Banks' Loan Charge-Offs and Macro-Level Risk

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Abstract

Prior studies document that delayed loan loss provisions can worsen financial stability by triggering a capital inadequacy concern. We extend prior literature and investigate how the treatment of loan charge-offs (LCOs) in financial statements is tied to macro-level risk in the U.S. banking industry. We hypothesize and find that nondiscretionary LCOs are positively linked to banks' future systemic risk, whereas discretionary LCOs are negatively correlated with banks' future systemic risk. We further show that these effects are driven by two economic mechanisms: banks' common risk exposure and interconnectedness. This study is the first to document the linkage between banks' discretionary LCOs and macro-level risk in the banking industry.

Keywords: Banks; Financial Statements; Loan Charge-Offs; Systemic Risk; Macroeconomy

JEL Classifications: E32; G; G21; M41.

1. Introduction

This study examines the link between loan charge-offs and macro-level risk in the banking industry. Over the decades, understanding the functioning of the banking industry and its effect on the macroeconomy has attracted vast intellectual effort from academic researchers and financial professionals. Prior research has found strong linkages of financial crises to overall economic activities and sovereign defaults in the economic histories of the U.S. and other countries (e.g., Bernanke 1983; Yellen 2008; Rose and Spiegel 2009a, 2009b; Reinhart and Rogoff 2011). Indeed, macro-level financial risk is the major high-dimensional distinct risk that underpins economic growth (e.g., Joslin et al. 2014). The 2007-2008 U.S. financial crisis, which triggered the Great Recession and struck economies worldwide, demonstrated the central role of the banking industry in the economy and revived the interest of academics, regulators, and the public in systemic risk. Systemic risk involves macro-level risk in the banking industry that features interconnections among institutions through which losses, illiquidity, and crashes can quickly spread. When such propagation occurs, systemic risk often affects the entire macroeconomy.[1]

The effects of financial crises on the economy (e.g., in 1929 and 2008-2009), often stronger than expected, have highlighted the importance of understanding how bank practices, including financial statement practices, relate to systemic risk. Security and banking regulators argue that loan charge-offs (LCOs) precipitated the meltdown of 2008-2009 because the impairment rule excessively postponed loan losses (see, e.g., International Monetary Fund, IMF

[1] Systemic risk is different from systematic risk. Systemic risk is generally used in reference to an event or a variable that can trigger an industry collapse; systematic risk refers to overall market risk. We use the term "systemic risk" almost exclusively throughout the study because of our focus on the banking industry.

2008; Securities and Exchange Commission, SEC 2008; Financial Stability Forum 2009). To date, however, research on LCOs and asset write-downs overwhelmingly focuses either on the micro-level determinants of LCOs and their effect on stock prices, or on the determinants of asset write-down timeliness in financial institutions (e.g., Wahlen 1994; Vyas 2011).

The treatment of net LCOs is a standard financial statement practice for bank loans. The balance of an uncollectable loan is charged off. An allowance for loan losses (LLA) is reduced by the same amount, but earnings are not. LCOs are thus the net amount of loans a bank charges off minus any recoveries of previously charged-off loans. Thus, LCOs are recognized, or realized, loan losses resulting from the application of impairment rules to bank loans, wherein such loan losses represent a bank's realized credit risk. This treatment is essentially different from loan loss provisions (LLPs), which are estimated provisions for loan losses.

In this study, we investigate whether and how LCOs are linked to the macro-level risk of the banking industry. Such an examination can shed new light on the link between LCOs and financial crises, and is relevant to ongoing regulatory reforms over financial statement impairment rules that aim to limit or prevent future financial crises. The research topic is also important for other reasons. LCOs involve discretion in recognizing loan losses, allowing for managerial judgment over the timing and magnitude of writing off or writing down non-performing loans (NPLs) (e.g., Liu and Ryan 2006).[2] LCO discretion is crucial to LCO timeliness and thus financial crisis. In addition, investigating this link informs us of the usefulness of LCOs as a credit risk measure. Like NPLs, LCOs are an important credit risk

[2] Admittedly, some prior studies report that LCOs are not as discretionary as other bank accounts, such as loan loss provisions (Moyer 1990; Wahlen 1994; Collins, Shackelford, and Wahlen 1995; Beaver and Engel 1996), but do not negate discretions over LOCs. More importantly, Liu and Ryan (2006) document that banks do exert discretions over LCOs, such as over business cycles.

metric for evaluating LLA adequacy and loan default risk (e.g., Keeton and Morris 1987). However, unlike NPLs that ignore the protection provided by collateral, LCOs more accurately reflect realized credit risk (e.g., Beaver et al. 1989; Wahlen 1994), but are less timely in reflecting future credit risk, because their recognition takes longer.

Following a common approach used in prior research that separates an account into discretionary and non-discretionary components, we separate discretionary from non-discretionary LCOs. Discretionary LCOs reflect managerial discretion over timeliness in the recognition of loan losses; non-discretionary LCOs correspond to the realization of "probable" and "reasonably estimated" expected loan losses that are normally covered by LLPs. The two LCOs have different associations with buffers (i.e., reserves or cushions) and credit risk, and bank investors and other bank stakeholders can distinguish them and value them differently (e.g., Wahlen 1994; Beaver and Engel 1996). Therefore, we posit that LCOs are tied to future systemic risk in various ways depending on their two parts—discretionary and non-discretionary LCOs.

We hypothesize that the discretionary part of LCOs is linked to lower future systemic risk through the mechanism of common risk exposure, a major source of sector-wide risk (e.g., Adrian and Brunnermeier 2016). This prediction is justified by the following observations. Although most loans are deemed uncollectible only after a certain number of delinquency days, banks have some discretion over LCOs; for instance, in measuring the amount of loan loss or in deciding the amount to be charged off (see Liu and Ryan 2006). We propose that this discretion allows LCOs projected for future periods to be charged off more quickly in the current period, eliminating future credit risk and the need to make provision for these loans in the future.

In addition, profitable banks often herd in adopting policies that increase discretionary

LCOs; banks are generally profitable in good macroeconomic states when asset return volatility and common risk exposure are high (Liu and Ryan 2006). Therefore, a counter-cyclical herding pattern of discretionary LCOs associated with common macroeconomic risk exposure can develop, reducing the accumulation of sector-wide systemic risk over time.[3]

The counter-cyclical herding of high discretionary LCOs mitigates cross-sectional risk contagion. High discretionary LCOs in an at-risk bank signal the availability of sufficient buffers for future losses and suggest that the bank risk is unlikely to spill over to other banks. As a result, investors of other banks are unlikely to simultaneously withdraw their investments from their banks, thus constraining cross-sectional risk spillovers.[4] While this reasoning proposes that LCO discretion favors a negative linkage between discretionary LCOs and future systemic risk, such discretion can generate unexpected credit risk shocks when it conveys management's insider information about increased future credit risk (e.g., Wahlen 1994). If this effect is sector-wide, it will exacerbate risk spillovers and systemic risk (e.g., Kannan and Kohler-Gieb 2009). Our empirical analysis is designed to address this tension.

Our second hypothesis is that non-discretionary LCOs are linked to higher future systemic risk. Non-discretionary LCOs signify a realization of the current credit risk of expected loan losses. In good macroeconomic states with high common risk exposure, loan and loan losses increase, and credit risk is normally high. High non-discretionary LCOs can lead to a cyclical herding pattern which increases the accumulation of sector-wide systemic risk over time. In

[3] Liu and Ryan (2006) report that profitable banks discretionarily accelerated the recognition of LCOs during the 1990s boom, which accumulated buffers for losses in subsequent busts.

[4] Here the underlying assumption is that due to high information asymmetry in the banking industry, investors of other banks need this information from the bank to adjust their beliefs and investments concerning their own invested banks and the banking industry (e.g., Morgan 2002; Allen et al. 2012a).

addition, non-discretionary LCOs can increase risk contagion because prior research suggests that credit risk can facilitate cross-sectional risk contagion (e.g., Allen and Gale 1998, 2004; Caballero and Krishnamurthy 2008; Gertler et al. 2011; Hovakimian et al. 2012).[5] However, non-discretionary LCOs deliver substantially less timely information about banks' credit risk (e.g., Beaver et al. 1989; Wahlen 1994), which can weaken an observable link between non-discretionary LCOs and systemic risk. Our empirical analysis will address these opposing forces.

To test our predictions regarding the links of LCO components with future systemic risk, we use a comprehensive sample of 24,078 bank quarters for 919 U.S. commercial banks. We operationalize systemic risk as a bank's contribution to systemic risk in the stock market, whose systematic component captures sector-wide systemic risk. We gauge a bank's contribution to systemic risk as the impact of the value at risk (VaR) of a bank's stock return on the VaR of the stock return of a portfolio of stocks belonging to the banking industry in a quarter. This measure captures systemic risk buildup during boom periods and facilitates investigation of the mechanisms for systemic risk—bank herding and bank interconnectedness (Adrian and Brunnermeier 2016). This measure focuses on the stock market and has relevance for capital market and banking regulators. For example, the SEC has been undertaking reforms to diminish systemic risk in the stock market, as mandated by the Dodd-Frank Act (e.g., White 2013), and bank capital regulation regarding contingent capital is based on stock valuations. It is also crucial to the decision making of equity investors who are not protected by deposit insurance, and incur heavier losses during a financial crisis, even if the crisis does not originate from the stock market.

[5] A bank's high non-discretionary LCOs can inform investors of other banks' possible high credit risk and low buffers in both their invested banks and other banks, leading investors to withdraw their investments, which increases common systemic risk in the banking industry.

We measure LCO components following prior research (e.g., Wahlen 1994; Nichols et al. 2009) as the percentile-ranked residuals and the raw predicted values from LCO prediction models.

Two key findings emerge from our empirical analysis. The first is that discretionary LCOs are linked to lower subsequent systemic crash risk. This evidence is consistent with the benefits of LCO discretion in creating hidden buffers and forming a counter-cyclical herding pattern outweighing the costs of triggering unexpected credit-risk shocks. The second finding is that non-discretionary LCOs are linked to higher subsequent systemic risk, in line with our prediction and the underlying argument that non-discretionary LCOs reconfirm realized credit risk and form a cyclical herding pattern. Notably, the opposing effects of the two LCO parts highlight the benefit of our decision to examine them separately.

We then explore the mechanism underlying the link between LCO and systemic risk: common risk exposure and/or the bank interconnectedness. First, we find that both LCO components are linked to systemic risk through the common risk exposure mechanism, which is consistent with the arguments underlying our hypotheses. The evidence includes: (a) discretionary (non-discretionary) LCOs are positively (negatively) tied to future capital adequacy and to past GDP growth; (b) the average cross-sectional correlation of each LCO component is relatively high at all times, and increases with GDP growth; and (c) discretionary (non-discretionary) LCOs are negatively (positively) linked to pro-cyclical loan growth operating as increasing future systemic risk. Second, using an indicator for high levels of bank interconnectedness by extending Billio et al. (2012), we find that discretionary LCOs are linked to systemic risk through the bank interconnectedness mechanism and through the common risk exposure mechanism.

This study is the first to posit and document that banks' loan charge-off accounting practices are tied to macro-level risk in the banking industry. Our work makes three contributions to research in finance and accounting. First, by identifying LCOs as a relevant channel for understanding macro-level risk in the banking industry, we contribute to the growing influential line of research that centers on improving the understanding of financial crises (e.g., Iyer and Peydro 2011; Allen et al. 2012a, 2012b; Beltratti and Stulz 2012; Goldstein and Razin 2013; Khandani et al. 2013; Afonso et al. 2014; Bouvard et al. 2015; He and Manela 2016; Levine et al. 2016). Our research also extends a series of studies about discretionary accounting choices that focus on earnings and their relation to financial crisis and systemic risk (e.g., Huizinga and Laeven 2012; Bushman and Williams 2015; Ma and Song 2016; Kim et al. 2016) by exploring the systemic risk implications of LCOs that do not directly manage current earnings but affect future earnings. Our evidence extends research on the systemic risk-enhancing effect of fair value accounting and its feedback by demonstrating the usefulness of LCOs for understanding overall risk in the banking industry.

Second, our evidence that systemic risk is linked to banks' LCO financial statement information sheds new light on the growing body of research that examines the link between financial statement information and the macroeconomy (e.g., Kothari et al. 2006; Shivakumar 2007; Hirshleifer et al. 2009; Cready and Gurun 2010; Konchitchki 2011). This contribution is especially notable given the importance of the banking industry in the economy, as demonstrated by the 2007-2008 U.S. financial crisis. Our study informs research by identifying a new source of macro-level risk that is linked to the treatment of LCOs in the banking industry. Finally, by identifying LCO practices as related to macro-level risk, this study informs regulators on the potential effects of regulatory proposals regarding loan loss impairment rules on financial crises.

The remainder of this study proceeds as follows. Section 2 reviews the prior literature and develops our hypotheses. Section 3 describes our empirical measures, data, sample, and descriptive statistics. Section 4 presents the research design and reports the evidence. Section 5 reports additional analyses. Section 6 concludes.

2. Literature Review and Hypotheses Development

Loan loss accounting also has strong implications for bank capital adequacy (Ng and Roychowdhury, 2014). Regulatory capital, consisting mostly of Tier 1 and Tier 2 capital, serves as a buffer against future expected and unexpected loan losses. Specifically, Tier 1 capital primarily includes shareholders' equity and retained earnings, which can be a buffer against unexpected losses, whereas Tier 2 capital is composed of LLA that functions as a cushion against expected losses. Because of the mechanical negative relationship between LLA and LCO, recognizing LCOs can decrease Tier 2 capital and hence compromise the adequacy of regulatory capital.[6]

Prior research has decomposed LCOs into discretionary and nondiscretionary portions, and suggested that bank investors and other bank stakeholders can distinguish them and value them differently (Wahlen 1994; Beaver and Engel 1996). Even though some prior studies report that LCOs are not as discretionary as other bank accounts, such as loan loss provisions (Moyer 1990; Wahlen 1994; Collins, Shackelford, and Wahlen 1995; Beaver and Engel 1996), evidence suggests that banks do exert discretion over LCOs, such as over business cycles. For instance,

[6] The LLA balance increases with LLP recognition and decreases with LCO recognition. This relation is represented by the formula $LLA_t = LLA_{t-1} + LLP_t - LCO_t$.

Liu and Ryan (2006) document that profitable banks manipulate earnings downward during booms by overestimating the amount of LLPs to smooth earnings, causing LLA to be volatile. To smooth the fluctuation of LLA, banks accelerate LCOs during boom periods as a way of obscuring their income smoothing and to avoid regulatory scrutiny.

