panel (b)). Accounting discretion is calculated for each bank by its abnormal loan loss provisions (i.e., the residuals in equation (1)). Then it is averaged cross-sectionally for banks with above-median and below-median core deposit percentages relative to total liabilities in Panels (a) and (b), respectively. The average discretion is normalized with a mean of 0 and a standard deviation of 1. The data are from the Federal Reserve Economic Data (FRED) and the U.S. bank regulatory Call Reports. The sample is from January 1990 to December 2019. The gray bars indicate the NBER-defined recession periods.

(a) Banks with Above-Median Core Deposits (%)   **(b)** Banks with Below-Median Core Deposits (%)

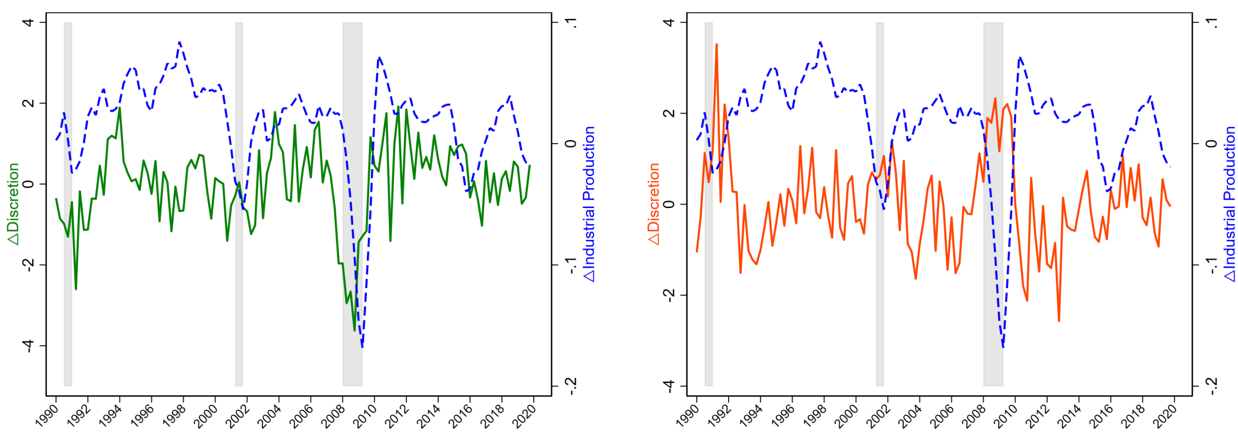


Figure 2: Discretion Beta and Wholesale Funding

This figure presents binned scatter plots of discretion betas against wholesale funding reliance: Panel (a) shows results without any controls, and Panel (b) includes controls of bank loan composition. Discretion beta refers to the sensitivity of a bank's abnormal loan loss provisions to industrial production (i.e., the estimated coefficient β in equation (2)). The estimation is conducted for each bank by using all historical information. A bank's wholesale funding reliance is calculated as the average percentage of its noncore liabilities (i.e., total liabilities excluding core deposits) relative to total liabilities. Only banks with at least 40 quarterly observations are included. Loan composition reflects the average shares of real estate loans, commercial and industrial loans, and consumer loans in a bank's loan portfolio. The red line represents the line of best fit from an OLS regression. The underlying data are from FRED and the Call Reports. The sample period is from 1990 to 2019.

(a) Not Control for Bank Loan Composition

(b) Control for Bank Loan Composition

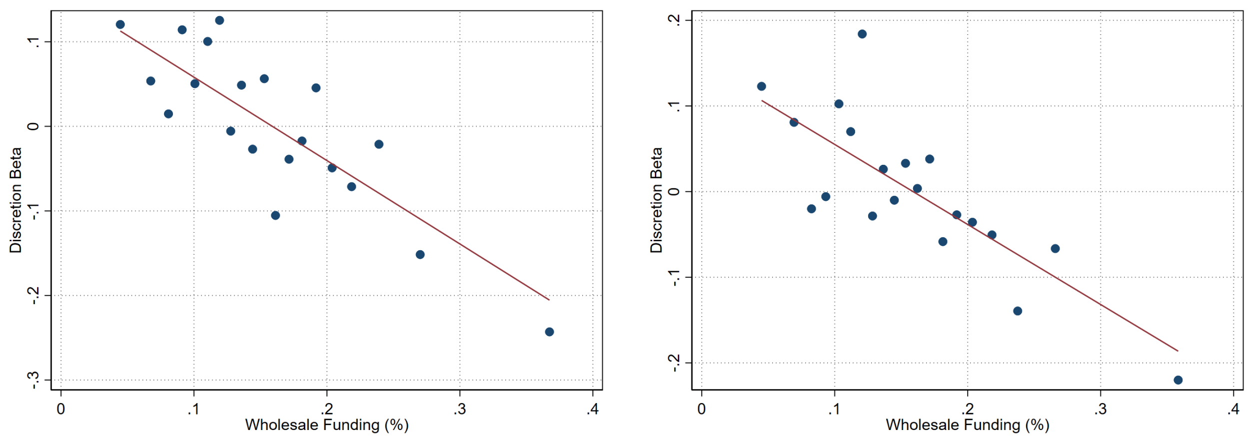


Figure 3: Mechanism of the Paper

This figure describes the main mechanisms of the paper. In boom periods, banks with limited core deposits understate loan loss provisions to increase wholesale funding and expand lending (via *the risk-taking channel*). Their increased loans, especially informational opaque loans, prompt greater accounting discretion in recognizing loan losses (via *the feedback channel*). The risk-taking channel reflects the banks' *willingness* to apply accounting discretion to facilitate their growth, whereas the feedback channel reveals their *ability* to do so. The interaction between the *willingness* and *ability* to exercise accounting discretion forms an *accounting accelerator*, speeding up the credit supply in boom periods. However, such credit expansion is associated with greater reliance on wholesale funding and higher risk in the lending process. Therefore, it also exacerbates the severity of bust periods when understated loan losses eventually come to light and wholesale funding sharply declines. As a result, the accounting accelerator amplifies business cycle fluctuations and threatens financial stability.

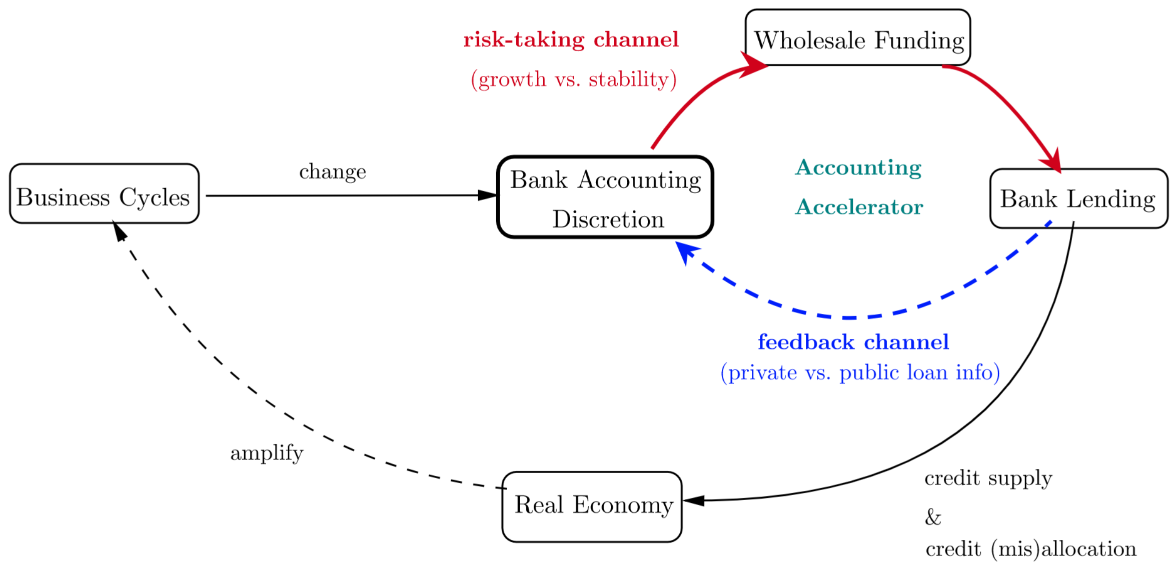


Table 1: Summary Statistics

This table reports summary statistics for the main model variables. Panel A presents statistics for bank characteristics at the bank-quarter level from 1990Q1 to 2019Q4. Panel B presents statistics for mortgage loan originations at the bank-county-year level from 1990 to 2019. Appendix A provides variable definitions. Variables are winsorized at the 1st and 99th percentiles.