Prior literature has examined how a bank's financial statement could potentially alleviate or exacerbate its risk of a stock crash and risk spillover. Specifically, researchers focus on the equity-based measures of banks' risk spillovers because these measures reflect the risk perception of equity investors, which is derived from a wide range of underlying sources, including risk spillover. Acharya et al. (2017) show the validity of this equity-based construct by providing evidence that the codependence of downside risk (i.e., a bank's contribution to future systemic risk) possessed substantial power for predicting emerging risks during the financial crisis of 2007–2009. Following this literature, Bushman and Williams (2015) use equity-based measures to estimate a financial institution's contribution to future systemic risk and examine how accounting discretion regarding LLP is linked to an individual bank's contribution to future systemic risk. However, managers have differential incentives in terms of manipulating LLP and LCO. It is unclear whether accounting discretion regarding LCOs influences a bank's contribution to systemic risk.

To bridge this gap, we explore the extent to which the accounting treatment of LCOs influences a bank's contribution to systemic risk. While prior studies explore the role of LLPs in relation to financial stability, our focus on LCOs is motivated by the following facts. First, while LLPs are forward-looking information regarding future credit loss, LCOs provide a more reliable source of information to equity investors regarding the realized credit risk. LCOs, in this sense, effectively update investors' belief about the credit risk of the banking sector since all the banks are interconnected and subject to the same macro-economic fundamentals (e.g., Morgan 2002; Allen et al. 2012). Second, LLPs have offsetting effects on capital adequacy. The timing and magnitude of discretionary LLPs affect financial stability in more complicated ways (Bushman and William 2015). LCOs decrease capital adequacy, and its effect on financial stability is more straightforward. Third, banks do have incentives to accelerate charge-offs during boom periods as a way of obscuring their income smoothing and to avoid regulatory scrutiny (Liu and Ryan, 2006).

2.1. The role of discretionary LCOs

While capital inadequacy concerns, combined with financing frictions, can lead to severe balance sheet contractions (e.g., Bernanke and Lown 1991; Van den Heuvel 2009), we argue that accounting discretions over LCOs can mitigate financial friction by improving transparency and extenuate capital inadequacy concerns by changing the timing of LCOs. We elaborate our arguments as follows.

Reducing financial frictions

In the previously mentioned herding causal chains, deterioration in the quality of loan portfolios and increased loan losses in downturns give rise to the need to build up bank capital as a cushion against future losses (Bernanke and Lown 1991; Van den Heuvel 2009). During an economic downturn, capital becomes more expensive or even unavailable, given external financing frictions; banks may be forced to sell off assets and reduce lending (Kashyap and Stein 1994). Equity financing frictions can be mitigated by upgrading the transparency of bank financial reporting (e.g., Amihud et al. 2006; Brunnermier and Pedersen 2009; Lang and Maffett

2011). Brunnermeier and Pedersen (2009), for instance, find that the illiquidity of firms with more uncertainty about intrinsic value tends to be less predictable, more sensitive to economy-wide shocks, and more vulnerable to shocks to the funding of liquidity providers and co-movement in liquidity across assets.

One way of improving transparency is by providing financial information in a more timely manner. Liu and Ryan (2006) report that during the 1990s boom, profitable banks accelerated the discretionary recognition of LCOs. Such acceleration provides information on realized credit risk in a timely manner. We conjecture that the accounting discretion regarding LCOs that accelerates LCO recognition can improve bank transparency, thereby extenuating a bank's financial frictions during a downturn, and weakening the pro-cyclical effect of nondiscretionary LCOs on risk spillovers.[7]

Mitigating capital inadequacy concern

Prior studies document that profitable banks often exhibit herd behavior by accelerating the recognition of discretionary LCOs during a boom (Liu and Ryan 2006). This herding can reduce risk spillover and serve as a counter-cyclical force by extenuating herding as a response to managers' capital inadequacy concerns during a downturn. By accelerating the recognition of LCOs during a boom, banks recognize less LCOs during an economic downturn than would otherwise be required. Since LCOs are charged against Tier-2 capital, and compromise adequate regulatory capital, this accounting discretion regarding LCOs reduces the amount of regulatory capital required, and hence alleviates capital inadequacy concerns during a downturn.

[7] This argument is also similar to the one made in Bushman and William (2015), who show that LLP recognized in a timely manner can improve bank transparency, thereby mitigating systemic risks.

Consequently, accelerating LCO recognition weakens the highly correlated balance sheet contraction and reduces risk spillover.

Further, extenuating an individual bank's capital inadequacy concerns can compromise its ability to shift its risk of a stock crash to other interconnected banks. As equity investors need bank-specific information to adjust their beliefs about the banking industry (Morgan 2002; Allen et al. 2012), accelerating LCO recognition mitigates bank investors' panic regarding the banking sector during an economic downturn. Thus, we argue that herd acceleration of LCOs for profitable banks' homogeneous loans during booms could be counter-cyclical. We develop our first hypothesis as follows:

Hypothesis 1: Discretionary LCOs are negatively associated with banks' future systemic risk.

2.2. The role of nondiscretionary LCOs

Adrian and Brunnermeier (2016) posit that the contribution of an individual firm to system-wide risk can come in two forms: (1) herd reactions (i.e., positively correlated bank behaviors) to a common factor (e.g., economic shocks), and (2) causal contributions of an individual bank to systemic risk (i.e., a large bank's risk spills over to other interconnected banks). We consider both herd reactions and causal effects as plausible channels for increasing the contribution of individual banks to the risk of a systemic stock crash.

Herd reactions to common shocks

We argue that herd behavior reflected in an individual bank's nondiscretionary LCOs is caused primarily by negative shocks, including monetary policy or recession (e.g., Adrian and Brunnermeier 2016). During an economic downturn, the quality of loan portfolios deteriorates, and the number of nonperforming loans increases. Banks, therefore, tend to accumulate more nondiscretionary LCOs during busts (Berger and Udell 2004). Recognizing a significant amount of LCOs decreases Tier 2 capital, and hence triggers banks' capital inadequacy concerns. In response, banks are forced to sell off assets and reduce lending. These actions give rise to severe balance sheet contractions. A bank's probability of survival is lowered when the fire sale of bank assets is combined with severe financial frictions (e.g., Bernanke and Lown 1991; Kashyap and Stein 1994; Van den Heuvel 2009; Bushman and William 2015). Therefore, we conjecture that when a group of banks recognizes more LCOs in response to common risk exposure to economic shocks, these highly correlated balance sheet contraction decisions among banks could give rise to systemic effects (i.e., herd reactions to the common factor).

Causal contributions via bank interconnectedness

Banks can be connected through interbank loans, stock returns, stock ownership, and counterparties in derivative transactions. We posit that distress at large interconnected banks directly causes negative spillover effects on others, thus contributing to the risk of a systemic stock crash. Prior research argues that credit risk can cause cross-sectional risk contagion (e.g., Allen and Gale 1998, 2004; Caballero and Krishnamurthy 2008; Hovakimian et al. 2012). In essence, due to high information asymmetry in the banking industry during an economic downturn, small bank investors need financial information from large interconnected banks to adjust their investments in the banking industry (e.g., Morgan 2002; Allen et al. 2012). The nondiscretionary LCOs inform and confirm investors' beliefs regarding the realization of a specific bank's credit risk because banks are interconnected through interbank loans, stock returns, stock ownership, and counterparties in derivative transactions. A bank's high nondiscretionary LCOs can inform other banks about possible high credit risk and low buffers, leading investors to withdraw their investments, which magnifies common systemic risk in the banking industry.

To summarize, when several banks are exposed to common economic shocks, they will recognize significantly more LCOs and simultaneously face the consequences of balance sheet contraction (i.e., herd reactions to common shocks). Meanwhile, a bank's high nondiscretionary LCOs also inform about possible high credit risk and low buffers in other interconnected banks (i.e., causal contributions via bank interconnectedness). The consequence of both channels will be realized in the reduced market assessments of the banking sector's asset values. Since nondiscretionary LCOs serve as an important mediator in the causal chain between an economic shock and the banking sectors' systemic risks, we develop our second hypothesis as follows:

Hypothesis 2: Nondiscretionary LCOs are positively associated with banks' future systemic risk.

3. Empirical measures, data, sample, and descriptive statistics

3.1. Measures for discretionary and non-discretionary LCOs

We use LCO prediction models to estimate the LCO components.[8] Drawing upon Wahlen (1994) and Nichols et al. (2009), we measure non-discretionary LCOs by the predicted LCOs

[8] To precisely define these models, we begin by articulating the definitions, features, and relations of the major variables that are closely relevant to the models, as follows: (1). Non-performing loan (NPL). A bank loan is non-performing when the payment of its interest and principal are past due, or when other evidence indicates that the loan is in default. (2). Net loan charge-off (LCO) is the value of NPLs that are uncollectible, written off and charged against the loan loss allowance (LLA), minus recoveries of previously charged-off loans. It represents net loan losses and realized credit risk in the current period. (3). Loan loss provision (LLP) is the expense that charges against current earnings and increases LLA in the current period. It represents provisions for the potential loss and credit risk of NPLs that are not yet charged off. The value of LLP net of LCO is equal to the change of LLA in the current period. (4). Allowance for loan loss (LLA) is a balance sheet account that reduces the gross loan to arrive at the net carrying value of the loan portfolio. It represents the part of earnings reserved to cover credit losses from NPLs that will be charged off. The relation among LLA, LLP, and LCO is expressed by the formula $LLA_t = LLA_{t-1} + LLP_t - LCO_t$, wherein t indicates the current period. (5). Bank capital (CAP). The shareholders' equity of a bank buffers the bank against unexpected future losses. Bank capital has several tiers, and Tier-one capital includes total shareholders' equity, qualifying hybrid securities, and non-controlling interest, excluding some intangibles.

from the LCO expectation model in Equation (1) and denote it as *LCON*.[9] We use percentile ranking rather than the raw value of the residuals estimated from Equation (1) to measure discretionary LCOs and denote them as *LCOD*. The rationale is that the original values of the residuals can be noisy, whereas using rankings reduces possible outlier-driven bias in the estimated coefficients and improves test power.

$$LCO_{it} = \alpha_0 + \alpha_1\Delta NPL_{it} + \alpha_2\Delta NPL_{it\text{-}1} + \alpha_3 LLP_{it} + \alpha_4 CAP_{it} + \alpha_5 Size_{it} + \alpha_6\Delta LOAN_{it} + \alpha_7 Q4_t + v_{it} \quad (1)$$

where LCO_{it} is the ratio of net loan charge-offs to the market value of equity for bank i at the beginning of the fiscal quarter t. The independent variables include the following determinants of LCOs: NPL growth for bank i at the current quarter t, ΔNPL_{it}, measured as the ratio of the change in NPLs of bank i to the market value of equity at the beginning of the fiscal quarter t; NPL growth at the prior quarter, $\Delta NPL_{it\text{-}1}$; ratio of LLPs to the market value of equity LLP at the beginning of fiscal quarter t; Tier-one capital ratio for bank i at the end of the fiscal quarter t, CAP_{it}; loan growth for bank i at the current quarter t, $\Delta LOAN_{it}$, measured as the ratio of the changes of total loans for bank i in the current quarter t to total loans at the end of the prior fiscal quarter t-1; bank size, $Size_{it}$, measured as the natural logarithm of the market value of equity for bank i at the beginning of fiscal quarter t; and a fourth-quarter indicator that captures the incentives for discretionary LCOs at the end of the fiscal year, $Q4_t$. We predict LCO_{it} to be positively associated with LLP_{it} and lagged $\Delta NPL_{it\text{-}1}$, but negatively related with $Size_{it}$ (e.g., Wahlen, 1994; Nichols et al., 2009). We use pooled ordinary least squares (OLS) regressions

[9] Jackson (2018) discusses some limitations of discretionary accruals measures. Benson, Faff, and Smith (2014) and Benson, Clarkson, Smith, and Tutticci (2015) have a comprehensive review of accounting and finance research on earnings management.

with fixed time effects to estimate Equation (1).[10] Appendix C provides statistics and estimation results for Equation (1).

We strive to provide an accurate estimate of the determinants of loan charge-offs by including a comprehensive set of determinants of loan charge-offs mentioned in prior studies (Wahlen 1994; Liu and Ryan 2006; Nichols et al. 2009). We nevertheless note that this estimate we adopted from the accounting literature may be sensitive to the determinants used in Equation (1). Omitted variables in the regression, if there are any, can substantially affect the estimate of residual terms, which is our measure of the discretionary loan charge-offs. To control for the omitted variables, we implement different functional specifications, including (1) pooled ordinary least squares (OLS) regressions with fixed time effects and (2) bank-specific OLS regressions to estimate Equation (1), and we report that the results are qualitatively unchanged.

In additional analyses, we use asset-based LCO component measures, *LCODT* and *LCONT*, which are the percentile-ranked residuals and original values of predicted LCOs, respectively, estimated from the LCO prediction model in Equation (1), with LCO_{it}, ΔNPL_{it}, $\Delta NPL_{it\text{-}1}$, and LLP_{it} using total assets as a denominator, and the other variable definitions remaining unchanged. We also adopt loan-based LCO component measures, *LCODL* and *LCONL*. We estimate both from the LCO prediction model in Equation (1), with LCO_{it}, ΔNPL_{it}, $\Delta NPL_{it\text{-}1}$, and LLP_{it} using total loans as a denominator and other variables remaining unchanged.

3.2. Systemic risk measures

We focus on a bank's contribution to systemic risk in the stock market, that is, systemic stock price crash risk, which we denote as $\Delta CoVaR\_stk$ and gauge by a bank's contribution to the

[10] We follow Wahlen (1994) and Nichols et al. (2009). We also use bank-specific OLS regressions to estimate Equation (5), with results qualitatively unchanged.

sector-wide risk of a systemic stock crash. This measure captures how an individual bank's stock price crash risk affects that of the banking industry. We calculate *ΔCoVaR_stk* as the percentile ranking of minus one multiplied by the difference between the 1% VaR of the stock return in the banking industry conditional on a bank's stock return at its 1% VaR and in its median state in a quarter.[11] This measure draws on the systemic risk measure in Adrian and Brunnermeier (2016) that is based on the growth of market equity, but makes three extensions: (a) replacing growth of market equity by stock return; (b) multiplying the original value by minus one such that a higher value indicates a higher contribution to systemic risk; and (c) using the percentile ranking because the measure is left-skewed and noisy.[12] Therefore, our systemic crash risk measure better captures how a bank's stock price crash risk affects that of the banking sector, and it is more relevant to the interests of investors and regulators in the equity market.