Variables	**Mean**	**Std. Dev.**	**25th**	**Median**	**75th**
Panel A: Bank-Quarter Level					
△Discretion	−0.005	1.680	−0.464	0.004	0.468
△Discretion (standardized)	0.002	1.211	−0.447	0.004	0.455
△IP	0.019	0.038	0.011	0.027	0.041
WFR	0.155	0.100	0.079	0.134	0.210
Size	11.50	1.234	10.65	11.40	12.21
Capital Ratio	10.09	2.943	8.130	9.430	11.33
ROE	10.06	9.478	6.757	10.69	14.81
Audit Quality	0.560	0.496	0	1	1
Diversification	1.432	0.748	0.693	1.386	1.792
Core Deposit Rate	2.438	0.768	1.901	2.416	2.939
Wholesale Interest Rate	4.114	0.891	3.560	4.217	4.727
Collateral	1.741	2.862	0.345	0.798	1.821
Maturity	1.585	1.754	0.562	0.991	1.921
△Wholesale	0.008	0.423	−0.148	0.046	0.229
△Wholesale Interest Rate	−0.187	1.648	−0.985	−0.203	0.553
△Collateral	0.223	1.682	−0.154	0	0.276
△Uninsured	0.004	0.035	−0.015	0.004	0.023
△Insured Deposits	0.006	0.030	−0.008	0.005	0.020
△Total Liabilities	0.010	0.034	−0.011	0.010	0.032
Panel B: Bank-County-Year Level					
Acceptance Rate	0.779	0.306	0.667	0.930	1.000
Mortgage Amount	6.313	1.920	4.977	6.031	7.513
Sold Fraction	0.462	0.436	0	0.427	1

Table 2: The Role of Wholesale Funding Reliance

This table shows the results on how wholesale funding reliance affects bank accounting discretion over business cycles. The sample includes observations of commercial banks from 1990 to 2019. The dependent variable in columns 1 to 3, $\triangle$*Discretion,* is the change in a bank's abnormal loan loss provisions. The dependent variable in columns 4 to 6, $\triangle$*Discretion (standardized),* is the change in a bank's abnormal loan loss provisions standardized by its own standard deviation. The main independent variable $\triangle IP$ is the change in the natural logarithm of industrial production. This table reports results on the heterogeneity across the quartiles of banks' wholesale funding reliance (WFR). WFR is defined as the ratio of noncore liabilities to total liabilities. $\triangle IP$ is interacted with dummy variables based on bank WFR quartiles. Additional bank controls include *size*, *capital ratio*, *ROE*, *loan composition, audit quality,* and *diversification*. Refer to Appendix A for detailed variable definitions. Standard errors are clustered by bank, and t-statistics are reported in parentheses below each estimate. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	△Discretion			**△Discretion (standardized)**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
△IP	0.3422***	0.4858***		0.6681***	0.7620***	
	(2.68)	(3.71)		(6.79)	(7.43)	
△IP × Q2 WFR	−0.3422*	−0.2499	−0.3506*	−0.3052**	−0.2639*	−0.3301**
	(−1.92)	(−1.37)	(−1.93)	(−2.26)	(−1.89)	(−2.37)
△IP × Q3 WFR	−0.7857***	−0.6278***	−0.7806***	−0.5751***	−0.4976***	−0.5975***
	(−4.31)	(−3.34)	(−4.15)	(−4.17)	(−3.45)	(−4.14)
△IP × Q4 WFR	−1.3826***	−1.0680***	−1.3194***	−1.1773***	−1.0180***	−1.1795***
	(−7.16)	(−5.27)	(−6.50)	(−8.41)	(−6.87)	(−7.95)
Bank FE	No	Yes	Yes	No	Yes	Yes
Quarter FE	No	No	Yes	No	No	Yes
Observations	604,769	604,769	604,769	604,769	604,769	604,769
Adjusted R^2	0.046	0.075	0.081	0.030	0.050	0.056

Table 3: The Risk-Taking Channel

This table examines whether the effect of wholesale funding reliance on bank accounting discretion over business cycles is stronger for banks with worse pre-provision performance. The sample includes observations of commercial banks from 1990 to 2019. In Panel A, the dependent variable △*Discretion* is the change in a bank's abnormal loan loss provisions. In Panel B, the dependent variable △*Discretion (standardized)* is the change in a bank's abnormal loan loss provisions standardized by its own standard deviation. The main independent variable △*IP* is the change in the natural logarithm of industrial production. Both panels report results on the heterogeneity across the quartiles of banks' wholesale funding reliance (*WFR*). *WFR* is defined as the ratio of noncore liabilities to total liabilities. △*IP* is interacted with dummy variables based on bank *WFR* quartiles. Columns 1, 2, and 3 present results for banks with the lowest tercile, middle tercile, and highest tercile of *pre-provision ROE*, respectively. Column 4 presents tests of the differences in coefficients on the products of △*IP* and *WFR* variables for the low versus high terciles. Additional bank controls include *size*, *capital ratio*, *loan composition, audit quality,* and *diversification*. Refer to Appendix A for detailed variable definitions. Standard errors are clustered by bank, and t-statistics are reported in parentheses below each estimate. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: △Discretion

	Low ROE (1)	Medium ROE (2)	High ROE (3)	Difference (4)
△IP × Q2 WFR	−0.4012	−0.0189	0.0686	−0.4698
	(−1.04)	(−0.07)	(0.22)	(−0.96)
△IP × Q3 WFR	−1.2507***	−0.4633	−0.1821	−1.0686**
	(−3.04)	(−1.57)	(−0.60)	(−2.11)
△IP × Q4 WFR	−1.4358***	−1.0902***	−0.4440	−0.9918*
	(−3.29)	(−3.34)	(−1.38)	(−1.82)
Bank FE	Yes	Yes	Yes	
Quarter FE	Yes	Yes	Yes	
Observations	200,600	200,598	200,497	
Adjusted R^2	0.047	0.059	0.062	

Panel B: △Discretion (standardized)

	Low ROE (1)	Medium ROE (2)	High ROE (3)	Difference (4)
△IP × Q2 WFR	−0.4131	−0.1639	0.0886	−0.5017
	(−1.62)	(−0.69)	(0.35)	(−1.40)
△IP × Q3 WFR	−0.9437***	−0.4760**	−0.0530	−0.8907**
	(−3.48)	(−1.98)	(−0.21)	(−2.40)
△IP × Q4 WFR	−1.2988***	−0.9612***	−0.5924**	−0.7064*
	(−4.77)	(−3.76)	(−2.23)	(−1.86)
Bank FE	Yes	Yes	Yes	
Quarter FE	Yes	Yes	Yes	
Observations	200,600	200,598	200,497	
Adjusted R^2	0.043	0.050	0.050	

Table 4: Accounting Discretion and Debt Capacity

This table shows the effect of banks' accounting discretion on their wholesale debt capacity. The dependent variables are $\triangle$ *Wholesale* (log changes in the amount of bank noncore liabilities) in columns 1 and 2, $\triangle$ *Wholesale Interest Rate* (changes in the interest rate of bank noncore liabilities) in columns 3 and 4, and $\triangle$ *Collateral* (changes in the collateral ratio of bank noncore liabilities) in columns 5 and 6. The independent variable in Panel A, $\triangle\widehat{Discretion}$, is the change in a bank's abnormal loan loss provisions. The independent variable in Panel B, $\triangle\widehat{Discretion}$*(standardized)*, is the change in a bank's abnormal loan loss provisions standardized by its own standard deviation. Both independent variables are instrumented by the interaction term between a bank's predetermined wholesale funding reliance and the change in log industrial production. Additional bank controls include *size*, *capital ratio*, *ROE*, *loan composition, audit quality, diversification, wholesale interest rate*, *collateral*, and *maturity*. The "Control Interactions" means that interaction terms between the control variables and changes in log industrial production are included in the regression. Refer to Appendix A for detailed variable definitions. Standard errors are clustered by bank, and t-statistics are reported in parentheses below each estimate. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A:

	(1)	(2)	(3)	(4)	(5)	(6)
	$\triangle$Wholesale		$\triangle$Wholesale Interest Rate		$\triangle$Collateral	
$\triangle\widehat{\text{Discretion}}$	-0.4185^{***}	-0.5289^{***}	2.0891^{***}	2.2793^{***}	2.2322^{***}	1.5956^{***}
	(-5.25)	(-2.92)	(5.52)	(2.96)	(5.49)	(2.79)
Controls	Yes	No	Yes	No	Yes	No
Control Interactions	No	Yes	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	396,841	396,841	396,841	396,841	396,841	396,841
Cragg-Donald F statistic	73.32	20.16	73.32	20.16	73.32	20.16

Panel B:

	(1)	(2)	(3)	(4)	(5)	(6)
	$\triangle$Wholesale		$\triangle$Wholesale Interest Rate		$\triangle$Collateral	
$\triangle\widehat{\text{Discretion}}$ **(standardized)**	-0.4795^{***}	-0.5249^{***}	2.3936^{***}	2.2618^{***}	2.5576^{***}	1.5833^{***}
	(-5.96)	(-3.80)	(6.41)	(3.94)	(6.37)	(3.55)
Controls	Yes	No	Yes	No	Yes	No
Control Interactions	No	Yes	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	396,841	396,841	396,841	396,841	396,841	396,841
Cragg-Donald F statistic	101.4	37.17	101.4	37.17	101.4	37.17

Table 5: Accounting Discretion and Bank Lending

This table shows the effect of accounting discretion on bank lending by using mortgage origination data from HMDA. The analysis is conducted at the bank-county-year level by aggregating individual mortgage loan data. The dependent variables are the average acceptance rate for mortgage applications (columns 1 and 4), the log of mortgage lending volume (columns 2 and 5), and the fraction of mortgages that are sold in the origination year (columns 3 and 6). The independent variable in columns 1 to 3, $\triangle \widehat{Discretion}$, is the change in a bank's abnormal loan loss provisions. The independent variable in columns 4 to 6, $\triangle \widehat{Discretion}$*(standardized),* is the change in a bank's abnormal loan loss provisions standardized by its own standard deviation. Both independent variables are instrumented by the interaction term between a bank's predetermined wholesale funding reliance and the change in log industrial production. Additional bank controls include *size*, *capital ratio*, *ROE*, *loan composition, audit quality,* and *diversification*. Refer to Appendix A for detailed variable definitions. Standard errors are clustered by county, and t-statistics are reported in parentheses below each estimate. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Acceptance Rate	(2) Mortgage Amount	(3) Sold Fraction	(4) Acceptance Rate	(5) Mortgage Amount	(6) Sold Fraction
$\triangle\widehat{\text{Discretion}}$	-0.2433^{***}	-0.2479^{***}	-0.1526^{***}			
	(-34.66)	(-9.21)	(-21.26)			
$\triangle\widehat{\text{Discretion}}$ (standardized)				-0.3577^{***}	-0.3357^{***}	-0.2066^{***}
				(-33.19)	(-9.15)	(-21.43)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,087,115	1,844,856	1,844,856	2,087,115	1,844,856	1,844,856
Cragg-Donald F statistic	2873	2381	2454	2241	2454	2241

Table 6: The Feedback Channel

This table examines whether the effect of wholesale funding reliance on bank accounting discretion over business cycles is stronger for banks with high opacity share. Opacity share is defined as the proportion of a bank's total assets comprised of heterogeneous loans, which include both commercial and industrial loans as well as commercial real estate loans. The dependent variable in columns 1 to 3, $\triangle$*Discretion,* is the change in a bank's abnormal loan loss provisions. The dependent variable in columns 4 to 6, $\triangle$*Discretion (standardized),* is the change in a bank's abnormal loan loss provisions standardized by its own standard deviation. The main independent variable $\triangle IP$ is the change in the natural logarithm of industrial production. This table reports results on the heterogeneity across the quartiles of banks' wholesale funding reliance (*WFR*). *WFR* is defined as the ratio of noncore liabilities to total liabilities. $\triangle IP$ is interacted with dummy variables based on bank *WFR* quartiles. Columns 1 and 4 present results for banks with the above-median opacity shares. Columns 2 and 5 present results for banks with the below-median opacity shares. Columns 3 and 6 present tests of the differences in coefficients on the products of $\triangle IP$ and *WFR* variables for the high versus low opacity shares. Additional bank controls include *size*, *capital ratio*, *ROE, audit quality,* and *diversification.* Refer to Appendix A for detailed variable definitions. Standard errors are clustered by bank, and t-statistics are reported in parentheses below each estimate. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	△Discretion			**△Discretion (standardized)**		
	High Opacity	**Low Opacity**	**Difference**	**High Opacity**	**Low Opacity**	**Difference**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
△IP × Q2 WFR	-0.9068^{***}	0.1305	-1.0373^{***}	-0.6764^{***}	0.0693	-0.7457^{**}
	(−2.95)	(0.58)	(−2.72)	(−2.96)	(0.38)	(−2.54)
△IP × Q3 WFR	-1.3098^{***}	-0.5057^{**}	-0.8041^{**}	-0.9187^{***}	-0.3623^{*}	-0.5564^{*}
	(−4.37)	(−2.10)	(−2.09)	(−4.05)	(−1.89)	(−1.87)
△IP × Q4 WFR	-1.5911^{***}	-1.0757^{***}	−0.5154	-1.2811^{***}	-0.9859^{***}	−0.2952
	(−5.11)	(−3.53)	(−1.18)	(−5.72)	(−4.37)	(−0.93)
Bank FE	Yes	Yes		Yes	Yes	
Quarter FE	Yes	Yes		Yes	Yes	
Observations	302,068	302,080		302,068	302,080	
Adjusted R^2	0.105	0.071		0.075	0.053	

Table 7: Bank Debt Information Sensitivity

This table examines whether the bank debt information sensitivity was more salient for banks with high wholesale funding reliance during the 2008 financial crisis. The dependent variables are $\triangle$*Uninsured* (changes in bank uninsured liabilities) in columns 1 and 2, $\triangle$*Insured Deposits* (changes in bank insured deposits) in columns 3 and 4, and $\triangle$*Total Liabilities* (changes in bank total liabilities) in columns 5 and 6. All dependent variables are scaled by lagged bank assets. *ROE* is the return on bank equity. *WFR* is wholesale funding reliance, calculated as the ratio of noncore liabilities to total liabilities, measured at the fourth quarter of 2006 and standardized to a mean of 0 and a standard deviation of 1. Additional bank controls include *size*, *capital ratio*, *loan composition*, *audit quality, diversification*, *core deposit rate,* and *wholesale interest rate*. Refer to Appendix A for detailed variable definitions. Standard errors are clustered by bank, and t-statistics are reported in parentheses below each estimate. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	△Uninsured		**△Insured Deposits**		**△Total Liabilities**	
ROE	0.0248***	0.0348***	0.0214**	0.0087	0.0463***	0.0423***
	(2.63)	(3.28)	(2.57)	(1.01)	(5.21)	(3.99)
ROE × WFR	0.0208**	0.0210**	0.0119	0.0102	0.0340***	0.0325***
	(2.54)	(2.39)	(1.58)	(1.36)	(4.48)	(4.01)
Controls	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42,735	42,735	42,735	42,735	42,735	42,735
Adjusted R^2	0.112	0.157	0.165	0.179	0.201	0.285

Table 8: Capital (Mis)allocation

This table examines the capital (mis)allocation decisions of banks that hide their accounting losses. The dependent variable is the log of syndicated loans at the bank-firm-year level. The main independent variable *Hiding Loss* is an indicator variable that equals one if a bank had negative abnormal loan loss provision in the previous year. *TFP* is the firm-level total factor productivity, measured following the methodology of İmrohoroğlu and Tüzel (2014). Additional bank controls include *size*, *capital ratio*, *ROE*, *loan composition*, *audit quality,* and *diversification*. Refer to Appendix A for detailed variable definitions. Columns 1 to 3 exhibit the results for bubble periods (i.e., years 2004-2006). Columns 4 to 6 show the results for non-bubble periods (i.e., years 2010-2012). Standard errors are clustered by bank, and t-statistics are reported in parentheses below each estimate. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
		Bubble Period			**Non-Bubble Period**	
TFP	0.4936***	0.4940***		0.0405	0.0413	
	(5.28)	(5.28)		(0.38)	(0.39)	
TFP × Hiding Loss	−0.0631*	−0.0631*	−0.0511*	0.0586	0.0577	0.0463*
	(−1.98)	(−2.00)	(−1.75)	(1.57)	(1.54)	(1.90)
Controls	No	Yes	Yes	No	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	Yes	Yes	No
Year FE	Yes	Yes	No	Yes	Yes	No
Firm× Year FE	No	No	Yes	No	No	Yes
Observations	10,808	10,808	10,784	8,087	8,087	8,081
Adjusted R^2	0.766	0.767	0.819	0.761	0.761	0.812

Appendix A: Variable List

Variable	Definition
△Discretion	Year-over-year change in abnormal loan loss provisions (i.e., $\varepsilon_{i,t}$ in equation (1) multiplied by 1000)
△Discretion (standardized)	Year-over-year change in standardized abnormal loan loss provisions (i.e., $\varepsilon_{i,t}$ in equation (1) scaled by bank-specific standard deviation)
△IP	Year-over-year change in the natural logarithm of industrial production index (i.e., FRED IPB50001NQ series)
Core Deposits	The sum of retail checking, savings, and small-time deposits, where small-time deposits are defined as those below $100,000 before 2010Q1 and below $250,000 from 2010Q1 onward
Wholesale	Noncore liabilities (i.e., total liabilities minus core deposits)
WFR	The ratio of noncore liabilities (i.e., total liabilities minus core deposits) to total liabilities
LLP	Loan loss provision scaled by lagged total loans
NPL	Non-performing loans scaled by lagged total loans
Size	The natural logarithm of total assets
Capital Ratio	The Tier 1 leverage ratio (%)
ROE	The ratio of net income to total equity capital (annualized, %)
Pre-Provision ROE	The sum of pre-tax income and provision for loan losses divided by the sum of total equity capital and provision for loan losses (annualized, %)
Loan Composition	The ratios of real estate loans, commercial and industrial loans, and consumer loans to total loans
Core Deposit Rate	Interest expense of core deposits divided by lagged core deposits (annualized, %)
Wholesale Interest Rate	Total interest expense minus interest expense of core deposits divided by lagged noncore liabilities, where noncore liabilities equal total liabilities minus core deposits (annualized, %)
Audit Quality	Dummy variable that equals one if a bank's parent holding company or the bank itself received an independent audit, and zero otherwise
Diversification	The natural logarithm of one plus the number of deposit branches
Collateral	The sum of pledged securities and pledged loans divided by noncore liabilities (i.e., total liabilities minus core deposits)
Maturity	The weighted average of the maturities of noncore liabilities (i.e., total liabilities minus core deposits)
△Uninsured	The change in uninsured liabilities scaled by lagged total assets
△Insured Deposits	The change in insured deposits scaled by lagged total assets
△Total Liabilities	The change in total liabilities scaled by lagged total assets
Acceptance Rate	The average acceptance rate for non-agency mortgage applications
Mortgage Amount	The natural logarithm of non-agency mortgage originations
Sold Fraction	The fraction of non-agency mortgages sold in their origination year

Appendix B: Stylized Model

In this Appendix, I present a simple stylized model that formalizes the empirical predictions discussed in Section 5 of the paper. The model highlights how wholesale funding affects a bank's incentives to manage earnings over the business cycle. I begin by characterizing the model framework and setup, followed by a discussion of the equilibrium to derive empirical predictions about the optimal bank reporting strategy. Finally, I explore model extensions and their implications.

Model Framework

The model features two types of players: a bank and wholesale lenders. The bank funds itself by issuing risk-free core deposits and risky wholesale debt. For simplicity, I assume that core deposits are fixed and the bank does not issue equity. This assumption echoes the common views that core deposits are scarce (Hanson et al., 2015; Drechsler et al., 2017) and banks rarely issue equity (Baron, 2020). It also highlights the role of wholesale debt in the model relative to other funding sources. Similar to Hart and Moore (1994) and Stein (2012), the bank has limited commitment, so it cannot make credible promises to wholesale lenders without having high-quality assets to back them. Wholesale lenders do not directly observe the quality of bank assets, but they can update their beliefs about the bank's asset quality by observing bank earnings and adjust collateral requirements accordingly.[26] The bank has discretion in reporting earnings but misreporting is costly. In addition to the information from the bank's reported earnings, wholesale lenders' beliefs also vary based on the state of the economy. This uncertainty is taken into account by the bank when deciding how to report.