The estimation procedures for *ΔCoVaR_stk* are as follows. We first designate $VaR^{i}_{1\%}$ as the weekly stock return bank *i* may experience with a 1% probability over a pre-set horizon of 100 weeks, as shown in Equation (2):

$$Prob\ (R^{i} \leq VaR^{i}_{1\%}) = 1\%\ . \tag{2}$$

We then estimate $VaR^{i}_{1\%}$ of bank *i* using the quantile regression approach (e.g., Adrian and Brunnermeier 2016). Using the same method, we estimate $CoVaR^{system|i}_{1\%}$, the 1% VaR of the weekly stock return in the banking industry conditional upon the $VaR^{i}_{1\%}$ of the weekly stock return of bank *i*, which is expressed as follows:

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11 The 1% VaR refers to the threshold value at which the realization of a variable is equal to, or lower than, that value, with a given probability of 1% and a time horizon of 100 weeks, following Adrian and Brunnermeier (2016).
12 Adrian and Brunnermeier (2016) gauge a bank's contribution to systemic risk as the difference in the 1% *VaR* of the balance-sheet asset growth in the banking industry when the asset growth in a bank is at its 1% *VaR* and in its median state.

$$Prob\ (R^{system} \leq CoVaR^{system|i}{}_{1\%}|R^i = VaR^i{}_{1\%}) = 1\%\ . \tag{3}$$

We also estimate $CoVaR^{system|i,medain}{}_{1\%}$, the 1% VaR of the weekly stock return in the banking industry conditional upon the weekly stock return of bank *i* at its median state, by quantile regression:

$$Prob\ (R^{system} \leq CoVaR^{system|i,median}{}_{1\%}|R^i = median^i) = 1\%\ . \tag{4}$$

Then, we compute $\Delta CoVaR\_stk_w{}^i$ as the difference between the 1% VaR of the weekly stock return in the banking industry when bank *i*'s weekly stock return is at its 1% VaR ($CoVaR^{system|i}{}_{1\%}$), and when bank *i*'s weekly stock return functions in its median state ($CoVaR^{system|i,median}{}_{1\%}$):

$$\Delta CoVaR\_stk_w{}^i = CoVaR^{system|i,}{}_{1\%} - CoVaR^{system|i,median}{}_{1\%}\ . \tag{5}$$

Next, we gauge a bank's contribution to systemic crash risk in a quarter, $\Delta CoVaR\_stk_{it}$, by taking the sum of $\Delta CoVaR\_stk_w{}^i$ across all weeks within the quarter, extending Adrian and Brunnermeier (2016). We then multiply it by minus one and take the percentile ranking, such that a higher value indicates higher systemic risk, and outliers or non-linearity will not affect our estimation. This ranking measure is also consistent with the intuition of available systemic risk-ranking measures (Benoit et al. 2013; Van de Leur, Lucas, and Seeger 2017). We use systemic risk estimated by the quantile approach, *ΔCoVaR_stk*, in the main tests, and systemic risk estimated by the GARCH approach, *GARCH ΔCoVaR_stk*, in additional analyses. In contrast to bivariate GARCH estimation models that require strong distributional assumptions and complex optimizations—which increases estimation difficulties and substantially reduces our sample size due to the non-convergence estimation—quantile regressions can generate similar estimation results (e.g., Adrian and Brunnermeier 2016) but are more parsimonious and efficient in the estimation and do not lose as many observations. Appendix B provides estimation details for both methods.

Several systemic risk measures in the literature measure systemic risk from different dimensions. We use the *CoVaR*-based systemic crash risk measure for the following reasons. Unlike other systemic risk measures, the *ΔCoVaR* measure could measure systemic risk buildups during boom times when asset price volatility is low (Adrian and Brunnermeier 2016), and the *CoVaR* approach allows us to identify mechanisms for how bank-specific variables such as LCOs link to systemic risk. In addition, by capturing a bank's contribution rather than its exposure to systemic risk, our measure is superior to other systemic risk measures that focus on a bank's risk exposure to the negative externalities of other banks or a crisis. For example, the marginal expected shortfall, *MES*, in Acharya et al. (2012) captures the expected bank loss when the overall market declines substantially, and thus actually reflects a bank's exposure to systemic risk. The *SRISK* and *SRISK%* measures in Acharya et al. (2012) similarly gauge a bank's expected capital undercapitalization in a financial crisis.[13] Our measure also relies on high-frequency bank-specific stock price data and macroeconomic state variables, thus accurately capturing variation in both bank-specific and macroeconomic events, and is appropriate for analyzing the cross-sectional relations between bank-specific LCOs and systemic risk. This is in contrast to the systemic risk measure *CATFIN*, a sector-specific measure that focuses on the predictability of the sector-wide tail risk for future economic downturns (e.g., Allen et al. 2012b).

[13] Acharya et al. (2012) measure *MES* as the average daily marginal expected shortfall for the stock return of a bank in a quarter given that the market return is below its 2%-percentile. Acharya et al. (2012) also introduce the concepts and measures for *SRISK* and *SRISK%*. *SRISK%* gauges the contribution of bank *i*'s average daily expected capital shortfall that the bank needs to cover in a quarter if there is a financial crisis to the aggregate expected capital shortfall in the banking industry. *SRISK* measures bank *i*'s average daily expected capital shortfall that the bank needs to cover in a quarter if there is a financial crisis.

Lastly, *CoVaR*-based systemic risk measures and their extensions are influential and widely used in prior studies (e.g., Bernal et al. 2014; Lopez-Espinosa et al. 2014). Nonetheless, Benoit et al. (2013) criticize *CoVaR* for adding little incremental value over *VaR* in forecasting systemic risk. In response to this concern, we use other types of equity-market-based systemic risk measures in additional analyses, such as *MES*, *CATFIN*, and *SRISK*.

3.3. Data, sample, and summary statistics

We obtain financial and stock data from Wharton Research Data Services (WRDS). We extract financial statement data from the Compustat Bank Fundamentals Quarterly dataset (WRDS: BANK_FUNDQ) and Report of Condition and Income ("Call Reports") from the Bank Regulatory database (WRDS: BANK). We extract monthly raw stock returns (Monthly Stock File; WRDS: MSF) and daily raw stock returns (Daily Stock File; WRDS: DSF) from the Center for Research in Security Prices (CRSP).

Our sample consists of bank quarters for publicly listed commercial banks in the three major U.S. stock exchanges (i.e., the New York Stock Exchange, NYSE; the National Association of Securities Dealers Automated Quotations, NASDAQ; and the American Stock Exchange, AMEX). The sample starts in 1993 because this is the first year of full implementation of risk-based capital and the Federal Deposit Insurance Corporation Improvement Act (FDICIA) enacted in 1991. The sample ends in 2009, the last year of the 2008-2009 financial crisis. We first retrieve 59,245 bank quarters for 1,870 public and private banks from Compustat for the fiscal years 1993-2009, covering almost all banks in the U.S. Excluding private banks, banks listed on over-the-counter (OTC) markets and other non-major stock exchanges, and banks with SIC codes 6311, 6552, and 9995 leaves 46,729 bank quarters for

1,430 publicly listed banks.[14] The estimation of LCO components requires non-missing data for the Tier-one capital ratio and other determinants of the LCO prediction models, and at least 13 bank quarters for a bank. These criteria result in 26,446 bank quarters for 1,196 banks. We then merge them with measures for systemic risk and other control variables and delete observations with missing data.

These sampling procedures yield a final sample consisting of 24,078 bank quarters for 919 listed banks on the NYSE, AMEX, and NASDAQ over our sample period. The final comprises 17,535 observations for 576 commercial banks and 6,543 observations for 343 savings institutions. It covers 40.64% of bank quarters for all listed banks in the U.S. banking industry in the sampling period, indicating that our sample is a good representation of the U.S. banking industry.[15] Data for all variables are winsorized to the 1% and 99% tails of their distributions to eliminate the effects of outliers.

Table 1 reports summary statistics for the variables used in the empirical analyses (in Panel A) and Pearson correlation matrix for the main testing variables (in Panel B). Panel A shows that the mean and median values of a bank's contribution to systemic crash risk, *ΔCoVaR_stk*, are 21.660% and 18.538%, respectively, while those of *CATFIN* are 0.257 and 0.233, respectively. Our statistics for the several systemic measures, including *MES*, *SRISK%*, and *GARCH ΔCoVaR_stk*, are consistent with evidence reported in prior studies. For example,

[14] Private banks and banks listed on non-primary stock markets tend to be small banks that have little influence on systemic risk in the stock market. In addition, it is difficult to calculate systemic risk measures for private banks.

[15] We exclude 20,283 bank quarters for 234 banks because of missing data for LCO components. To address possible selection bias thus caused, we perform two-sample *t*-tests on the difference in the mean of the bank size, MB ratio, return on assets, and earnings volatility for the deleted sample of banks with missing data and for the final sample. The results show no significant difference between the two samples, indicating that a selection bias does not play a role in our setting.

the mean and median values of a bank's contribution to systemic risk measured based on market equity growth, *ΔCoVaR_at*, are 19.161% and 15.947%, respectively, comparable to those in Brunnermeier et al. (2012) and Adrian and Brunnermeier (2016).[16] The mean (median) of the LCO components, *LCOD* and *LCON*, are -0.005 (-0.075) and 0.755 (0.312), respectively.

In Panel B, the Pearson correlations for *ΔCoVaR_stk* with the alternative systemic risk measures, *MES* and *SRISK%*, are significantly positive, with coefficients of 0.828 and 0.337, respectively. *ΔCoVaR_stk* is significantly positively correlated with all other systemic risk measures except for *SRISK*. The LCO measures, *LCOD* and *LCON*, are both significantly positively correlated with *ΔCoVaR_stk*. However, the Pearson correlations only measure partial correlations between two variables, without controlling the effect of other determinants. Therefore, the signs of the correlations between *LCOD*, *LCON,* and *ΔCoVaR_stk* may be spurious and fail to reflect their underlying relations. This consideration also justifies the necessity for multivariate regression analysis.

In addition, the Pearson correlation between *LCOD* and the alternative discretionary LCO measures, *LCODA*, *LCODT*, and *LCODL*, are all positive, with coefficients of 0.932, 0.920, and 0.906, respectively, and all are statistically significant except for *LCODT*. The alternative non-discretionary LCO measures, *LCONA*, *LCONT*, and *LCONL*, are all significantly positively correlated with *LCON*, with coefficients of 0.987, 0.750, and 0.708, respectively. The evidence suggests that *LCOD* and *LCON* have convergent validity for measuring LCO components.

[Insert Table 1 here]

[16] The mean and median values of a bank's contribution to systemic risk based on the weekly growth of market equity in Brunnermeier et al. (2012) and Adrian and Brunnermeier (2016) range from 1.00 to 1.20, corresponding to 14.00% to 19.60% of the same measure calculated on a quarterly basis.

4. Research design and empirical evidence

4.1. The link between LCOs and future systemic risk

We employ the following OLS regression model with fixed time effects to examine the links between LCOs and future systemic risk:

$$\Delta CoVaR_{it} = \varphi_0 + \varphi_1 LCO_{it\text{-}1} + Controls + FixedTimeEffect + \zeta_{it}\ , \tag{6}$$

where $\Delta CoVaR$ refers to a bank's contribution to systemic crash risk $\Delta CoVaR\_stk$; and *LCO* refers to either discretionary LCOs, *LCOD*, or non-discretionary LCOs, *LCON*. Extending Adrian and Brunnermeier (2016), *Controls* includes the following control variables: market-to-book ratio, *MB*; market beta, *Beta*; ratio of short-term debt to total liabilities, *Short-termDebt*; equity return volatility, *Sigma*; natural logarithm of the market value of equity, *Size*; return on assets, *ROA*; maturity mismatch, *Mismatch*; return momentum, *Momentum*; total loans outstanding, *Loan*; ratio of non-interest income to total income, *NonInterestIncome*; and a crisis indicator variable, *Crisis*. We also consider as controls bank interconnectedness, *BankConnectedness*, and the relative stock return kurtosis, *Cokurt*, because *BankConnectedness* affects systemic risk (e.g., Billio et al. 2012), and *Cokurt* affects return downside risk (Ang et al. 2006). *FixedTimeEffect* includes year and quarter dummies. Appendix A provides detailed definitions of all the variables. We expect that $\varphi_1 < 0$ for *LCOD* and $\varphi_1 > 0$ for *LCON*.

In addition, we use the following OLS regression model with fixed time effects to examine how the 2008-2009 financial crisis affects relations between the LCO components and systemic risk:

$$\Delta CoVaR_{it} = \beta_0 + \beta_1 LCO_{it\text{-}1} + \beta_2 Crisis_t{*}LCO_{it\text{-}1} + Controls + FixedTimeEffect + \zeta_{it}\ , \tag{7}$$

where *Crisis* is an indicator of the 2008-2009 crisis covering all quarters in 2008 and the first two quarters in 2009. All other variables are the same as in Equation (6). Following the intuition of Petersen (2009), we estimate both Equations (6) and (7) by adjusting standard errors for bank-specific clusters.

We choose OLS regression models with fixed time effects to estimate Equations (6) and (7) because they are the most appropriate for this study. We use *F*-tests and Hausman tests to compare this fixed effects OLS model with the corresponding pooled OLS regression model without fixed effects, and the corresponding random effects model. As reported at the bottom of Panel A of Table 2, both *F*-test statistics and Chi-square statistics for the Hausman tests are consistently statistically significant with *p*-values being 0.00 in all the tests. Therefore, the *F*-tests and Hausman tests reject the null hypothesis H_0 that we should use a pooled OLS model or random effects model, and justify our fixed effects OLS models. In addition, because our data cover 919 banks, and fixed bank effects significantly inflate the R^2 and lower the power of the *t*-tests of the coefficients, we choose a pooled OLS regression model with fixed time rather than fixed bank effects.

Panel A of Table 2 presents the estimation results for Equations (6) and (7). Models 1 to 3 report the results for the measures of LCO components, *LCOD* and *LCON*, and indicate that *LCOD* is significantly negatively associated with subsequent systemic crash risk *ΔCoVaR_stk*, with a coefficient (*t*-statistic) of -0.028 (-2.71) in Model 1 and -0.028 (-2.75) in Model 3. This means that when a bank's *LCOD* increases by 1%, future *ΔCoVaR_stk* tends to decrease correspondingly by 0.028%; when many banks do so collectively, future systemic risk will reduce remarkably. This evidence suggests that discretionary LCOs mitigate a bank's contribution to systemic crash risk, consistent with our expectation. It also implies that their beneficial function of the timely charging of future loan loss and creating additional buffers dominates their function of conveying unexpected credit risk shocks, leading to a net mitigating effect on systemic crash risk. In addition, the non-discretionary LCO measure *LCON* is significantly positively associated with subsequent *ΔCoVaR_stk*, with a coefficient (*t*-statistic) of 0.004 (3.30) in Model 2, and 0.004 (3.30) in Model 3. These findings support our expectation that non-discretionary LCOs are positively linked to systemic risk by confirming the realization of credit risk, decreasing buffers for future losses, and forming a pro-cyclical herding pattern.