Model Setup

The detailed setup of the model is as follows. There are two dates in the model: an initial date t=0 and a payoff date t=1. At t=0, an initial balance sheet of the bank is given exogenously. Bank assets are risky loans denoted by L_0. The loan return rate is given by r^R, and the rate of loan losses is denoted by d. So the interest revenue equals $\left(r^R - d\right) L_0$. Bank liabilities include wholesale debt, which is denoted by W_0, and a fixed amount of core deposits denoted by D. The cost of the wholesale debt is denoted by fW_0, where f is the interest rate that the bank pays on the wholesale debt. The core deposit rate that the bank pays depositors is normalized to zero. As a result, the bank's true (or unmanaged) earnings are Π_0:

$$\Pi_0 = \left(r^R - d\right) L_0 - fW_0. \tag{8}$$

[26] A strand of the banking literature emphasizes the role of collateral constraints for bank liquidity creation (e.g., Kiyotaki and Moore, 1997; Geanakoplos, 2003; Gorton and Ordonez, 2014; Gertler and Kiyotaki, 2015; Maggiori, 2017).

Unlike other initial parameters, the loan loss rate $d \sim N(\mu_d, \sigma_d^2)$ and its realization is privately observed by the bank. In other words, d captures the average loan quality unknown to outsiders and dL_0 can be considered as the bank's recognized accounting loan losses (i.e., provisions for loan losses). Given true earnings Π_0, the bank can choose to manipulate it and report Π_0^m:

$$\Pi_0^m = \Pi_0 + b_0, \tag{9}$$

where b_0 is the chosen bias. A positive (or negative) value of b_0 indicates that the bank exercises accounting discretion over loan loss provisions to increase (or decrease) its reported earnings. However, the bank's manager incurs a direct personal cost from biasing earnings. In particular, I assume that the biasing cost is:

$$\frac{c}{2}\left(b_0 + \varepsilon\right)^2, \tag{10}$$

where $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. ε is the reporting noise and may reflect, for example, distortions by accounting rules, errors in internal control systems, and idiosyncratic circumstances that affect a bank's misreporting incentives, as in Dye and Sridhar (2008). The realization of ε is privately observed by the bank before it makes its reporting decision.

Wholesale lenders observe the reported earnings Π_0^m and adjust their lending decision for the next date (i.e., t=1). There is a continuum of wholesale lenders, with a total mass of one. For ease of analysis, I assume there is perfect competition in the wholesale market. Wholesale debt is adjusted only through quantities, not rates. The quantities are determined by a collateral constraint, which depends on the aggregate economic state at t=1 and is described in more detail below.

In t=1, there are two types of aggregate economic states: good and bad. A bad state happens with probability λ and a good state happens with probability $1 - \lambda$. If the good state prevails, the economy booms and loans don't default. The bank's profit in a good state during period 1 is given by Π_1^g:

$$\Pi_1^g = r^R L_1 - f\delta W_1, \tag{11}$$

where L_1 is total loans and W_1 is available wholesale debt. The parameter δ captures the fraction of wholesale debt utilized by the bank, with the remainder of its funding coming from core deposits. Thus, this fraction δ serves as a measure of the bank's reliance on wholesale funding. The amount of W_1 is determined by a collateral constraint imposed by wholesale lenders. As argued by Kashyap and Stein (1995), because wholesale debt is not insured by FDIC deposit insurance, it requires banks to have enough assets to back them. In the model, wholesale lenders form their beliefs about the quality of bank assets based on reported earnings. Specifically, they impose the following collateral constraint:

$$L_0 \left(1 - \underbrace{kE\left[d|\Pi_0^m\right]}_{\text{loss belief}}\right) \geq W_1, \tag{12}$$

where k represents a haircut parameter. The collateral constraint (12) says that the value of the bank's existing loans L_0 must be sufficient to pay off the amount of wholesale debt that can be issued.

If the bad state (e.g., a bust or crisis) occurs, wholesale lenders receive an additional signal, s, about bank asset quality:[27]

$$s = d + \upsilon, \tag{13}$$

where $\upsilon \sim N(0, \sigma_\upsilon^2)$. This unbiased signal, s, can arise from wholesale lenders acquiring more information during crisis periods or from regulators releasing more information about banks, such as stress tests. Wholesale lenders incorporate the signal s into their belief updating and will withdraw funding from the bank if the signal s indicates a sufficiently low quality of bank assets. Specifically, the collateral constraint in the bad state is:

$$L_0 \left(1 - kE\left[d|\Pi_0^m, s\right] - \underbrace{\phi\left(E\left[d|\Pi_0^m, s\right] - E\left[d|\Pi_0^m\right]\right)}_{\text{panic withdrawal}}\right) \geq W_1. \tag{14}$$

The difference between $E\left[d|\Pi_0^m, s\right]$ and $E\left[d|\Pi_0^m\right]$ captures the panic withdrawal from wholesale lenders caused by their revised beliefs. ϕ is a commonly known coefficient that captures the magnitude of the funding withdrawal regarding wholesaler lenders' updates on the default upon observing the additional signal, s. This way of modeling withdrawal reflects the rollover risk of wholesale funding and is consistent with wholesale lenders being vigilant to negative news during the 2008 financial crisis (Pérignon et al., 2018). Note that the difference between $E\left[d|\Pi_0^m, s\right]$ and $E\left[d|\Pi_0^m\right]$ can be negative. In such a case, it reflects that greater assurance over bank asset quality leads to more wholesale debt, which is similar to the flight-to-quality phenomenon occurred in the crisis (Krishnamurthy, 2010; Beber et al., 2009).

When the economy is in a bad state, the number of delinquent and defaulted loans also increases. The increase is captured by a multiplier, θ, that scales up the loan loss rate, d. As such, the bank's profit in period 1 when a bad state occurs is given by Π_1^b:

$$\Pi_1^b = \left(r^R - \theta d\right) L_1 - f\delta W_1. \tag{15}$$

[27]Modeling crises as a change of the information structure in credit markets is motivated by Gorton and Ordonez (2014, 2020).

The Bank's Optimization Problem

The optimization problem for the bank is to decide its earnings bias b_0 in the face of future economic uncertainty. The bank's expected net profit at time t=1 is given by:

$$(1-\lambda)\Pi_1^g + \lambda\Pi_1^b - \frac{c}{2}\left(b_0+\varepsilon\right)^2. \tag{16}$$

The three terms in equation (16) are easily interpreted. The first, $(1-\lambda)\Pi_1^g$, is the expected bank profits in the good state. The second term, $\lambda\Pi_1^b$, is the expected bank profits in the bad state. The last term, $\frac{c}{2}\left(b_0+\varepsilon\right)^2$, captures the direct cost of earnings manipulation.

The bank chooses its reporting bias b_0 to maximize equation (16), subject to the collateral constraints (12) and (14). In the model, there is no restriction on the size of the bank, so collateral constraints are binding.

As discussed earlier, the central feature of the model is that earnings manipulation affects wholesale lenders' beliefs about bank asset quality (i.e., $\frac{\partial E\left[d|\Pi_0^m\right]}{\partial b_0}$ and $\frac{\partial E\left[d|\Pi_0^m,s\right]}{\partial b_0}$) and thereby changes how much wholesale debt the bank can raise in different states of the world. Despite being static, the model presents a key trade-off of manipulating earnings over the business cycle.[28] On the one hand, inflated earnings can facilitate bank growth in a boom by relaxing the collateral constraint (12). On the other hand, they will force banks to reduce their intermediation activities in a bust by tightening the collateral constraint (14). As a result, optimal b_0^* is pinned down when its marginal benefits equal its marginal costs.

Equilibrium

This paper studies pure strategy Bayesian Nash equilibria. The equilibrium is characterized by the optimal behavior of the bank and wholesale lenders. The bank chooses its reporting strategy optimally given its conjecture about the future demand for wholesale debt. Wholesale lenders are also rational, anticipate the bank's reporting decision given their information set, and incorporate these beliefs when financing the bank. In equilibrium, both the bank and wholesale lenders formulate correct conjectures and make their best decisions.

To simplify the analysis and maintain generality, I first solve the model in the case where the signal s is precise (i.e., $\sigma_v^2 = 0$). I then illustrate that the main insights of the model remain valid when signal s is imprecise (i.e., $\sigma_v^2 > 0$). Overall, the results provide some insights into why different banks manage their earnings differently over the business cycle, and in particular why the difference is related to wholesale funding.

[28] Due to the static nature of the model, there is no explicit restriction that the bias in reported earnings must reverse in the future. However, since the unbiased signal s partially reveals the reporting bias in the bad state, the model implicitly captures some reversal effect during downturns.

(1) Equilibrium when signal s is precise (i.e., $\sigma_v^2 = 0$)

Similar to Fischer and Verrecchia (2000) and Dye and Sridhar (2008), this paper focuses on the equilibrium in which the bias in reported earnings is a linear function of the bank's private information. In particular, I consider the equilibrium where the optimal reporting bias b_0^* take the following linear function form (I later show that this conjecture is correct).

$$b_0^* = \alpha + \beta\varepsilon + \gamma d$$

In a good state, wholesale lenders update their beliefs according to

$$\begin{aligned} E\left[d|\Pi_0^m\right] &= E\left[d|\left(r^R - d\right)L_0 - fW_0 + \alpha + \beta\varepsilon + \gamma d\right] \\ &= \mu_d + \frac{\left(-L_0+\gamma\right)\sigma_d^2}{\left(-L_0+\gamma\right)^2\sigma_d^2 + \beta^2\sigma_\varepsilon^2}\left(\left(-L_0+\gamma\right)\left(d-\mu_d\right)+\beta\varepsilon\right) \\ &= \mu_d + \frac{\left(-L_0+\gamma\right)\sigma_d^2}{\left(-L_0+\gamma\right)^2\sigma_d^2 + \beta^2\sigma_\varepsilon^2}\left(b_0 - L_0\left(d-\mu_d\right) - \gamma\mu_d - \alpha\right) \end{aligned}$$

In a bad state, wholesale lenders update their beliefs according to

$$E\left[d|\Pi_0^m, s\right] = E\left[d|s\right] + \frac{\left(-L_0+\gamma\right)Var\left[d|s\right]}{\left(-L_0+\gamma\right)^2 Var\left[d|s\right] + \beta^2\sigma_\varepsilon^2}\left(b_0 - L_0\left(d - E\left[d|s\right]\right) - \gamma E\left[d|s\right] - \alpha\right),$$

where

$$\begin{aligned} E\left[d|s\right] &= \mu_d + \frac{\sigma_d^2}{\sigma_d^2+\sigma_v^2}\left(s-\mu_d\right) \\ Var\left[d|s\right] &= \frac{\sigma_d^2\sigma_v^2}{\sigma_d^2+\sigma_v^2} \end{aligned}$$

We can use these beliefs to derive two useful terms

$$\begin{aligned} \frac{\partial E\left[d|\Pi_0^m\right]}{\partial b_0} &= \frac{\left(-L_0+\gamma\right)\sigma_d^2}{\left(-L_0+\gamma\right)^2\sigma_d^2+\beta^2\sigma_\varepsilon^2} \\ \frac{\partial E\left[d|\Pi_0^m, s\right]}{\partial b_0} &= \frac{\left(-L_0+\gamma\right)Var\left[d|s\right]}{\left(-L_0+\gamma\right)^2 Var\left[d|s\right]+\beta^2\sigma_\varepsilon^2} \end{aligned}$$

Then we can solve the bank's objective function

$$\max_{b_0}\left\{(1-\lambda)\Pi_1^g + \lambda\Pi_1^b - \frac{c}{2}\left(b_0+\varepsilon\right)^2\right\}$$

The first-order condition with respect to b_0 is

$$\left[(1-\lambda)\left(r^R-f\right)k-\lambda\left(r^R-\theta d-f\right)\phi\right]\delta L_0\left(-\frac{\partial E\left[d|\Pi_0^m\right]}{\partial b_0}\right)$$
$$+\left(r^R-\theta d-f\right)\lambda\delta L_0\left(k+\phi\right)\left(-\frac{\partial E\left[d|\Pi_0^m,s\right]}{\partial b_0}\right)-c\left(b_0+\varepsilon\right)=0$$

Putting everything together, we obtain

$$\alpha=-\frac{\left(r^R-f\right)\delta L_0}{c}\left(\left((1-\lambda)k-\lambda\phi\right)\frac{\left(-L_0+\gamma\right)\sigma_d^2}{\left(-L_0+\gamma\right)^2\sigma_d^2+\sigma_\varepsilon^2}+\lambda\left(k+\phi\right)\frac{\left(-L_0+\gamma\right)Var\left[d|s\right]}{\left(-L_0+\gamma\right)^2Var\left[d|s\right]+\sigma_\varepsilon^2}\right)$$
$$\beta=-1$$
$$\gamma=\frac{\lambda\theta\delta L_0}{c}\left(-\phi\frac{\left(-L_0+\gamma\right)\sigma_d^2}{\left(-L_0+\gamma\right)^2\sigma_d^2+\sigma_\varepsilon^2}+\left(k+\phi\right)\frac{\left(-L_0+\gamma\right)Var\left[d|s\right]}{\left(-L_0+\gamma\right)^2Var\left[d|s\right]+\sigma_\varepsilon^2}\right)$$

To simplify the analysis while keeping its generality, I focus on the case where the signal s is precise (i.e., $\sigma_v^2=0$). Then the optimal reporting bias b_0^* is simplified as

$$b_0^*=\left((1-\lambda)\left(r^R-f\right)k-\lambda\left(r^R-\theta d-f\right)\phi\right)\frac{\delta L_0(L_0-\gamma)\sigma_d^2}{c\left((L_0-\gamma)^2\sigma_d^2+\sigma_\varepsilon^2\right)}-\varepsilon, \tag{17}$$

where γ satisfies the following equation:

$$\gamma=\frac{\lambda\theta\phi\delta L_0(L_0-\gamma)\sigma_d^2}{c\left((L_0-\gamma)^2\sigma_d^2+\sigma_\varepsilon^2\right)} \tag{18}$$

In equation (18), the right-hand side approaches 0 as γ approaches positive or negative infinity. Furthermore, the right-hand side is equal to 0 when $\gamma=L_0$, and is positive when $\gamma=0$. Therefore, the values of γ must fall within the range of $(0,L_0)$. In other words, there exists a unique solution γ under some technical conditions.

Since $\gamma\in(0,L_0)$, one important observation of equation (17) is that if $(1-\lambda)\left(r^R-f\right)k>\lambda\left(r^R-\theta d-f\right)\phi$ and the realization of ε is sufficiently small, the optimal bias b_0^* will be positive. Intuitively, these conditions imply that if the bank's incentive to grow in boom periods is stronger (e.g., because λ is small or k is large), earnings are more likely to be distorted upwards. This result does not conform with the conventional view of income smoothing documented in prior banking literature (Greenawalt and Sinkey, 1988; Liu and Ryan, 2006). The reason is that earnings manipulation in this model is utilized by banks to facilitate their risk-taking, which I refer to as *the risk-taking channel.* That is, the bank will strategically inflate its earnings to support growth and capitalize on the boom, although this approach also heightens the risk of losing wholesale funding during a bust.

The model is useful for understanding how a bank's liability structure affects its reporting bias. Specifically, I analyze the role of wholesale funding reliance by differentiating the optimal reporting bias b_0^* with respect to δ . The following comparative statics can be obtained.

$$\frac{\partial b_0^*}{\partial \delta} = \left(\frac{(1-\lambda)\left(r^R - f\right)k - \lambda\left(r^R - \theta d - f\right)\phi}{\lambda\theta\phi} \right) \frac{\partial \gamma}{\partial \delta}$$

Applying implicit differentiation to equation (18), one can find that γ is an increasing function of δ. Under the innocuous assumption $(1-\lambda)\left(r^R - f\right)k > \lambda\left(r^R - \theta d - f\right)\phi$, it is easy to show that reporting bias increases with the bank's dependency on wholesale debt (i.e., $\frac{\partial b_0^*}{\partial \delta} > 0$). This result reflects the notion that banks with limited core deposits receive more benefit for the same amount of earnings manipulation. Consequently, a bank reliant on wholesale funding has a stronger incentive to use provisions to manage earnings to support its risk-taking activities. This implication is formalized in Prediction 1, reproduced here.

PREDICTION 1: *Banks with limited core deposits are more likely to understate loan loss provisions during economic booms to facilitate growth, leading to larger provisions being revealed during downturns. This risk-taking behavior intensifies as the bank's reliance on wholesale funding increases.*

Moreover, the equilibrium reporting bias also varies with the loan loss rate, which is private information held by the bank. The relationship is reflected in $\frac{\partial b_0^*}{\partial d} = \frac{L_0\lambda\theta\phi\delta\sigma_d^2(L_0-\gamma)}{c\left((L_0-\gamma)^2\sigma_d^2+\sigma_\varepsilon^2\right)} > 0$. As the loan loss rate rises, the bank benefits more from inflating its reported earnings. This insight is formalized in Prediction 2.

PREDICTION 2: *Banks with lower pre-provision profitability are more likely to understate loan loss provisions to engage in risk-taking during economic booms, leading to larger provisions during economic downturns.*

(2) Equilibrium when signal s is not precise (i.e., $\sigma_v^2 > 0$)

Based on the previous derivations, the optimal reporting bias b_0^* when $\sigma_v^2 > 0$ is

$$\begin{aligned} b_0^* = &\left((1-\lambda)\left(r^R - f\right)k - \lambda\left(r^R - \theta d - f\right)\phi\right)\frac{\delta L_0(L_0-\gamma)\sigma_d^2}{c\left((L_0-\gamma)^2\sigma_d^2+\sigma_\varepsilon^2\right)} \\ &+ \lambda\left(r^R - \theta d - f\right)(k+\phi)\frac{\delta L_0(L_0-\gamma)Var\left[d|s\right]}{c\left((L_0-\gamma)^2 Var\left[d|s\right]+\sigma_\varepsilon^2\right)} - \varepsilon \end{aligned}$$

γ is determined by the following equation:

$$\begin{aligned} \gamma &= \frac{\lambda\theta\delta L_0}{c}\left(-\phi\frac{\left(-L_0+\gamma\right)\sigma_d^2}{\left(-L_0+\gamma\right)^2\sigma_d^2+\sigma_\varepsilon^2} + (k+\phi)\frac{\left(-L_0+\gamma\right)Var\left[d|s\right]}{\left(-L_0+\gamma\right)^2 Var\left[d|s\right]+\sigma_\varepsilon^2}\right) \\ &= \underbrace{\frac{\lambda\theta\delta L_0}{c}\left(-\phi+(k+\phi)\frac{\sigma_v^2}{Var\left[d|\Pi_0^m\right]+\sigma_v^2}\right)\frac{(-L_0+\gamma)\sigma_d^2}{(-L_0+\gamma)^2\sigma_d^2+\sigma_\varepsilon^2}}_{\equiv F(\gamma)}, \end{aligned}$$

where

$$Var\left[d|\Pi_0^m\right] = \frac{\sigma_d^2\sigma_\varepsilon^2}{(-L_0+\gamma)^2\sigma_d^2+\sigma_\varepsilon^2}$$

Note that $Var\left[d|\Pi_0^m\right] \in (0, \sigma_d^2]$. Thus,

$$\left(-\phi + (k+\phi)\frac{\sigma_v^2}{Var\left[d|\Pi_0^m\right]+\sigma_v^2}\right) \in \left[-\phi + (k+\phi)\frac{\sigma_v^2}{\sigma_d^2+\sigma_v^2},\ k\right)$$

Moreover, it can be shown that

$$\max_{\gamma \geq L_0} \frac{(-L_0+\gamma)\sigma_d^2}{(-L_0+\gamma)^2\sigma_d^2+\sigma_\varepsilon^2} = \frac{\sigma_d}{2\sigma_\varepsilon}$$