Model 4 in Panel A of Table 2 presents the estimation results for Equation (7) and indicates that the coefficient of the interactions of the indicator for a financial crisis, *Crisis*, with discretionary LCO measure *LCOD* is insignificant, but the coefficient of *LCOD* per se remains significant, suggesting the relation between discretionary LCOs and systemic risk is significantly negative during both crisis and non-crisis periods. A crisis does not qualitatively change their relation. Meanwhile, the coefficient of *LCON* remains significantly positive, and the coefficient of the interactions of *Crisis* with *LCON* is insignificant. The results suggest that the link between non-discretionary LCOs and systemic risk is significantly positive during both crisis and non-crisis periods, and a crisis does not qualitatively change their relation either. Overall, Panel A of Table 2 shows that discretionary (non-discretionary) LCOs are negatively (positively) related with a bank's contribution to systemic risk in general, and that their relations are qualitatively unchanged during crisis and non-crisis periods.

The results for the control variables are consistent with evidence in Brunnermeier et al. (2012), Billio et al. (2012), and Adrian and Brunnermeier (2016). In particular, the estimated coefficient of bank interconnectedness, *BankConnectedness*, is significantly positive, consistent with the conclusion of Billio et al. (2012) and Adrian and Brunnermeier (2016) that more interconnected banks contribute more to systemic risk. The coefficient on bank size, *Size*, is also significantly positive, consistent with the systemic significance of large banks. The coefficients on *NonInterestIncome*, *MB*, *Beta*, *Mismatch*, *Short-termDebt*, *Sigma*, and *Cokurt* are all positive, whereas that on *Momentum* is negative. In the next sections, we conduct a series of analyses to probe the rationale for the link between LCOs and systemic risk.

4.2. Rationales for the link between LCOs and future systemic risk: the role of timely loan loss recognition

We have explained the negative link of discretionary LCOs with future systemic risk by their timely incorporation of future loan loss, and the derived function, such as creating additional cushions. We also explain the positive relation of non-discretionary LCOs with future systemic risk by their function of reflecting realized credit risk. To provide further support for these arguments, we construct "pseudo" non-discretionary LCOs that capture future loan loss in addition to reflecting realized credit risk, and "pseudo" discretionary LCOs that do not capture future loan loss. Therefore, if the timely charging off of future loan loss partially accounts for the link between LCO components and future systemic risk, the negative (positive) relation between "pseudo" discretionary (non-discretionary) LCOs weakens or disappears.

We estimate "pseudo" discretionary and non-discretionary LCOs, *LCODA* and *LCONA*, *using* the LCO expectation model that adds the controls ΔNPL three extra periods ahead, capturing future loan loss and credit risk:

$$LCO_{it} = \alpha_0 + \alpha_1\Delta NPL_{it} + \alpha_2\Delta NPL_{it-1} + \alpha_3\Delta NPL_{it+1} + \alpha_4\Delta NPL_{it+2} + \alpha_5\Delta NPL_{it+3} + \alpha_6 LLP_{it} + \alpha_7 CAP_{it} + \alpha_8 Size_{it} + \alpha_9\Delta LOAN_{it} + \alpha_{10} Q4_t + v_{it}\,, \tag{8}$$

where variable definitions are as in Equation (1). Measures for NPL growth for bank *i* in future quarters *t*+1, *t*+2 and *t*+3, ΔNPL_{it+1} to ΔNPL_{it+3}, help to factor out the effects of timely recognition of future loan loss and credit risk on estimated discretionary LCOs, *LCODA*, and incorporate the effect into estimated non-discretionary LCOs, *LCONA*. We gauge *LCONA* and *LCODA* as the original values of the predicted LCOs and percentile ranking of the estimated residuals from Equation (8).

Using these "pseudo" LCO component measures, *LCODA* and *LCONA*, we re-estimate Equations (6) and (7), and report the results in Panel B of Table 2. Models 1 and 3 indicate that the "pseudo" discretionary LCO measure *LCODA* is insignificantly negatively associated with subsequent systemic risk. Models 1 and 3 show that the "pseudo" non-discretionary LCO measure, *LCON*, is insignificantly positively associated with subsequent *ΔCoVaR_stk*. These findings support our expectation that, by shifting the function of timely charging off future loan loss and credit risk from *LCODA* to *LCONA*, the link between both "pseudo" measures with future systemic risk disappears. Model 4 presents the estimation results for Equation (7) and indicates that the coefficients of *LCODA* and *LCONA* per se remain insignificant, consistent with the results in Models 1 to 3. The coefficient of *Crisis* interacted with *LCODA* is also insignificant, but the coefficient of *Crisis* interacted with *LCONA* is significantly positive, suggesting that recognition of realized and future credit risk brings negative shocks and increases systemic risk during crisis periods. Overall, the findings in Panel B of Table 2 provide further support for the argument that timely (untimely) charging off of future loan loss accounts for the negative (positive) link between discretionary (non-discretionary) LCOs and future systemic risk.

[Insert Table 2 here]

4.3. Rationales for the LCOs and systemic risk link: LCO components and future capital adequacy

We continue to explore rationales for the LCOs and systemic risk link by examining how the two components of LCOs are associated with future capital adequacy, and thus affect systemic risk. Prior research shows that bank capital helps a bank buffer against unexpected future losses (e.g., Laeven and Majnoni 2003) and that bank capital adequacy reduces bank failure, especially during a crisis (e.g., Berger and Bouwman 2013). Therefore, capital adequacy is important in maintaining financial stability and constraining systemic risk, and is the primary focus of banking regulation (e.g., BASEL 2010b; Hart and Zingales 2011). One major argument for our prediction about the LCO-systemic-risk link is that discretion in LCOs helps with the timely elimination of future credit risk and loan losses at present, which reduces expected loss overhangs, increases future bank performance and capital sufficiency, and buffers against future negative shocks. In contrast, non-discretionary LCOs consume reserves and capital to cover realized credit risk, thus reducing capital adequacy for future losses. We use Equation (9) to examine how LCO components relate to future bank capital adequacy, and Equation (10) to check whether a financial crisis affects their relation:

$$\begin{aligned} CAP_{it} = {} & \theta_0 + \theta_1 LCO_{it\text{-}1} + \theta_2 GDP_{it\text{-}1} + \theta_3 Size_{it\text{-}1} + \theta_4 MB_{it\text{-}1} + \theta_5 ROA_{it\text{-}1} + \theta_6 Sigma_{it\text{-}1} \\ & + \theta_7 Mismatch_{it\text{-}1} + \theta_8 Deposits_{it\text{-}1} + \theta_9 NonInterestIncome_{it\text{-}1} + \theta_{10} Crisis \\ & + FixedTimeEffect + \varepsilon_{it}\ , \end{aligned} \tag{9}$$

$$\begin{aligned} CAP_{it} = {} & \theta_0 + \theta_1 LCO_{it\text{-}1} + \theta_2 LCO_{it\text{-}1} {*} Crisis + \theta_3 GDP_{it\text{-}1} + \theta_4 GDP_{it\text{-}1} {*} Crisis + \theta_5 Size_{it\text{-}1} \\ & + \theta_6 MB_{it\text{-}1} + \theta_7 ROA_{it\text{-}1} + \theta_8 Sigma_{it\text{-}1} + \theta_9 Beta_{it\text{-}1} + \theta_{10} Mismatch_{it\text{-}1} + \theta_{11} Deposits_{it\text{-}1} \\ & + \theta_{12} NonInterestIncome_{it\text{-}1} + \theta_{13} Crisis + FixedTimeEffect + \varepsilon_{it}\ , \end{aligned} \tag{10}$$

where *CAP* is the Tier-one capital ratio; *LCO* refers to *LCOD* or *LCON*; and *Crisis* is a dummy variable for the crisis period. In both equations, $\theta_1 > 0$ suggests that discretionary or non-discretionary LCOs are tied to higher future capital sufficiency; in Equation (10), $\theta_2 \neq 0$ indicates that their relation changes during a crisis period. Following prior studies on capital ratio (e.g., Berger et al. 2008), we include the following variables as controls in both equations: bank size, *Size*; market-to-book ratio, *MB*; return on assets, *ROA*; equity return volatility, *Sigma*; maturity mismatch, *Mismatch*; growth in Gross Domestic Product (GDP), *GDP*; and the interaction of *GDP* with the indicator for financial crisis. We also add as control variables: total deposits, *Deposits*, as these increase capital adequacy, and depositors usually prefer banks with high capital adequacy; ratio of non-interest income to total income, *NonInterestIncome*, as managers with strong risk-taking incentives adopt lower capital adequacy; and market beta, *Beta*, which captures investors and capital markets effects. *FixedTimeEffect* includes year and quarter indicator variables.

The first two columns in Table 3 report the estimation results for Equations (9) and (10) for the full sample, and indicate that the discretionary LCO component, *LCOD*, is significantly positively associated with future capital ratio; however, its interaction with crisis indicator *Crisis* is significantly negative, suggesting that their positive relation weakens during crisis periods. The evidence suggests that discretionary LCOs are tied to stronger future capital sufficiency and help buffer against unexpected losses in both crisis and non-crisis times. The capital sufficiency effect of *LCOD* slightly weakens during the crisis period, possibly because worsened performance in busts constrains bank discretion over LCOs. In contrast, non-discretionary LCOs, *LCON*, significantly decrease future capital adequacy; however, their interaction with crisis indicator *Crisis* is significantly positive, implying that this detrimental effect weakens during the crisis period. The evidence suggests that *LCON* is related to lower future capital adequacy, and consumes a larger capital buffer in the non-crisis period. Results for the controls are consistent with the literature and our intuition.[17]

4.4. Explore the rationales for the LCOs–systemic risk link: LCO components and loan growth

Next, we examine how LCO components influence the pro-cyclical lending growth that exacerbates the business cycle and systemic risk (e.g., Berger and Udell 2004). Pro-cyclical loan growth captures the accumulation of common risk exposure; therefore, examining its relation with LCO components provides further insights into the common risk exposure mechanism of LCO-systemic-risk link. Discretionary LCOs can be negatively associated with lending growth through consuming current LLA, which increases future LLPs that charge against earnings and discourages lending growth (e.g., Liu and Ryan 2006; Dugan 2009). High non-discretionary LCOs need high LLA and LLPs to cover, and LLPs directly charge against earnings and discourage lending growth.[18] This study examines their relations using the following OLS regression model with fixed time effects:

$$\begin{aligned} Logdloan_{it+3} = {} & \gamma_0 + \gamma_1 LCO_{it-1} + \gamma_3 Size_{it-1} + \gamma_4 MB_{it-1} + \gamma_5 ROA_{it-1} + \gamma_6 Sigma_{it-1} + \gamma_7 Beta_{it-1} + \\ & + \gamma_8 Mismatch_{it-1} + \gamma_9 Deposits_{it-1} + \gamma_{10} NonInterestIncome_{it-1} + \gamma_{11} CAP_{it-1} \\ & + \gamma_{12} Unrate_{it-1} + {}_{13}Crisis + FixedTimeEffect + \tau_{it}, \end{aligned} \tag{11}$$

$$\begin{aligned} Logdloan_{it+3} = {} & \gamma_0 + \gamma_1 LCO_{it-1} + \gamma_2 LCO_{it-1}{*}Crisis + \gamma_3 Size_{it-1} + \gamma_4 MB_{it-1} + \gamma_5 ROA_{it-1} + \gamma_6 Sigma_{it-1} \\ & + \gamma_7 Beta_{it-1} + \gamma_8 Mismatch_{it-1} + \gamma_9 Deposits_{it-1} + \gamma_{10} NonInterestIncome_{it-1} + \gamma_{11} CAP_{it-1} \\ & + \gamma_{12} Unrate_{it-1} + {}_{13}Crisis + FixedTimeEffect + \tau_{it}, \end{aligned} \tag{12}$$

where $Logdloan_{it+3}$ refers to the natural logarithm of the ratio of total loan changes one year ahead to total loans at the end of the current fiscal quarter, *LCO* refers to *LCOD* or *LCON*, and

[17] For example, the coefficient on *GDP* is positive in the non-crisis period and negative in the crisis period, consistent with counter-cyclical capital buffers. Bank size is negatively associated with the capital ratio, in line with Berger et al. (2008).

[18] However, high discretionary LCOs are better buffers against future loan losses, which encourages lending growth. An active loan policy increases high lending growth and non-discretionary LCOs, inducing a positive relation between them. We expect these effects to be secondary.

Unrate denotes changes in the unemployment rate in a quarter. Other control variables are the same as in Equation (9). We estimate Equation (12) for non-crisis and crisis periods.

The results reported in the last two columns of Table 3 show that discretionary LCOs constrain pro-cyclical lending growth, on average, in both crisis and non-crisis periods. Their relations do not qualitatively change during the crisis period. In contrast, non-discretionary LCOs encourage pro-cyclical lending growth only in the non-crisis period. Untabulated results of regressing systemic crash risk on lending growth indicate that lending growth increases systemic crash risk during the non-crisis period, consistent with its pro-cyclical nature. The findings collectively provide further evidence of, and help explain, the rationale for the link between LCO components and systemic risk.

[Insert Table 3 here]

4.5. Exploring the mechanisms for the LCOs–systemic risk link: common risk exposure

4.5.1. The cyclicality of LCO components as a reaction to common risk exposure

One major argument for the associations between LCO components and systemic risk is their co-movement with the common macroeconomic risk exposures of the banking industry and their counter- or pro-cyclical nature. Specifically, by increasing buffers in profitable banks, especially during economic booms, discretionary LCOs tend to be counter-cyclical; in contrast, non-discretionary LCOs are pro-cyclical by reconfirming realized credit risk and herding in applying the impairment rule under GAAP. Berger and Udell (2004) argue that the values of LCOs (mainly those of non-discretionary LCOs) tend to be low during booms but high during busts. We use the following model to test the cyclicality of LCO components:

$$\begin{aligned} LCO_{it} = {} & \delta_0 + \delta_1 GDP_{it\text{-}1} + \delta_2 Size_{it\text{-}1} + \delta_3 MB_{it\text{-}1} + \delta_4 ROA_{it\text{-}1} + \delta_5 Sigma_{it\text{-}1} + \delta_6 Beta_{it\text{-}1} \\ & + \delta_7 Mismatch_{it\text{-}1} + \delta_8 Deposits_{it\text{-}1} + \delta_9 NonInterestIncome_{it\text{-}1} + \delta_{10} CAP_{it\text{-}1} \end{aligned}$$

$$+ \, FixedTimeEffect + \varepsilon_{it} \, , \qquad (13)$$

where *LCO* refers to either *LCOD* or *LCON*, *GDP* refers to quarterly GDP growth, which represents the common risk exposure of the banking industry, and the other controls are the same as in Equation (6). We follow intuition and prior studies to include the determinants of *LCO* as controls,[19] and use an OLS regression model with fixed time effects to estimate Equation (10) for the full sample. We expect that $\delta_1 > 0$ for *LCOD* and $\delta_1 < 0$ for *LCON*.