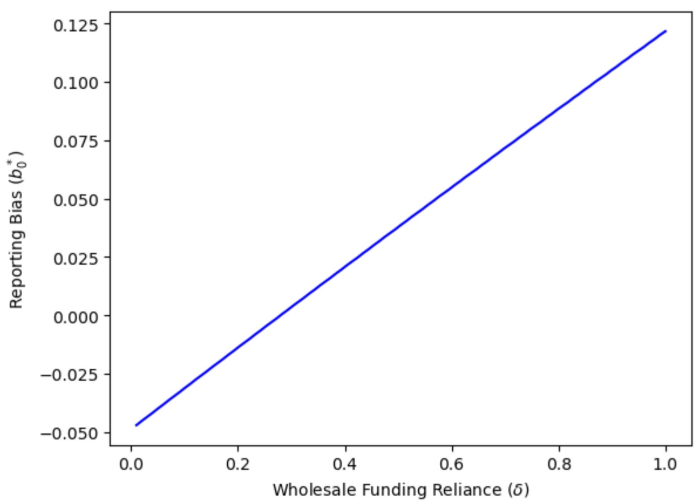
As a result,

$$\max_{\gamma \geq L_0} F(\gamma) = \frac{\lambda\theta\delta L_0 k\sigma_d}{2c\sigma_\varepsilon}$$

If $\lambda\theta\delta k\sigma_d < 2c\sigma_\varepsilon$, then for $\forall\gamma \geq L_0$, $F(\gamma) < L_0 \leq \gamma$. Since γ^* satisfies $\gamma = F(\gamma)$, we know that $\gamma^* < L_0$. Under the condition that $(1-\lambda)\left(r^R - f\right)k > \lambda\left(r^R - \theta d - f\right)\phi$ and the realization of ε is sufficiently small, the optimal bias b_0^* will still be positive. Therefore, *the risk-taking channel* persists when $\sigma_v^2 > 0$.

Since it is difficult to derive $\frac{\partial b_0^*}{\partial \delta}$ analytically, I rely on numerical simulations to analyze the effect of wholesale funding reliance on reporting bias. To do so, I calibrate the model parameters and plot the reporting bias b_0^* with different values of wholesale funding reliance δ. The result in figure 4 shows that the reporting bias shifts from negative to positive as reliance on wholesale funding increases, aligning with Prediction 1. Moreover, it can be demonstrated that if $\frac{\phi}{k+\phi} \geq \frac{\sigma_v^2}{\sigma_d^2+\sigma_v^2}$, the reporting bias will strictly increase with the loan loss rate (i.e., $\frac{\partial b_0^*}{\partial d} > 0$), as indicated by Prediction 2.

Figure 4: Equilibrium Reporting Bias



Note: This figure shows the optimal reporting bias for different levels of wholesale funding reliance. Model parameters as calibrated as follows: $c = 5,\ \lambda = 0.1,\ \theta = 2,\ L_0 = 10,\ D = 2,\ k = 10,\ \phi = 5,\ \sigma_d^2 = 0.02,\ \sigma_\varepsilon^2 = 0.05,\ \sigma_v^2 = 0.01,\ r = 0.1,\ f = 0.01,\ d = 0.02,\ \varepsilon = 0.04.$

Model Extensions

I have deliberately kept the model stylized and simple. First, I have assumed that bank core deposits are fixed and only wholesale debt is adjustable. In a more general model, the supply of core deposits would depend on the bank's deposit franchise value and be upward-sloping (i.e., higher rates for more core deposits). However, as long as core deposits are scarcer and less elastic than wholesale debt, my key results on the risk-taking channel still obtain: banks manage earnings upward to attract wholesale funding to finance their growth in good times.

Second, the model assumes that the loan loss rate is not indicative of future economic uncertainty (i.e., d and λ are independent). This assumption is starker than it needs to be. The model can be extended to allow the bank to estimate the probability of a bad state from its loan performance. The main insights of the model persist, although the results are attenuated because the bank's foresight of the future economic state reduces its ex ante incentives to take risks.

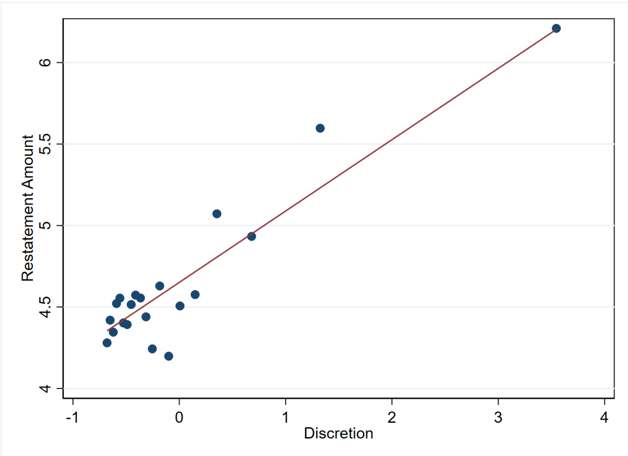
Finally, I have also assumed that the bank holds loans as a single asset, which serves as collateral for its wholesale debt. One might extend the model with two types of assets that cost the same to produce but have different risk-return profiles. Specifically, a bank can hold safe assets (e.g., Treasury securities) and risky assets (e.g., commercial loans). Safe assets are not information sensitive with stable returns over time. In contrast, risky assets are information sensitive with higher returns in booms but lower returns in busts. With the heterogeneous assets, the model can speak to both bank earnings management and capital allocation decisions, as well as the interaction between them.

Appendix C: Additional Tables and Figures

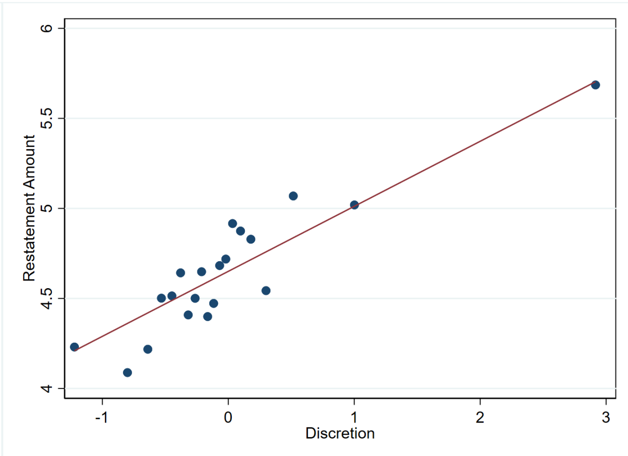
Figure 5: Validity Check: Restatements

This figure displays the association between a bank's accounting discretion and its restatements. Accounting discretion is measured by the residuals in equation (1). Following Costello et al. (2019), I use the data item "RIADB507" in the Call Reports to identify bank restatements. The figure is constructed in two steps. The first is to group banks into 20 bins by their absolute values of accounting discretion. The second step is to plot the conditional mean of restatements over the next four quarters within each bin. Panels (a) and (b) show the results for the total absolute amount of restatements (i.e., quantity) without and with bank and quarter fixed effects, respectively. Panels (c) and (d) show the results for restatement dummies (i.e., likelihood) without and with bank and quarter fixed effects, respectively. The discretion variable is standardized with a mean of zero and a standard deviation of one. All variables are winsorized at the 1% level. Each panel also includes the line of best fit from an OLS regression. The sample period is from 1990 to 2019.

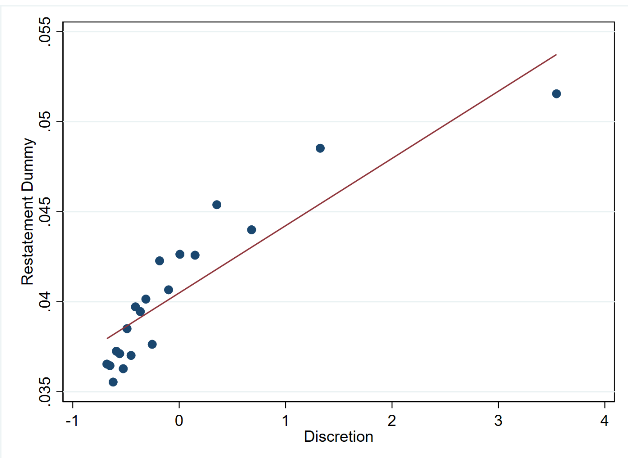
(a) Quantity (no FEs)



(b) Quantity (with FEs)



(c) Likelihood (no FEs)



(d) Likelihood (with FEs)

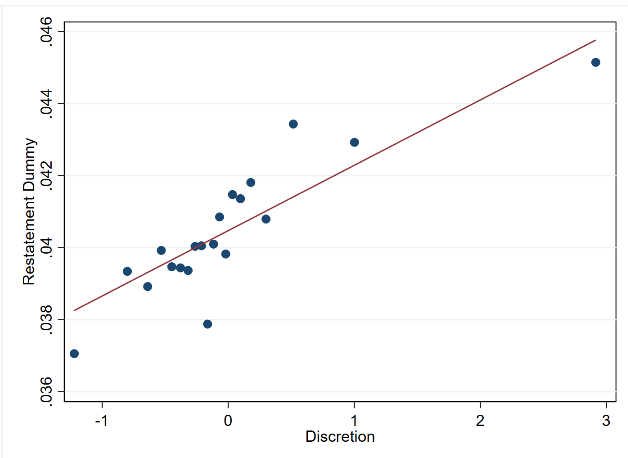


Figure 6: Validity Check: Residual Properties

This figure documents the properties of the residuals in equation (1) used for measuring bank accounting discretion. Panel (a) plots squared residuals against the future changes in nonperforming loans. Panel (b) plots the kernel density of AR(1) coefficient for each bank's residuals. The vertical dashed red lines indicate the mean of estimated coefficients.