The *LCOD-GDP* Model and the *LCON-GDP* Model in Table 4 report the results for estimating Equation (13) and show that GDP growth is significantly positively associated with future discretionary LCOs. The result confirms that discretionary LCOs and their counter-cyclical nature are driven by the common risk exposure of the banking industry, which serves as a mechanism for the link between LCOs and systemic risk. The finding also suggests that discretionary LCOs facilitate banks' accumulation of more buffers in boom periods, thus reducing the pro-cyclicality of lending activities. In contrast, GDP growth is shown to be significantly negatively associated with future non-discretionary LCOs. The evidence reconfirms that the pro-cyclical nature of LCOs documented in prior studies is a reaction to the common risk exposure of the banking industry, which serves as a mechanism for the link between LCOs and systemic risk.

4.5.2. Patterns in LCO components and common risk exposures

To provide additional support for the mechanism underlying predictions about the LCO-systemic-risk link, we examine banks' herding patterns in using LCOs and how those patterns

[19] For example, we include the previous period, *ROA*, as Liu and Ryan (2006) report that more profitable banks discretionarily accelerate loan charge-offs; and we include the Tier-one capital ratio, *CAP*, as prior research finds that LCOs are used to manage regulatory capital (e.g., Collins et al. 1995).

are linked to common macro risk exposures. We measure bank herding in adopting discretionary and non-discretionary LCOs by the average cross-sectional correlation of *LCOD*, *CORR_LCOD*, and the average cross-sectional correlation of *LCON*, *CORR_LCON*, of different banks. We estimate *CORR_LCOD* and *CORR_LCON* for each quarter based on a rolling window of eight quarters. We run the following OLS regression model:

$$CORR\_LCO_t = V_0 + V_1 GDP_{t-1} + \varepsilon_t \,, \tag{14}$$

where *CORR_LCO* refers to *CORR_LCOD* or *CORR_LCON*; and *GDP* is the GDP growth in a quarter as a proxy for macroeconomic risk exposure of the banking industry. In Equation (14), $V_1 > 0$ means that the herding pattern enhances common risk exposure.

The *CORR_LCOD* Model and *CORR_LCON* Model in Table 4 report the estimation results and indicate that GDP growth is positively associated with future *CORR_LCOD* and *CORR_LCON*, but the coefficient is significant only in the case of *CORR_LCOD*. The evidence supports our conjecture that discretionary LCOs are linked to systemic risk through counter-cyclical herding as a response to the common macroeconomic risk exposure. The relatively weak relation between *CORR_LCON* and GDP growth suggests that the herding of high *CORR_LCON* may also result from the nationwide application of the GAAP rule.

[Insert Table 4 here]

4.6. Exploring the mechanisms for the LCOs–systemic risk link: bank interconnectedness

Thus far we have shown how LCO components are linked to systemic risk by reacting to the common macroeconomic risk exposure of the banking industry. We now focus on whether and how the LCO-systemic risk link works through the mechanism of bank interconnectedness. Conceptually, interconnectedness measures the extent to which a bank is connected with other banks in a network through which bank risk could easily spill over. Therefore, interconnectedness works as another mechanism for systemic crash risk, although Elsinger et al. (2006) and Trapp and Wewel (2013) indicate that risk contagion through interconnected networks is secondary to common risk exposure in affecting systemic risk.[20] When the crash risk of a bank spills over through a network, discretionary (non-discretionary) LCOs could mitigate (enhance) the risk contagion, and the effect should be stronger for banks with stronger connections with other banks in the network.

Bank interconnectedness could have varied dimensions and it is not easy to come up with a comprehensive measure. For example, banks can be connected through interbank loans, stock returns, stock ownership, and counterparties in derivative transactions. We thus use several measures for bank interconnectedness from different dimensions.

HConnected_stk. This is our main measure for high bank interconnectedness, and it captures the high interconnectedness based on stock returns of a bank and other banks, or the strong connections of a bank with other banks as perceived by the market. It is measured as an indicator of the number of banks that are significantly Granger-caused by a bank to be higher than the sample tertile, calculated based on the PCA and Granger-causality tests of monthly stock returns of all banks. To estimate *HConnected_stk* for a bank in a quarter, we extend Billio et al. (2012) to derive the stock return interconnectedness measure of all sample banks using a rolling window of 36 months.

HBeta. This proxies for the high correlations of a bank with all other banks in the

[20] Elsinger et al. (2006) report that, through a network of interbank loans, correlations of banks' asset portfolios dominate risk contagion as the main source of systemic risk. Trapp and Wewel (2013) find that bank interconnectedness and interconnectedness between banks and their non-financial borrowing firms are less crucial for systemic risk than banks' exposures to common risk factors.

banking industry and in the economy as perceived by the stock market, following Acharya et al. (2011) and Allen et al. (2012a).[21] It is measured as an indicator for the stock return correlation between a bank and the market to be higher than the sample tertile.

HShortermDebt. This is not a direct measure of bank interconnectedness, but it indirectly captures the potential of a bank's connections with other banks in the interbank lending markets that serve as a debt contractual network among banks and facilitate risk contagion of bank failures (e.g., Iyer and Peydro 2011). This also accounts for the high systemic risk exposure of banks with high short-term debts. If LCO components link to systemic risk via interconnectedness in the interbank debt market, then their relation should be stronger for banks with high short-term debts. We measure high short-term debts *HShortermDebt* as an indicator for the short-term debt of a bank to be higher than the sample median.

This study tests the moderating effect of bank interconnectedness using the following OLS regression model:

$$\Delta CoVaR_{it} = \gamma_0 + \gamma_1 INT_{it\text{-}1} * LCO_{it\text{-}1} + \gamma_2 LCO_{it\text{-}1} + \gamma_3 INT_{it\text{-}1} + Controls + FixedTimeEffect + \tau_{it} \quad (15)$$

where *INT* refers to either an indicator for high stock return interconnectedness *HConnected_stk*, an indicator for high market beta *HBeta*, or an indicator for high short-term debt *HShortermdebt*. Other variables are the same as in Equation (6). If *HConnected_stk*, *HBeta*, and *HShortermdebt* enhance the links between LCO components and systemic risk, then we expect $\gamma_1 < 0$ for discretionary LCOs and $\gamma_1 > 0$ for non-discretionary LCOs.

Table 5 reports the results for estimating Equation (15). Models 1 to 3 show that the

[21] Acharya et al. (2011) point out that the correlations of one financial firm with other financial firms and the economy capture one dimension of systemic risk. Allen et al. (2012a) use the correlation between a bank's daily stock returns and the S&P500 index returns in a quarter to measure the interconnectedness dimension of systemic risk.

interactions of discretionary LCOs with *HConnected_stk*, *HBeta*, and *HShort-termDebt* are all significantly negatively associated with $\Delta CoVaR\_stk$. The evidence is consistent with the proposition that discretionary LCOs affect systemic crash risk by constraining cross-sectional risk contagion within interconnected networks, and that the link between discretionary LCOs and systemic risk is stronger for banks with strong connections in the stock return network and in the interbank debt network. Regarding non-discretionary LCOs, the coefficients of their interaction with each of *HConnected_stk*, *HBeta*, and *HShort-termDebt* are consistently insignificant, suggesting that they do not function through the interconnected network. Overall, the evidence supports the notion that discretionary LCOs are related to future systemic crash risk through the mechanism of bank interconnectedness.

[Insert Table 5 here]

5. Additional analyses

Banks may use discretion at the same time over different accounts, and implement different discretionary practices over the same account. For example, banks execute three types of discretions over LLP – earnings smoothing through LLP, earnings management through LLP, and LLP untimeliness – to smooth or manage earnings. In contrast, discretion over LCOs is purported to adjust the timeliness of loan loss recognition rather than earnings, and is thus qualitatively different from any type of discretions over LLP. Earnings smoothing through LLP is negatively linked to systemic risk (Kim et al. 2016), whereas the other two types of LLP discretions are positively associated with systemic risk (Bushman and Williams 2015; Ma and Song 2016). To examine whether the association between LCOs and systemic risk is sensitive to discretions over LLP, we add additional controls of earnings management through LLP (*LLPEMGMT*), earnings smoothing through LLP (*LLPSMOOTH*), and LLP untimeliness (*LLPDELR*) to re-examine Equation (6).

We calculate *LLPEMGMT, LLPSMOOTH*, and *LLPDELR* following Ma and Song (2016), Kim et al. (2016), and Bushman and Williams (2015), respectively. *LLPEMGMT* is calculated by regressing the loan loss provisions on a wide range of determinants and taking the percentile-ranked absolute value of the regression residuals. The determinants of the loan loss provisions include current earnings before loan loss provisions, current and future changes in nonperforming loans, lagged bank size, lagged loan loss allowance, the ratio of net loan charge-offs to total assets, loan growth, and dummy variables for financial crisis and quarter four. *LLPSMOOTH* is calculated by regressing the loan loss provisions on the same set of determinants and taking the coefficient on current earnings before loan loss provisions as the measure of earnings smoothness. *LLPDELR* is proxied by the incremental R^2. We estimate the following two equations using a 12-quarter rolling window:

$$LLP_t = b_0 + b_1NPA_{t-1} + b_2NPA_{t-2} + b_3Cap_{t-1} + b_4LLP_{t-1} + b_5Size_{t-1} + \varepsilon_t \quad (16)$$

$$LLP_t = b_0 + b_1NPA_{t+1} + b_2NPA_{t+2} + b_3NPA_{t-1} + b_4NPA_{t-2} + b_5Cap_{t-1} + b_6LLP_{t-1} + b_7Size_{t-1} + \varepsilon_t \quad (17)$$

where the variables are defined in Appendix A and C. We compute *DELR* as the incremental R^2 by subtracting the adjusted R^2 of equation (16) from that of equation (17), and set the indicator variable, *DELR*, to be 1 if the bank's incremental R^2 is below the median, and 0 otherwise.

Given the importance of earnings management in prior literature, we further include various measures of accounting discretion (i.e., *LLPEMGMT*, *LLPSMOOTH*, *LLPDELR*) as additional control variables and rerun the regression analysis. The results are shown for models 3 and 4 in Table 6. We find that the main results are qualitatively unchanged, suggesting that our baseline results are robust to controlling for earnings smoothing, earnings management, and the timeliness of accruals.

Return-based measures of tail risk can be influenced by stock illiquidity, which casts doubt on our conclusion about the link between LCOs and systemic risk. Thus, we use as an additional control an illiquidity measure gauged by the extended *Amihud* proxy in Goyenko et al. (2009) to re-examine Equation (6). To calculate the illiquidity measure, we first compute the proportion of days with zero return, *Zeros*, and then deflate it by the average daily dollar volume. The results reported in the last column of Table 6 show that stock illiquidity does not qualitatively change our baseline results.

[Insert Table 6 here]

We include *Homo* (homogeneous loans scaled by total loans) and *Hetero* (heterogeneous loans scaled by total loans) as additional control variables in the baseline regression. The inclusion of the loan controls in the second stage partials out the discretionary and nondiscretionary LCOs calculated from the first stage and generates more robust results (Chen et al. 2018). Following Liu and Ryan (2006), we measure *Homo* as the sum of consumer loans, family residential mortgages, loans to financial institutions, and acceptance by other banks, scaled by total loans. We measure *Hetero* as the sum of commercial and industrial loans and direct lease financing, scaled by total loans. Bank loan data are collected from FR Y-9C reports and call reports. The results in Model 1 of Table 7 show that the coefficients on *LCOD* and *LCON* are statistically significant at the 1% and 5% level, respectively, suggesting that the main inferences remain robust and are not sensitive to controlling for the loan type.

[Insert Table 7 here]

Following Liu and Ryan (2006), we do some cross-sectional tests based on these loan types to further validate our discretionary LCOs' construct. Liu and Ryan (2006) consider the effect of homogeneous and heterogeneous loans on bank behavior, and find that banks with a greater proportion of homogeneous loans accelerate charge-offs more aggressively. If accelerating charge-offs is negatively correlated with a bank's contribution to systemic risks, then we should expect this negative relation to be more pronounced among banks with more homogeneous loans. We partition our sample based on the ratio of homogeneous loans to total loans. The results in model 2 of Table 7 show the regression results for banks with above-median homogeneous loans, whereas the results in model 3 of Table 7 show the results for banks with below-median homogeneous loans. We find that the coefficient on *LCOD* for the above-median homogeneous loans subsample is negative and significant at the 1% level, whereas that for the below median homogeneous loans subsample is not statistically significant, even at the 10% level. More importantly, the test of equality is performed to compare the variable of interest in these two subsamples. The null hypothesis is rejected at the 1% level. This finding adds another layer of confidence to the validity of the measurement of discretionary LCOs.

Beltratti and Stulz (2012) and Fahlenbrach et al. (2012) use the period Q3:2008 to Q4:2009 as an alternative definition of the crisis period; Adrian and Brunnermeier (2016) use 1994, 1997-1998, 2001, and 2008 as crisis periods. We also use these alternative crisis measures to re-examine Equation (7). In addition, in response to the concern that internal markets inherent in bank holding companies may affect the relation between LCOs and systemic risk, we separately re-examine Equations (7) and (8) for bank holding companies. Untabulated analyses indicate that these treatments do not qualitatively change the results. Finally, we examine the implications of the internal control regulations of the FDICIA and SOX Acts, and find that our baseline results are insensitive to their effects.

6. Conclusions

The severe effects of financial crises on the economy, often stronger than expected, have highlighted the lack of knowledge on how financial crises develop. They also highlight the importance of understanding how bank practices relate to systemic risk. In this study, we investigate how the treatment of loan charge-offs, a discretionary accounting choice targeting loan loss recognition rather than provisions and earnings, is tied to systemic risk in the banking industry.

We document that the discretionary part of loan charge-offs is linked to lower future risk in the banking industry, consistent with banks' counter-cyclical herding in using their discretion to charge off loans and create buffers for future loan losses. We also document that, in contrast to the implications of the discretionary part, the non-discretionary part of loan charge-offs is linked to higher future systemic risk, stemming from the financial statement role of charging off loans to recognize actual losses and confirm realized credit risk. Probing the mechanisms of the charge-off-systemic-risk links, we find that both discretionary and non-discretionary loan charge-offs are related to systemic risk through common risk exposure, and that discretionary loan charge-offs are additionally related to systemic risk through bank interconnectedness. Investigating causal directions for the charge-off-systemic risk links, we find that loan charge-off components affect future systemic risk. Taken together, the findings of this study identify major implications of bank-level financial statement information not closely related to earnings for understanding macro-level risk in the banking industry.