(a) Heteroskedasticity **(b)** Autocorrelation

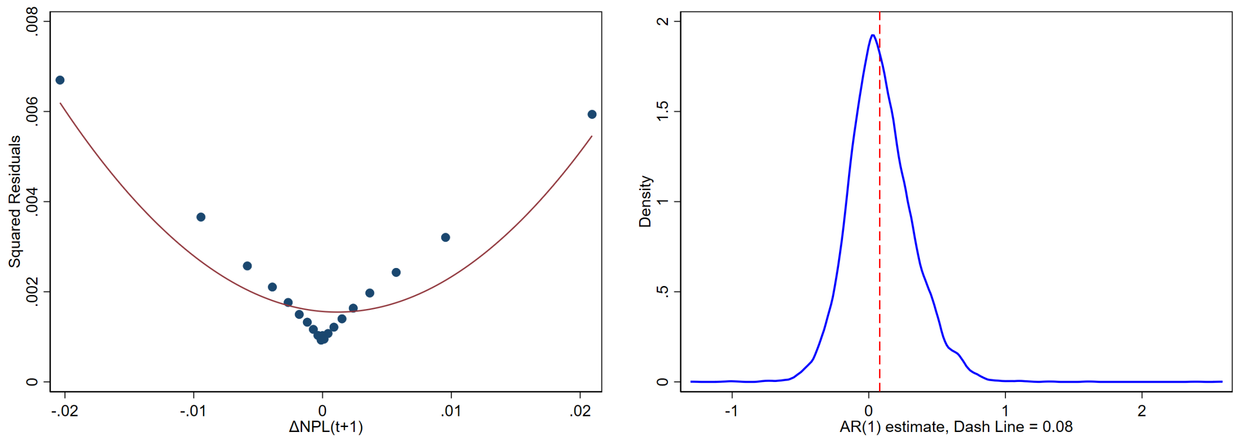
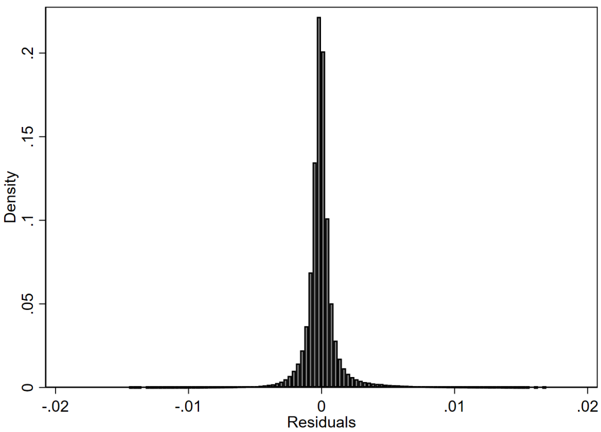


Figure 7: Distribution of Residuals

Panels (a) and (b) show the distributions of residuals and standardized residuals from the estimation of equation (1), respectively. A standardized residual is a residual scaled by the standard deviation of each bank's residuals.

(a) Residuals



(b) Standardized Residuals

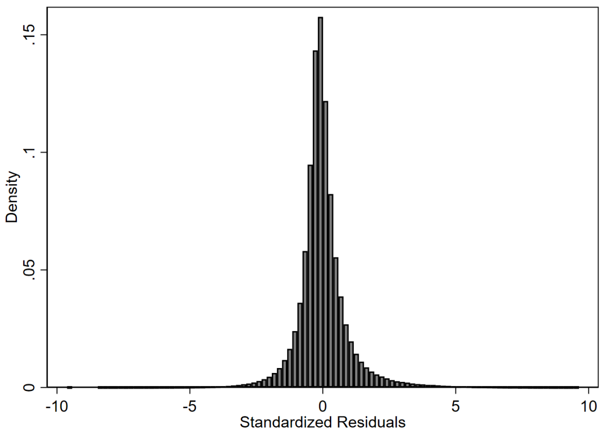
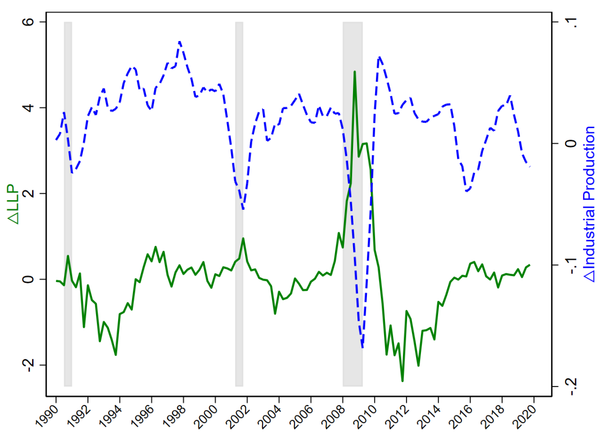


Figure 8: Loan Loss Provisions and Business Cycles

This figure plots year-over-year changes in log industrial production (blue dashed line) against year-over-year changes in the average bank loan loss provisions (green solid line in Panel (a); red solid line in Panel (b)). Loan loss provisions are averaged cross-sectionally for banks with above-median and below-median core deposit percentages relative to total liabilities in Panels (a) and (b), respectively. The average provision is normalized with a mean of 0 and a standard deviation of 1. The data are from the Federal Reserve Economic Data (FRED) and the U.S. bank regulatory Call Reports. The sample is from January 1990 to December 2019. The gray bars indicate the NBER-defined recession periods.

(a) Banks with Above-Median Core Deposits (%)



(b) Banks with Below-Median Core Deposits (%)

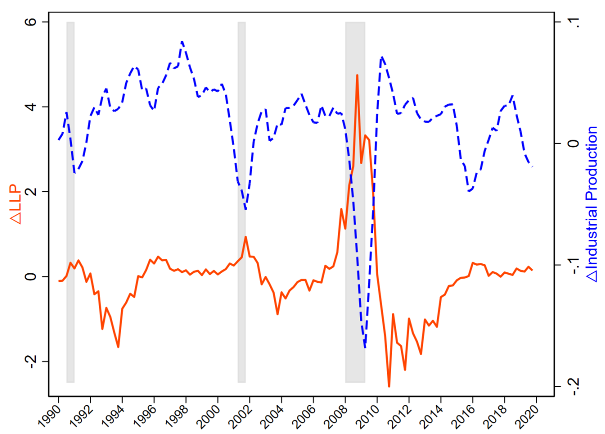


Table 9: Characteristics of Banks with Different Wholesale Funding Reliance

This table displays characteristics of banks with different wholesale funding reliance (WFR), defined as the ratio of noncore liabilities to total liabilities. Banks are classified into high and low WFR groups based on the sample median in each quarter. The left panel presents means, and the right panel shows medians, with variables winsorized at the 1st and 99th percentiles for each group. The characteristics include the following bank properties: *Public Banks (%)*, the percentage of banks that are publicly traded; *Assets*, measured as bank total assets (in millions); *Capital Ratio*, measured as the Tier 1 leverage ratio; *ROE*, measured as annualized net income divided by total equity, expressed as a percentage; *Profitability (per loan)*, measured as annualized net income divided by total loans, expressed as a percentage; *#Branch*, measured as the number of bank deposit branches; *Real Estate Loans*, measured as the fraction of real estate loans in total loans; *C&I Loan*s, measured as the fraction of commercial and industrial loans in total loans; *Consumer Loans*, measured as the fraction of consumer loans in total loans.

	Mean		**Median**	
VARIABLES	**Low WFR**	**High WFR**	**Low WFR**	**High WFR**
Public Banks (%)	5.513	12.72	3.995	12.82
Assets	144.5	506.0	70.74	121.1
Capital Ratio	10.58	9.850	9.860	9.290
ROE	9.938	10.09	10.22	11.10
Profitability (per loan)	1.966	1.774	1.896	1.755
#Branch	3.825	7.629	2	3
Real Estate Loans	0.609	0.618	0.633	0.640
C&I Loans	0.138	0.158	0.121	0.138
Consumer Loans	0.122	0.114	0.095	0.084

Table 10: List of Banks with Different Wholesale Funding Reliance

This table provides examples of banks with wholesale funding reliance below 5% (Panel A) and above 50% (Panel B), calculated as the average ratio of noncore liabilities to total liabilities in the sample. The table includes each bank's RSSD ID and full legal name.

Panel A: Banks with Wholesale Funding Reliance Below 5%

RSSD ID	Bank Name
388557	The Bank of Talmage
461946	The Delta State Bank
960560	The Oakwood State Bank
450669	The First National Bank of Ely
182652	The First National Bank of Fairland
354	Bison State Bank
409957	Farmers State Bank
583745	Sumner National Bank of Sheldon
377207	Suburban National Bank of Arlington
207957	Citizens State Bank of Tyler
3448425	Community Bank of Pleasant Hill
260149	Odebolt State Bank
636324	The Bank of McMechen
1014255	State Bank of Jeffers
1005440	The First National Bank of Odon
3635551	Guadalupe National Bank
581237	First Navy Bank
617538	Glasford State Bank
852973	Pioneer Trust Bank, National Association
835444	The Bank of Herrin

Panel B: Banks with Wholesale Funding Reliance Above 50%

RSSD ID	Bank Name
558172	Franklin Bank, National Association
35301	State Street Bank and Trust Company:
476810	Citibank, N.A.
210434	The Northern Trust Company
2594240	The Capital Bank
541101	The Bank of New York
1450620	Washington First International Bank
529958	Texas Independent Bank
455534	LaSalle National Bank
666031	The International Bank of Miami, National Association
140513	LBS Bank - New York
320119	Israel Discount Bank of New York
214807	Bankers Trust Company
800750	The Laredo National Bank
2721103	The Bank of Holland
161415	Morgan Guaranty Trust Company of New York
536219	Citibank (New York State)
852218	Chemical Bank
1225761	Wells Fargo Financial National Bank
651448	JPMorgan Chase Bank, Dearborn

Table 11: The Role of Wholesale Funding Reliance (Exclude Recessions)

This table shows the estimation results of equation (3) between 1990 and 2019, excluding NBER-defined recessions. The dependent variable in columns 1 and 2, $\triangle$*Discretion,* is the change in a bank's abnormal loan loss provisions. The dependent variable in columns 3 and 4, $\triangle$*Discretion (standardized),* is the change in a bank's abnormal loan loss provisions standardized by its own standard deviation. The main independent variable $\triangle IP$ is the change in the natural logarithm of industrial production. This table reports results on the heterogeneity across the quartiles of banks' wholesale funding reliance (*WFR*). *WFR* is defined as the ratio of noncore liabilities to total liabilities. $\triangle IP$ is interacted with dummy variables based on bank *WFR* quartiles. Additional bank controls include *size*, *capital ratio*, *ROE*, *loan composition, audit quality,* and *diversification*. Refer to Appendix A for detailed variable definitions. Standard errors are clustered by bank, and t-statistics are reported in parentheses below each estimate. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	△Discretion		**△Discretion (standardized)**	
	(1)	**(2)**	**(3)**	**(4)**
△IP × Q2 WFR	0.0993	−0.0513	−0.0834	−0.1786
	(0.39)	(−0.20)	(−0.43)	(−0.92)
△IP × Q3 WFR	−0.3261	−0.4013	−0.2559	−0.3122
	(−1.20)	(−1.50)	(−1.26)	(−1.55)
△IP × Q4 WFR	−0.8699***	−1.0941***	−0.7987***	−0.9464***
	(−3.02)	(−3.83)	(−3.88)	(−4.62)
Controls	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	555,078	555,078	555,078	555,078
Adjusted $\mathbf{R^2}$	0.017	0.084	0.014	0.058

Table 12: The Role of Wholesale Funding Reliance (Additional Controls)

This table shows the estimation results of equation (3) between 1990 and 2019 with additional control variables. The dependent variable in columns 1 and 2, $\triangle$*Discretion,* is the change in a bank's abnormal loan loss provisions. The dependent variable in columns 3 and 4, $\triangle$*Discretion (standardized),* is the change in a bank's abnormal loan loss provisions standardized by its own standard deviation. The main independent variable $\triangle IP$ is the change in the natural logarithm of industrial production. This table reports results on the heterogeneity across the quartiles of banks' wholesale funding reliance (*WFR*). *WFR* is defined as the ratio of noncore liabilities to total liabilities. $\triangle IP$ is interacted with dummy variables based on bank *WFR* quartiles. The "$\triangle IP \times$ Loan Composition" means that interaction terms between $\triangle IP$ and bank loan composition are included in the regression. The "$\triangle IP \times$ All Controls" means that interaction terms between $\triangle IP$ and all bank controls are included in the regression. Controls include *size*, *capital ratio*, *ROE*, *loan composition, audit quality,* and *diversification.* Refer to Appendix A for detailed variable definitions. Standard errors are clustered by bank, and t-statistics are reported in parentheses below each estimate. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	△Discretion		△Discretion (standardized)	
	(1)	(2)	(3)	(4)
△IP × Q2 WFR	−0.1762	−0.1493	−0.2222	−0.1784
	(−0.95)	(−0.82)	(−1.58)	(−1.28)
△IP × Q3 WFR	−0.6400***	−0.4430**	−0.4993***	−0.3408**
	(−3.36)	(−2.29)	(−3.44)	(−2.32)
△IP × Q4 WFR	−0.9682***	−0.7752***	−0.9574***	−0.7739***
	(−4.72)	(−3.61)	(−6.39)	(−4.96)
△IP × Loan Composition	Yes	No	Yes	No
△IP × All Controls	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	604,769	604,769	604,769	604,769
Adjusted R^2	0.015	0.081	0.013	0.056

Table 13: The Role of Wholesale Funding Reliance (Within-Group Discretion)

This table shows the estimation results of equation (3) between 1990 and 2019 by using within-group accounting discretion, which is measured as the residuals (i.e., abnormal loan loss provisions) from the estimation of equation (1) within different groups of banks based on their dominant loan types. The dependent variable in columns 1 to 3, $\triangle$*Discretion,* is the change in a bank's abnormal loan loss provisions. The dependent variable in columns 4 to 6, $\triangle$*Discretion (standardized),* is the change in a bank's abnormal loan loss provisions standardized by its own standard deviation. The main independent variable $\triangle IP$ is the change in the natural logarithm of industrial production. This table reports results on the heterogeneity across the quartiles of banks' wholesale funding reliance (*WFR*). *WFR* is defined as the ratio of noncore liabilities to total liabilities. $\triangle IP$ is interacted with dummy variables based on bank *WFR* quartiles. Additional bank controls include *size*, *capital ratio*, *ROE*, *loan composition, audit quality,* and *diversification.* Refer to Appendix A for detailed variable definitions. Standard errors are clustered by bank, and t-statistics are reported in parentheses below each estimate. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	△Discretion			△Discretion (standardized)		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
△IP	0.3370***	0.4778***		0.6750***	0.7681***	
	(2.66)	(3.67)		(6.83)	(7.46)	
△IP × Q2 WFR	−0.3407*	−0.2499	−0.3490*	−0.3214**	−0.2814**	−0.3475**
	(−1.93)	(−1.39)	(−1.94)	(−2.37)	(−2.01)	(−2.48)
△IP × Q3 WFR	−0.7443***	−0.5851***	−0.7354***	−0.5860***	−0.5074***	−0.6070***
	(−4.14)	(−3.15)	(−3.96)	(−4.25)	(−3.52)	(−4.21)
△IP × Q4 WFR	−1.3196***	−0.9958***	−1.2434***	−1.1690***	−1.0047***	−1.1660***
	(−6.92)	(−4.98)	(−6.20)	(−8.33)	(−6.76)	(−7.83)
Bank FE	No	Yes	Yes	No	Yes	Yes
Quarter FE	No	No	Yes	No	No	Yes
Observations	604,079	604,079	604,079	604,079	604,079	604,079
Adjusted R^2	0.044	0.072	0.078	0.029	0.049	0.054

Table 14: The Role of Wholesale Funding Reliance (Private Banks)

This table shows the estimation results of equation (3) for private commercial banks between 1990 and 2019. The dependent variable in columns 1 to 3, $\triangle$*Discretion,* is the change in a bank's abnormal loan loss provisions. The dependent variable in columns 4 to 6, $\triangle$*Discretion (standardized),* is the change in a bank's abnormal loan loss provisions standardized by its own standard deviation. The main independent variable $\triangle IP$ is the change in the natural logarithm of industrial production. This table reports results on the heterogeneity across the quartiles of banks' wholesale funding reliance (*WFR*). *WFR* is defined as the ratio of noncore liabilities to total liabilities. $\triangle IP$ is interacted with dummy variables based on bank *WFR* quartiles. Additional bank controls include *size*, *capital ratio*, *ROE*, *loan composition, audit quality,* and *diversification*. Refer to Appendix A for detailed variable definitions. Standard errors are clustered by bank, and t-statistics are reported in parentheses below each estimate. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	△Discretion			**△Discretion (standardized)**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
△IP	0.4347***	0.5643***		0.7330***	0.8180***	
	(3.25)	(4.11)		(7.10)	(7.62)	
△IP × Q2 WFR	−0.3662**	−0.2646	−0.3594*	−0.2860**	−0.2334	−0.2969**
	(−1.98)	(−1.41)	(−1.92)	(−2.04)	(−1.61)	(−2.06)
△IP × Q3 WFR	−0.6951***	−0.5291***	−0.6705***	−0.4893***	−0.3986***	−0.4929***
	(−3.66)	(−2.70)	(−3.43)	(−3.40)	(−2.65)	(−3.28)
△IP × Q4 WFR	−1.0997***	−0.8177***	−1.0519***	−0.9705***	−0.8186***	−0.9723***
	(−5.55)	(−3.95)	(−5.07)	(−6.73)	(−5.37)	(−6.37)
Bank FE	No	Yes	Yes	No	Yes	Yes
Quarter FE	No	No	Yes	No	No	Yes
Observations	545,320	545,320	545,320	545,320	545,320	545,320
Adjusted R^2	0.043	0.070	0.076	0.029	0.048	0.054

Table 15: Adequacy Analysis

This table shows the results on how wholesale funding reliance affects bank adequacy ratio over business cycles. The sample includes observations of commercial banks from 2006 to 2009. The dependent variable $\triangle$*Adequacy* is the change in adequacy ratio, defined as the ratio of loan loss allowance to nonperforming loans. The main independent variable $\triangle IP$ is the change in the natural logarithm of industrial production. This table reports results on the heterogeneity across the quartiles of banks' wholesale funding reliance (*WFR*). *WFR* is defined as the ratio of noncore liabilities to total liabilities. $\triangle IP$ is interacted with dummy variables based on bank *WFR* quartiles. Additional bank controls include *size*, *capital ratio*, *ROE*, *loan composition, audit quality,* and *diversification*. Refer to Appendix A for detailed variable definitions. Columns 1 to 3 exhibit the results for all banks. Columns 4 to 6 show the results for banks that existed throughout the entire sample period. Standard errors are clustered by bank, and t-statistics are reported in parentheses below each estimate. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	△Adequacy			△Adequacy (Fixed Sample)		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
△IP	12.7751***	5.3874		13.3826***	6.2105	
	(4.05)	(1.53)		(3.65)	(1.57)	
△IP × Q2 WFR	−9.0140**	−10.0179**	−9.7209**	−7.7335	−8.6481*	−8.3253
	(−2.21)	(−2.23)	(−2.16)	(−1.60)	(−1.68)	(−1.61)
△IP × Q3 WFR	−9.5287**	−9.8805**	−9.3641**	−10.5498**	−11.4358**	−10.8308**
	(−2.42)	(−2.23)	(−2.12)	(−2.31)	(−2.32)	(−2.20)
△IP × Q4 WFR	−6.3293	−7.8140*	−7.4013*	−8.4664*	−9.6923**	−9.0667*
	(−1.58)	(−1.74)	(−1.65)	(−1.85)	(−2.02)	(−1.89)
Bank FE	No	Yes	Yes	No	Yes	Yes
Quarter FE	No	No	Yes	No	No	Yes
Observations	65,713	65,713	65,713	46,904	46,904	46,904
Adjusted R^2	0.002	0.106	0.107	0.002	0.072	0.073