Appendix A
Variable definitions

A1. Measures for systemic risk

ΔCoVaR_stk: Proxy for a bank's contribution to systemic risk in the stock market and is calculated as the percentile ranking of minus one times the difference in the 1% VaR of the stock return in the banking industry conditional on a bank's stock return being at its 1% VaR and being in its median state in a quarter, estimated using a percentile regression approach. Appendix B describes the estimation details. A higher value indicates a higher contribution to systemic risk.

GARCH ΔCoVaR_stk: Proxy for a bank's contribution to systemic risk in the stock market and is calculated as the percentile ranking of minus one times the difference in the 1% VaR of the stock return in the banking industry conditional on a bank's stock return being at its 1% VaR and being in its median state in a quarter, estimated using a bivariate diagonal GARCH (DVECH (1,1)) approach. Appendix B describes the estimation details. A higher value indicates a higher contribution to systemic risk.

CATFIN: Proxy for systemic risk, and is a measure of the collective catastrophic (tail) risk of the banking system that forecasts economic downturns a year later. *CATFIN* is measured using the VaR approach following Allen et al. (2012b).

MES: Proxy for systemic risk in the stock market and is measured as the percentile ranking of the average daily marginal expected shortfall for the stock return of a bank in a quarter given that the market return is below its 2%-percentile, following Acharya et al. (2012).

SRISK: Proxy for systemic risk and is measured as the percentile ranking of average daily expected capital shortfall that a bank needs to cover in a quarter if there is a financial crisis, extending Acharya et al. (2012).

SRISK%: Proxy for systemic risk and is measured as the contribution of a bank's raw *SRISK* to the aggregate raw *SRISK* in the banking industry, following Acharya et al. (2012). It is equal to zero if a bank's raw *SRISK* < 0 and equal to the ratio of the raw *SRISK* over the aggregate raw *SRISK* if raw *SRISK* > 0, with the aggregate raw *SRISK* calculated as the sum of the positive raw *SRISK*.

ΔCoVaR_at: Proxy for a bank's contribution to systemic risk in a quarter and is calculated as the percentile ranking of minus one times the difference in the 1% VaR of the balance sheet asset growth in the banking industry conditional on a bank's balance sheet asset growth being at its 1% VaR and being in its median state in a quarter, estimated using a percentile regression approach. A higher value indicates a higher contribution to systemic risk.

A2. Measures for LCO components

LCOD: Proxy for discretionary LCOs and is measured as the percentile ranking of the residual estimated from the following LCO prediction model:

$$LCO_{it} = \alpha_0 + \alpha_1 \Delta NPL_{it} + \alpha_2 \Delta NPL_{it\text{-}1} + \alpha_3 LLP_{it} + \alpha_4 CAP_{it} + \alpha_5 Size_{it} + \alpha_6 \Delta LOAN_{it} + \alpha_7 Q4_t + v_{it}, \tag{1}$$

where *LCO* is the ratio of loan charge-offs to the market value of equity at the beginning of the fiscal quarter, ΔNPL is the quarterly growth of NPLs, *LLP* is the ratio of LLPs to the market value of equity, *CAP* is the Tier-one capital ratio reported in COMPUSTAT at the end of the fiscal quarter, $\Delta LOAN$ is the loan growth, *Size* is the bank size, $\Delta LOAN$ is the loan growth, and $Q4_t$ is an indicator variable for the fourth fiscal quarter.

LCON: Proxy for non-discretionary LCOs and is measured as the predicted value of the LCO from the above LCO prediction model in Equation (1).

LCODA: An alternative proxy for discretionary LCOs and is measured as the percentile ranking of the residual estimated from the following LCO prediction model:

$$LCO_{it} = \alpha_0 + \alpha_1 \Delta NPL_{it} + \alpha_2 \Delta NPL_{it\text{-}1} + \alpha_3 \Delta NPL_{it\text{-}2} + \alpha_4 \Delta NPL_{it\text{-}3} + \alpha_5 LLP_{it} + \alpha_6 CAP_{it} + \alpha_7 Size_{it} \\ + \alpha_8 \Delta LOAN_{it} + \alpha_9 Q4_t + v_{it}, \tag{2}$$

where all variable definitions are the same as in Equation (2). This model includes both prior and future growth in NPLs as determinants and thus factors out both timely and lagged LCOs from the estimated *LCODA*.

LCONA: An alternative proxy for non-discretionary LCOs and is measured as the estimated value of the LCO from the above LCO prediction model in Equation (2).

LCODT: An alternative proxy for discretionary LCOs and is measured as the percentile ranking of the residual estimated from the LCO prediction model in Equation (1) with *LCO*, ΔNPL and *LLP* measures using the total assets at the beginning of the fiscal quarter as the denominator. The other variable definitions remain unchanged.

LCONT: An alternative proxy for non-discretionary LCOs and is measured as the estimated value of the LCO from the LCO prediction model in Equation (1), where all variable definitions remain the same as in estimating *LCODT*.

LCODL: An alternative proxy for discretionary LCOs and is measured as the percentile ranking of the residuals estimated from the prediction model in Equation (1), with *LCO*, ΔNPL and *LLP* measures using loans at the beginning of the fiscal quarter as the denominator, and other variables unchanged.

LCONL: An alternative proxy for non-discretionary LCOs and is measured as the predicted LCOs from the prediction model in Equation (1), where all variable definitions are the same as in estimating *LCODL*.

A3. Main Measures used in probing the rationale for the LCO-systemic-risk links

CAP: Proxy for capital adequacy and is measured as the Tier-one capital ratio reported in COMPUSTAT at the end of the fiscal quarter.

GDP: Proxy for GDP growth and is measured as the percentage change of the annual nominal GDP in a quarter from the four quarters before.

CORR_LCOD: The average correlation of discretionary LCOs of a bank with every other bank in a quarter calculated using a rolling window of eight quarters.

CORR_LCON: The average correlation of non-discretionary LCOs of a bank with every other bank in a quarter calculated using a rolling window of eight quarters.

Logdloan: The natural logarithm of the difference between total loans for the future three quarters and the total loans for the current period.

A4. Measures for high level of bank interconnectedness

HConnected_stk: An indicator for the case that the number of banks that are significantly Granger-caused by a bank in a quarter are higher than the sample top tertile, calculated based on the PCA and Granger-causality networks of the monthly stock return of all commercial banks in our samples using a rolling window of 36 months, extending Billio et al. (2012).

HBeta: An indicator for the correlation of the stock return of a bank to that of the market to be higher than the sample top tertile in a quarter.

HShortermDebt: An indicator for the short-term debt ratio of a bank to be higher than the sample median in a quarter.

A5. Measures for control variables in multivariate analyses

Short-termDebt: The ratio of short-term debt to total liabilities at the end of a fiscal quarter.

Loan: The ratio of total loans to total assets at the end of a fiscal quarter.

Size: The natural logarithm of the market value of equity (in millions of dollars) at the end of a fiscal quarter.

ROA: The ratio of income before extraordinary items to total assets at the end of a fiscal quarter.

MB: The ratio of the market-to-book equity value at the end of a fiscal quarter.

Mismatch: The ratio of the difference between cash and short-term debt to total liabilities at the end of a fiscal quarter.

Cokurt: The kurtosis of the daily returns relative to that of the market returns for a bank in the year prior to a fiscal quarter.

Beta: The return sensitivity of the CRSP value-weighted market return calculated over the year prior to a fiscal quarter.

Sigma: The standard deviation of the daily stock returns in a fiscal quarter.

Momentum: The buy-and-hold return over the eleven-month period ending at a month prior to a fiscal quarter.

Unrate: Changes in the unemployment rate during a fiscal quarter.

Crisis: An indicator for the 2008-2009 financial crisis period, including all quarters in 2008 and the first two quarters in 2009.

BankConnectedness: The percentile ranking of the number of banks that are significantly Granger-caused by a bank in a quarter, calculated based on the PCA and Granger-causality networks of the monthly stock return of all commercial banks in our sample using a rolling window of 36 months, extending Billio et al. (2012).

NonInterestIncome: Proxy for a bank's business model and is measured as the ratio of non-interest income to total income.

Deposits: Total deposits scaled by lagged total loans in a fiscal quarter.

Appendix B
Estimation of a bank's contribution to systemic risk using quantile regression and GARCH methods

B1. Using the quantile regression method

Extending Adrian and Brunnermeier (2016) who calculate a bank's contribution to systemic risk based on the balance sheet asset growth, this study estimates a bank's contribution to systemic risk in the stock market $\Delta CoVaR\_stk_{it}$ based on the weekly stock return. Below we describe the estimation method in detail. First, we run the following 1% quantile regression model for the weekly stock return for bank *i* and for the whole banking industry, respectively, over a rolling window of one hundred weeks:

$$R^i_t = \alpha^i + \beta^i Z_{t\text{-}1} + \varepsilon^i \qquad \text{(b1)}$$
$$R^{system}_t = \alpha^{system|i} + \beta^{system|i} Z_{t\text{-}1} + \beta^{system|i} R^i_{t\text{-}1} + \varepsilon^{system|i}\ , \qquad \text{(b2)}$$

where R^i_t is the weekly stock return of bank *i* at time *t*. R^{system}_t is the value-weighted average of the weekly stock return of all banks in the banking industry at time *t*, using the market-valued equity MV^i_t as the weight. $Z_{t\text{-}1}$ is the vector of the macroeconomic variables and financial factors measured in the previous week, including the stock market return, equity volatility, short-term liquidity risk, interest rate risk, term structure, default risk, and real estate return. The weekly value-weighted equity returns (excluding ADRs) with all distributions proxy for the market return. Equity volatility is the standard deviation of the natural logarithm of stock returns three months prior to time *t*. Short-term liquidity risk is the difference between the three-month LIBOR rate and the three-month T-bill rate. Interest rate risk is the change in the three-month T-bill rate. The change in the slope of the yield curve, that is, the yield spread between the ten-year T-bond rate and the three-month T-bill rate, proxies for term structure. Default risk is the change in the credit spread between the ten-year BAA corporate bonds and the ten-year T-bonds. Real estate return is calculated based on the FHFA house price index.

Further, this study uses the predicted value from both models to obtain the 1% VaR of the stock return for bank *i* in week *w* and the corresponding 1% *CoVaR* for the banking industry as shown below:

$$VaR^i_t = \hat{R}^i_t = \alpha^i + \beta^i Z_{t\text{-}1} \qquad \text{(b3)}$$
$$CoVaR^{system|i,} = \hat{R}^{system}_t = \alpha^{system|i} + \beta^{system|i} Z_{t\text{-}1} + \beta^{system|i} VaR^i_t\ , \qquad \text{(b4)}$$

where $CoVaR^{system|i}$ indicates the 1% VaR of the stock return of the banking system in week *w* conditional on bank *i*'s stock return being at the 1% VaR.

Next, this study runs 50% quantile (median) regressions as expressed in Models (b5) and (b6):

$$R^i_t = \alpha^{i,median} + \beta^{i,median} Z_{t\text{-}1} + \varepsilon^{i,median} \qquad \text{(b5)}$$
$$R^{system}_t = \alpha^{system|i,median} + \beta^{system|\ i,median} Z_{t\text{-}1} + \beta^{system|i,median} R^i_{t\text{-}1}\ . \qquad \text{(b6)}$$

This study uses the predicted value from both models to calculate the median stock return for bank *i*, $R^{i,median}_t$, and the systemic risk conditional on bank *i* functioning in its median state, $CoVaR^{system|median}$, as below:

$$VaR^{i,median}_t = \alpha^{i,median} + \beta^{i,median} Z_{t\text{-}1} \qquad \text{(b7)}$$
$$CoVaR^{system|median} = \hat{R}^{system}_t = \alpha^{system|i,median} + \beta^{system|i,median} Z_{t\text{-}1} + \beta^{system|i,median} VaR^{i,median}_{t\text{-}1}\ . \qquad \text{(b8)}$$

Then, bank *i*'s contribution to systemic risk at the weekly frequency is estimated as the difference in the 1% *CoVaR* of the weekly stock return in the banking industry when bank *i*'s weekly stock return is at its 1% VaR and when it is in its median state:

$$\Delta CoVaR^{\ iw}_{1\%} = CoVaR^{system|\ i}_{1\%} - CoVaR^{system|\ i,medain}_{1\%}\ . \qquad \text{(b9)}$$

Finally, we measure bank i's contribution to systemic risk $\Delta CoVaR\_stk_{it}$ as the percentile ranking of minus one times the sum of the weekly $\Delta CoVaR^{iw}{}_{1\%}$ over a quarter.

B2. Estimation of an alternative measure for a bank's contribution to systemic risk using the GARCH method

In robustness tests, we follow Adrian and Brunnermeier (2016) and employ a diagonal vech bivariate GARCH model (DVECH) to estimate $\Delta CoVaR\_stk_{it}$ under the strict assumption that the joint distribution of $R_{system,t}$ and $R_{j,t}$ follows a bivariate Gaussian distribution. To obtain the time-varying *CoVaR* and *ΔCoVaR* measures using the GARCH approach, we include $Z_{t\text{-}1}$, a vector of seven *lagged* macroeconomic state variables and financial factors as defined above, as the independent variable in the mean equations of the bivariate GARCH model. Specifically, the conditional mean equations in the DVECH (1,1) model is specified as:

$$R^i{}_t = \alpha^i + \beta^i Z_{t\text{-}1} \tag{b10}$$
$$R^{\text{sysem}}{}_{\text{t}} = \alpha^{system} + \beta^{system} Z_{t\text{-}1}\,. \tag{b11}$$

Other specifications follow the standard DVECH (1,1) model.

Then, the 1% *CoVaR_stk* for bank i at week t has a closed form solution and is defined as:

$$CoVaR^{system|i}_{1\%,p,t} = \phi^{-1}(1\%)\sigma_t^{system}\sqrt{1-\rho^2_{system|i,t}} + \phi^{-1}(p)\rho_{system|i,t}\sigma_t^{system}\ , \tag{b12}$$

where $\rho_{system|i,t}$ is the conditional time varying correlation between the weekly stock returns of the banking industry and of bank i, and $\sigma^{system}{}_t$ is the time-varying standard deviation of the banking industry. Both $\rho_{system|i,t}$ and $\sigma^{system}{}_t$ are obtained from the DVECH (1,1) model. p refers to the pth possibility quantile that a stock return is lower than the 1% VaR threshold value. Φ^{-1} (1%) is the inverse normal distribution at the 1% level calculated from the left tail. It can be shown that the corresponding 1% *ΔCoVaR_stk* based on the weekly stock return is $\phi^{-1}(p)\rho_{system|i,t}\sigma_t^{system}$.

In the end, we calculate the percentile ranking of minus one times the sum of the 1% *ΔCoVaR_stk* calculated at the weekly frequency over a quarter and denote it as *GARCH ΔCoVaR_stk*. We use *GARCH ΔCoVaR_stk* in the robustness tests as an alternative measure for a bank's contribution to systemic risk in the stock market.

Appendix C
Descriptive statistics and estimation results for LCO prediction models

Panel A. Descriptive statistics of input variables for LCO prediction models

	Mean	Median	STD	Q1	Q3
LCO (%)	0.756	0.152	3.297	-0.007	0.488
LLP (%)	1.006	0.296	4.292	0.107	0.658
NPL (%)	9.838	3.149	2.971	1.228	7.713
ΔNPL	0.004	0.000	0.129	-0.004	0.006
CAP	0.112	0.107	0.035	0.088	0.129
Size	5.329	4.919	1.855	4.006	6.283
$\Delta LOAN$	0.033	0.021	0.098	0.002	0.045

Panel B. Coefficient estimates for LCO prediction models

	LCO Prediction Model in Equation (1)	
	Estimate	*t*-stat
Intercept	0.204	(4.16)***
$\Delta NPL_{it\text{-}1}$	1.908	(10.08)***
ΔNPL_{it}	-1.664	(-20.46)***
LLP_{it}	0.650	(246.69)***
CAP_{it}	-1.080	(-3.61)***
$\Delta LOAN_{it}$	-0.693	(-6.47)***
$Size_{it}$	-0.005	(-0.88)
$Q4_t$	0.249	(10.75) ***
Obs.	26,736	
Adj. R^2	0.723	

Table C1 reports the descriptive statistics of input variables in Panel A and the OLS estimation results in Panel B for the LCO prediction models specified in Equation (1) below:

$$LCO_{it} = \alpha_0 + \alpha_1\Delta NPL_{it} + \alpha_2\Delta NPL_{it\text{-}1} + \alpha_3 LLP_{it} + \alpha_4 CAP_{it} + \alpha_5 Size_{it} + \alpha_6\Delta LOAN_{it} + \alpha_7 Q4_t + v_{it} \qquad (1)$$

where LCO_{it} is the net loan charge-offs. *NPL* and ΔNPL refer to the NPL and its quarterly change, respectively. *LLP* is the loan loss provision, *CAP* is the Tier-one capital ratio, $\Delta LOAN$ denotes the loan growth, *Size* is the bank size, and *Q4* is a dummy variable for the fourth fiscal quarter. ***, **, and * indicate statistical significance at 1, 5, and 10 percent levels, respectively.

Table C1 reports the descriptive statistics for the LCO prediction models specified in Equation (1). Panel A reports statistics for input variables of Equation (1) and shows that the sample mean of *NPL* is 9.838%, ΔNPL is 0.004, *CAP* is 0.112, and $\Delta LOAN$ is 0.033, consistent with Beaver and Engel (1996) and Nichols et al. (2009). The mean *LCO* is 0.756%, consistent with Liu and Ryan (2006) and Nichols et al. (2009). Panel B presents the OLS estimation results for Equation (1), and indicates that the coefficients for all prior changes in NPLs ΔNPL are significantly positive, and the coefficient for *LLP* are significantly positive, consistent with the evidence and explanations in prior studies.[22] The significantly negative coefficients of bank size *Size* and

[22] All prior ΔNPL are expected to be positively related with *LCO* because changes in NPLs disclose information about changes in the loan portfolio credit quality and serve as leading indicators of LCOs (e.g., Wahlen 1994; Nichols et al. 2009). *LLP* should be positively associated with *LCO*, since banks prefer that their loan loss allowances do not fluctuate too much and often exercise discretions over LCOs when using discretionary LLPs to smooth income (e.g., Liu and Ryan 2006).

of $\Delta LOAN$ are consistent with Nichols et al. (2009). The relation between the current change of NPLs ΔNPL and *LCO* does not have a directional prediction, and the significantly negative coefficient of the current ΔNPL indicates a negative relation between them.[23]

[23] Although the current ΔNPL serves as a leading indicator or coincides with the LCOs (Wahlen 1994; Nichols et al. 2009), current LCOs can trigger a negative current ΔNPL, because when a bank charges off an uncollectible loan, it also removes the loan from its non-performing status (Nichols et al. 2009).

Table 1
Summary statistics

Panel A. Descriptive statistics					
	Mean	Median	STD	Q1	Q3
ΔCoVaR_stk (Raw, %)	21.660	18.538	18.770	9.233	30.444
ΔCoVaR_at (Raw, %)	19.161	15.947	19.672	6.906	28.417
MES (Raw)	0.014	0.011	0.015	0.004	0.022
SRISK ($million)	-213.512	-30.968	3882.24	-118.443	-0.697
SRISK%	0.003	0.000	3.494	0.000	0.009
CATFIN (Raw)	0.257	0.233	0.121	0.159	0.333
GARCH ΔCoVaR_stk	0.021	0.015	0.022	0.008	0.026
LCOD (Raw)	-0.005	-0.075	1.690	-0253	0.067
LCON	0.755	0.312	2.755	0.141	0.570
LCODA (Raw)	0.002	-0.065	1.660	-0.243	0.080
LCONA	0.740	0.300	2.639	0.128	0.561
LCODT (Raw)	0.0001	-0.008	0.076	-0.025	0.011
LCONT	0.059	0.037	0.087	0.019	0.065
LCODL (Raw)	0.000	-0.012	0.119	-0.040	0.016
LCONL	0.091	0.059	0.127	0.030	0.101
CAP	0.027	0.031	0.020	0.017	0.042
GDP	0.112	0.107	0.037	0.088	0.128
CORR_ LCOD	0.528	0.542	0.058	0.487	0.565
CORR_ LCON	0.630	0.648	0.068	0.574	0.680
Logdloan	4.644	4.440	1.874	3.439	5.696
MB	1.642	1.525	0.743	1.133	2.022
ROA	0.023	0.026	0.023	0.018	0.003
Sigma	3.732	3.134	2.321	2.317	4.355
Beta	0.501	0.348	0.521	0.107	0.817
Short-termDebt	0.053	0.030	0.066	0.000	0.079
Size	7.376	7.003	1.606	6.230	8.180
Mismatch	-0.060	-0.046	0.046	-0.074	-0.029
Loan	0.648	0.665	0.134	0.582	0.735
BankConnectedness	0.049	0.040	0.030	0.028	0.060
NonInterestIncome	0.009	0.007	0.139	0.004	0.010
Momentum	0.059	0.050	0.202	-0.058	0.175
Cokurt	1.144	0.843	1.268	0.219	1.852
Deposits	1.288	1.169	0.931	1.027	1.358
Unrate	0.684	0.000	5.466	-3.300	2.400

Table 1 (Continued)

Panel B. Correlation matrix for main testing variables

	1.	*2.*	*3.*	*4.*	*5.*	*6.*	*7.*	*8.*	*9.*	*10.*	*11.*	*12.*	*13.*	*14*
1. ΔCoVaR_stk	1													
2. ΔCoVaR_at	**0.637**	1												
3. MES (%)	**0.828**	**0.548**	1											
4. SRISK%	**0.337**	**0.291**	**0.382**	1										
5. SRISK	**-0.036**	-0.006	**-0.042**	**0.087**	1									
6. GARCH	**0.546**	**0.389**	**0.582**	**0.256**	**0.106**	1								
7. CATFIN	**0.183**	**0.171**	**0.022**	**0.065**	-0.001	**0.123**	1							
8. LCOD	**0.038**	0.007	**0.060**	**0.075**	**-0.042**	**0.096**	**-0.075**	1						
9. LCON	**0.055**	**0.078**	**0.038**	**0.165**	**0.079**	**0.063**	**0.139**	**-0.019**	1					
10. LCODA	**0.038**	-0.006	**0.057**	**0.059**	**-0.047**	**0.076**	**-0.081**	**0.932**	**-0.045**	1				
11. LCONA	**0.075**	**0.078**	**0.079**	**0.157**	**0.100**	**0.080**	**0.150**	**-0.091**	**0.987**	**-0.044**	1			
12. LCODT	-0.001	-0.01	**0.011**	**0.052**	**-0.041**	**0.041**	**-0.035**	0.920	**0.023**	**0.941**	**-0.027**	1		
13. LCONT	**0.162**	**0.143**	**0.167**	**0.261**	**0.067**	**0.243**	**0.212**	**-0.066**	**0.750**	**-0.053**	**0.799**	-0.010	1	
14. LCODL	-0.007	-0.014	0.002	**0.042**	**-0.038**	**0.029**	**-0.036**	**0.906**	**0.021**	**0.930**	**-0.031**	**0.988**	**-0.017**	1
15. LCONL	**0.172**	**0.142**	**0.183**	**0.279**	**0.109**	**0.267**	**0.207**	**-0.055**	**0.708**	**-0.044**	**0.749**	**-0.003**	**0.979**	-0.012

This table reports summary statistics for variables we use in the analysis, with Panel A presenting descriptive statistics and Panel B describing the Pearson correlation matrix for the main testing variables. Bold numbers indicate significance levels higher than 5 percent. We employ a sample period similar to that used in other crisis-related studies with a sample ending in 2009, the ending year of the 2008-2009 financial crisis, and starting in 1993 because this is the first year of full implementation of risk based capital and the Federal Deposit Insurance Corporation Improvement Act enacted in 1991. Accordingly, our sample is consistent with prior research and includes 24,078 bank-quarter observations spanning the fiscal years from 1993 to 2009.

Table 2
LCOs and future systemic risk

Panel A:

	Model 1		Model 2		Model 3		Model 4	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Intercept	0.064	(1.12)	0.051	(0.89)	0.064	(1.12)	0.059	(1.02)
LCOD	**-0.028**	**(-2.71)*****			**-0.028**	**(-2.75)*****	**-0.023**	**(-1.96)****
*LCOD*Crisis*							0.002	(0.83)
LCON			**0.004**	**(3.30)*****	**0.004**	**(3.30)*****	**0.003**	**(1.84)***
*LCON*Crisis*							0.020	(1.43)
Size	0.068	(14.6)***	0.067	(14.20)***	0.067	(14.50)***	0.068	(14.40)***
MB	0.0190	(1.90)*	0.019	(1.96)**	0.018	(1.86)*	0.018	(1.85)*
ROA	-1.010	(-0.634)	1.200	(0.65)	1.250	(0.68)	1.300	(0.71)
Sigma	0.004	(1.72)*	0.004	(1.40)	0.003	(1.42)	0.003	(1.46)
Beta	0.039	(3.15)***	0.036	(2.92)***	0.037	(3.00)***	0.042	(3.13)***
Short-termDebt	0.199	(2.13)**	0.201	(2.15)**	0.198	(2.12)**	0.200	(2.14)**
Mismatch	0.036	(0.267)	0.047	(0.35)	0.041	(0.31)	0.039	(0.30)
NonInterestIncome	0.0001	(2.05)**	0.0001	(2.26)**	0.0001	(2.27)**	0.0001	(2.27)**
BankConnectedness	0.034	(2.11)**	0.035	(2.14)**	0.035	(2.13)**	0.035	(2.16)**
Loan	0.069	(1.15)	0.067	(1.11)	0.063	(1.05)	0.063	(1.06)
Momentum	-0.066	(-5.86)***	-0.064	(-5.72)***	-0.064	(-5.77)***	-0.064	(-5.80)***
Cokurt	0.007	(1.90)*	0.008	(2.11)**	0.008	(2.05)**	0.008	(2.16)**
Crisis	0.036	(2.71)***	0.031	(2.31)**	0.031	(2.31)**	0.030	(2.30)**
FixedTimeEffect	Yes		Yes		Yes		Yes	
Obs.	24,078		24,078		24,078		24,078	
Adj. R^2	0.355		0.355		0.355		0.356	
F-test Stat. (p-value)	201.47 (0.00)		201.36 (0.00)		201.18 (0.00)		201.10 (0.00)	
Hausman test χ^2(p-value)	840.30 (0.00)		835.30 (0.00)		843.78 (0.00)		851.78 (0.00)	

Panel B:

	Model 1		Model 2		Model 3		Model 4	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Intercept	0.069	(1.15)	0.066	(1.11)	0.069	(1.15)	0.07	(1.17)
LCODA	-0.006	(-1.44)			-0.006	(-1.41)	-0.006	(-1.35)
*LCODA*Crisis*							-0.009	(-0.57)
LCONA			0.0001	(0.05)	0.0001	(0.02)	-0.006	(-1.44)
*LCONA*Crisis*							0.011	(2.33)**
Size	0.069	(14.34)***	0.069	(14.32)***	0.069	(14.32)***	0.068	(14.15)***
MB	0.017	(1.73)*	0.017	(1.73)*	0.017	(1.73)*	0.018	(1.84)*
ROA	-0.302	(-0.14)	-0.283	(-0.13)	-0.294	(-0.13)	-0.131	(-0.06)
Sigma	0.005	(2.01)**	0.005	(1.98)**	0.005	(1.99)**	0.002	(0.89)
Beta	0.047	(3.62)***	0.047	(3.61)***	0.047	(3.61)***	0.047	(3.67)***
Short-termDebt	0.174	(1.82)*	0.175	(1.82)*	0.174	(1.82)*	0.172	(1.80)*
Mismatch	0.037	(0.26)	0.037	(0.26)	0.037	(0.26)	0.021	(0.15)
NonInterestIncome	0.0001	(2.15)**	0.0001	(2.15)**	0.0001	(2.14)**	0.0001	(2.17)**

BankConnectedness	0.031	(1.80)*	0.031	(1.80)*	0.031	(1.80)*	0.028	(1.66)*
Loan	0.068	(1.09)	0.068	(1.09)	0.068	(1.09)	0.067	(1.09)
Momentum	-0.047	(-3.45)***	-0.047	(-3.44)***	-0.047	(-3.46)***	-0.035	(-2.71)***
Cokurt	0.007	(1.68)*	0.007	(1.68)*	0.007	(1.68)*	0.006	(1.60)
Crisis							0.070	(4.87)***
FixedTimeEffect	Yes		Yes		Yes		Yes	
Obs.	21,608		21,608		21,608		21,608	
Adj. R^2	0.370		0.370		0.370		0.372	

This table presents regression results from examining the link between LCOs and future systemic risk following Equations (6) and (7).

$$\Delta CoVaR_{it} = \varphi_0 + \varphi_1 LCO_{it\text{-}1} + Controls + FixedTimeEffect + \zeta_{it}\,, \quad (6)$$

$$\Delta CoVaR_{it} = \beta_0 + \beta_1 LCO_{it\text{-}1} + \beta_2 Crisis_t{*}LCO_{it\text{-}1} + Controls + FixedTimeEffect + \zeta_{it}\,, \quad (7)$$

where $\Delta CoVaR$ refers to a bank's contribution to systemic crash risk, $\Delta CoVaR\_stk$. *LCO* refers to the main measure of discretionary LCOs, *LCOD*, the alternative measure of discretionary LCOs that additionally excludes the impact of future NPL growth, *LCODA*, the main measure of non-discretionary LCOs, *LCON*, and the alternative measure of non-discretionary LCOs that additionally considers the impact of future NPL growth, *LCONA*, respectively. *Crisis* is an indicator for the 2008-2009 financial crisis, including all quarters in 2008 and the first two quarters in 2009. *Controls* include determinants for a bank's contribution to systemic risk: *MB*, market-to-book ratio; *Beta*, market beta; *Short-termDebt*, ratio of short-term debt to total liabilities; *Sigma*, equity return volatility; *Size*, bank size; *ROA*, return on assets; *Mismatch*, maturity mismatch; *BankConnectedness*, bank interconnectedness; *NonInterestIncome*, ratio of non-interest income to total income; *Loan*, total loans outstanding; *Momentum*, return momentum; *Cokurt*, relative stock return kurtosis; and *Crisis*, the crisis indicator variable. *FixedTimeEffect* refers to the year and quarter dummies. Appendix A provides detailed variable definitions for all variables we use in the analysis. ***, **, and * indicate statistical significance at 1, 5, and 10 percent levels, respectively. The *F*-test is for testing the pooled OLS model versus fixed effects model, and the Hausman test *chi*-square statistic is for testing the fixed effects model versus random effects model.

Table 3
Probing the rationale for the link between LCOs and future systemic risk

	CAP Model		*CAP-Crisis* Model		*Logdloan* Model		*Logdloan-Crisis* Model	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Intercept	11.366	(24.89)***	11.097	(23.92)***	0.682	(5.10)***	0.069	(5.12)***
LCOD	**1.790**	**(9.42)*****	**1.787**	**(7.87)*****	**-0.234**	**(-4.89)*****	**-0.220**	**(-4.35)*****
*LCOD*Crisis*			**-0.651**	**(-2.33)****			-0.013	(-0.92)
LCON	**-0.076**	**(-4.64)*****	**-1.033**	**(-6.69)*****	0.020	(0.97)	**0.007**	**(1.98)****
*LCON*Crisis*			**0.982**	**(6.45)*****			-0.007	(-1.51)
GDP	-22.734	(-6.48)***	8.898	(2.78)***				
*GDP*Crisis*			-30.945	(-5.59)***				
Size		(-5.91)***	-0.381	(-6.21)***	0.883	(54.95)***	0.089	(55.75)***
MB	0.246	(1.80)*	0.238	(1.70)*	-0.185	(-4.99)***	-0.020	(-5.25)***
ROA	-0.902	(-1.90)*	-0.844	(-1.82)*	-0.416	(-4.48)***	-0.042	(-4.55)***
Sigma	-0.081	(-2.38)**	-0.112	(-3.03)***	0.017	(1.84)*	0.003	(2.79)***
Beta	-0.147	(-0.87)	-0.220	(-1.33)	-0.002	(-0.04)	0.001	(0.21)
Mismatch	-15.286	(-5.97)***	-16.087	(-6.32)***	-0.841	(-1.80)*	-0.072	(-1.57)
Deposits	0.541	(3.44)***	0.506	(3.57)***	-0.083	(-4.69)***	-0.008	(-4.68)***
NonInterestIncome	-0.001	(-0.55)	-0.001	(-0.87)	0.001	(0.74)	0.000	(0.77)
CAP	0.246	(1.80)*			-4.421	(-6.94)***	-0.420	(-6.64)***
Unrate	-0.902	(-1.90)*			-0.006	(-3.05)***	-0.001	(2.23)**
Crisis			1.116	(4.90)***			-0.016	((-1.62)
FixedTimeEffect	Yes		Yes		Yes		Yes	
Obs.	21819		21,819		17,865		17,865	
Adj. R^2	0.118		0.147		0.676		0.671	

This table presents regression results for examining the rationale for the link between LCOs and future systemic risk by first reporting results for their association with future capital adequacy and loan growth. *CAP* Models report results for estimating Equations (9) and (10) below:

$$CAP_{it} = \theta_0 + \theta_1 LCO_{it-1} + \theta_2 GDP_{it-1} + \theta_3 Size_{it-1} + \theta_4 MB_{it-1} + \theta_5 ROA_{it-1} + \theta_6 Sigma_{it-1} + \theta_7 Mismatch_{it-1} + \theta_8 Deposits_{it-1} + \theta_9 NonInterestIncome_{it-1} + \theta_{10} Crisis + FixedTimeEffect + \varepsilon_{it}\,, \tag{9}$$

$$CAP_{it} = \theta_0 + \theta_1 LCO_{it-1} + \theta_2 LCO_{it-1}{*}Crisis + \theta_3 GDP_{it-1} + \theta_4 GDP_{it-1}{*}Crisis + \theta_5 Size_{it-1} + \theta_6 MB_{it-1} + \theta_7 ROA_{it-1} + \theta_8 Sigma_{it-1} + \theta_9 Beta_{it-1} + \theta_{10} Mismatch_{it-1} + \theta_{11} Deposits_{it-1} + \theta_{12} NonInterestIncome_{it-1} + \theta_{13} Crisis + FixedTimeEffect + \varepsilon_t\,, \tag{10}$$

where *CAP* is the capital ratio. *LCO* refers to discretionary LCOs *LCOD* or non-discretionary LCOs *LCON*. *FixedTimeEffect* includes the year and quarter dummies.

Second, this table also reports results for relations between discretionary LCOs, non-discretionary LCOs and a bank's future lending growth *Logdloan* using Equations (11) and (12) below:

$$Logdloan_{it+3} = \gamma_0 + \gamma_1 LCO_{it-1} + \gamma_3 Size_{it-1} + \gamma_4 MB_{it-1} + \gamma_5 ROA_{it-1} + \gamma_6 Sigma_{it-1} + \gamma_7 Beta_{it-1} + \gamma_8 Mismatch_{it-1} + \gamma_9 Deposits_{it-1} + \gamma_{10} NonInterestIncome_{it-1} + \gamma_{11} CAP_{it-1} + \gamma_{12} Unrate_{it-1} + {}_{13}Crisis + FixedTimeEffect + \tau_{it}\,, \tag{11}$$

$$Logdloan_{it+3} = \gamma_0 + \gamma_1 LCO_{it-1} + \gamma_2 LCO_{it-1}{*}Crisis + \gamma_3 Size_{it-1} + \gamma_4 MB_{it-1} + \gamma_5 ROA_{it-1} + \gamma_6 Sigma_{it-1} + \gamma_7 Beta_{it-1} + \gamma_8 Mismatch_{it-1} + \gamma_9 Deposits_{it-1} + \gamma_{10} NonInterestIncome_{it-1} + \gamma_{11} CAP_{it-1} + \gamma_{12} Unrate_{it-1} + {}_{13}Crisis + FixedTimeEffect + \tau_{it}\,, \tag{12}$$

where *Logdloan* refers to the natural logarithm of the difference between total loans at the end of the fiscal quarter one year ahead and at the end of the current fiscal quarter, and *LCO* refers to *LCOD* or *LCON*. Appendix A provides detailed definitions for all variables used in the analysis. ***, **, and * indicate statistical significance at 1, 5, and 10 percent levels, respectively.

Table 4
Probing mechanisms for the link between LCOs and future systemic risk: common risk exposure

	LCOD-GDP Model		*LCON-GDP* Model		*CORR_LCOD* Model		*CORR_LCON* Model	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Intercept	0.359	(17.15)***	1.713	(7.22)***	0.4776	(33.16)***	0.609	(31.30)***
GDP	**1.028**	**(4.34)*** **	**-12.784**	**(-3.45)*** **	**1.113**	**(4.02)*** **	0.464	(1.25)
Size	0.032	(12.05)***	-0.003	(-0.11)				
MB	-0.043	(-8.07)***	-0.554	(-11.69)***				
ROA	0.004	(0.28)	-0.738	(-6.34)***				
Sigma	0.002	(1.05)	0.361	(9.84)***				
Beta	0.024	(3.35)***	0.536	(3.98)***				
Mismatch	-0.228	(-2.75)***	-1.172	(-1.96)*				
Deposits	0.013	(2.72)***	-0.078	(-1.55)				
NonInterestIncome	0.000	(0.42)	-0.002	(-1.62)				
FixedTimeEffect	Yes		Yes		No		No	
Obs.	22,783		22,783		59		59	
Adj. R^2	0.116		0.212		0.205		0.010	

This table presents regression results for examining the rationale for the link between LCOs and future systemic risk by probing cyclicality and herding patterns in LCOs. The *LCOD-GDP* Model and *LCON-GDP* Model report the OLS estimation results for relations between GDP growth and LCO components using Equation (13) for the full sample:

$$LCO_{it} = \delta_0 + \delta_1 GDP_{it\text{-}1} + \delta_2 Size_{it\text{-}1} + \delta_3 MB_{it\text{-}1} + \delta_4 ROA_{it\text{-}1} + \delta_5 Sigma_{it\text{-}1} + \delta_6 Beta_{it\text{-}1} + \delta_7 Mismatch_{it\text{-}1} + \delta_8 Deposits_{it\text{-}1} + \delta_9 NonInterestIncome_{it\text{-}1} + \delta_{10} CAP_{it\text{-}1} + FixedTimeEffect + \varepsilon_t\ , \quad (13)$$

where *LCO* refers to discretionary LCOs *LCOD* or non-discretionary LCOs *LCON*, and *GDP* refers to the GDP growth rate. Appendix A presents definitions for the other control variables.

The *CORR_LCOD* Model and *CORR_LCON* Model report results for regressing the average *LCOD* correlation or *LCON* correlation of different banks in a quarter estimated using a rolling window of eight quarters on GDP growth using Equation (14) below for the full sample:

$$CORR\_LCO_t = V_0 + V_1 GDP_{t\text{-}1} + \varepsilon_t\ , \quad (14)$$

where *CORR_LCO* refers to *CORR_LCOD*, the average correlation of discretionary LCOs *LCOD* among all banks in a quarter, or *CORR_LCON*, the average correlation of non-discretionary LCOs *LCON* among all banks in a quarter. *GDP* is the annual GDP growth estimated in a quarter.
Appendix A provides detailed variable definitions for all variables we use in the analysis. ***, **, and * indicate statistical significance at 1, 5, and 10 percent levels, respectively. Table 1 provides detailed information about the sample period and summary statistics.

Table 5
Probing mechanisms for the link between LCOs and future systemic risk: Bank interconnectedness

	Model 1		Model 2		Model 3	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Intercept	0.057	(0.99)	0.059	(1.04)	0.057	(1.00)
LCOD	-0.018	(-1.50)	-0.013	(-1.08)	-0.012	(-0.96)
LCON	0.004	(2.60)***	0.003	(2.00)**	0.003	(2.07)**
*LCOD*HConnected_stk*	**-0.028**	**(-1.84)***				
*LCON*HConnected_stk*	0.001	(0.36)				
*LCOD*HBeta*			**-0.049**	**(-3.10)*****		
*LCON*HBeta*			0.001	(0.67)		
*LCOD*HShort-termDebt*					**-0.034**	**(-2.00)****
*LCON*HShort-termDebt*					0.003	(1.59)
HConnected_stk	0.009	(0.75)				
HBeta			0.033	(2.49)***		
HShort-termDebt					0.018	(1.03)
Size	0.068	(14.52)***	0.067	(14.34)***	0.068	(14.32)***
MB	0.018	(1.85)*	0.018	(1.81)*	0.018	(1.86)*
ROA	1.266	(0.69)	1.373	(0.75)	1.298	(0.71)
Sigma	0.003	(1.39)	0.003	(1.35)	0.003	(1.39)
Beta	0.037	(3.01)***	0.032	(2.21)**	0.037	(2.98)***
Short-termDebt	0.199	(2.14)**	0.2	(2.14)**	0.185	(1.83)*
Mismatch	0.039	(0.29)	0.037	(0.28)	0.041	(0.30)
NonInterestIncome	0.000	(2.23)**	0.000	(2.16)**	0.000	(2.25)**
BankConnectedness	0.041	(2.06)**	0.034	(2.13)**	0.035	(2.16)**
Loan	0.064	(1.07)	0.064	(1.07)	0.062	(1.04)
Momentum	-0.064	(-5.72)***	-0.064	(-5.75)***	-0.063	(-5.77)***
Cokurt	0.008	(2.03)**	0.008	(2.00)**	0.008	(2.08)**
Crisis	0.031	(2.35)**	0.03	(2.28)**	0.03	(2.25)**
FixedTimeEffect	Yes		Yes		Yes	
Obs.	24,078		24,078		24,078	
Adj. R^2	0.357		0.356		0.356	

This table presents regression results for examining the impact of bank interconnectedness on the link between LCO components and future systemic risk. The testing variables are the interaction terms of the measure for bank interconnectedness with discretionary and non-discretionary LCO measures, *LCOD* and *LCON*, respectively.

$$\Delta CoVaR_{it} = \gamma_0 + \gamma_1 INT_{it\text{-}1} * LCO_{it\text{-}1} + \gamma_2 LCO_{it\text{-}1} + \gamma_3 INT_{it\text{-}1} + Controls + FixedTimeEffect + \tau_{it}\,, \quad (15)$$

where *ΔCoVaR*, *LCO*, *Controls* and *FixedTimeEffect* are the same as in Equation (6). *INT* in this regression refers to *HConnected_stk* (an indicator for high stock return connectedness), *HBeta* (an indicator for high bank market beta), or *HShort-termDebt* (an indicator for high short-term debt). Appendix A provides detailed variable definitions for all variables we use in the analysis. ***, **, and * indicate statistical significance at 1, 5, and 10 percent levels, respectively.

Table 6
Alternative measures for systemic risk, discretionary and non-discretionary LCOs, and additional controls for discretionary LLP practices and stock liquidity

Independent variables	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat	Coef	*t*-stat
Intercept	0.083	(-1.44)	0.079	(138)	0.077	(1.05)	0.056	(0.77)	0.069	(1.15)
LCODT	**-0.034**	**(-3.22)*** **								
LCONT	**0.118**	**(2.14)** **								
LCODL			**-0.034**	**(-3.28)*** **						
LCONL			0.055	(1.47)						
LCOD					**-0.027**	**(-2.21)** **	**-0.027**	**(-2.17)** **	**-0.029**	**(-2.46)** **
LCON					**0.004**	**(2.21)** **	**0.005**	**(2.57)** **	0.007	(1.25)
LLPEMGMT					0.058	(2.75)***	0.055	(2.65)***		
LLPSMOOTH					-0.089	(-2.80)***	-0.088	(-2.76)***		
LLPDELR							0.041	(2.20)**		
Amihud									5.724	(1.60)
Controls and FixedTimeEffect	Yes		Yes		Yes		Yes		Yes	
Obs.	24,078		24,078		24,078		18,885		20,283	
Adj. R^2	0.356		0.356		0.356		0.365		0.314	

This table reports the robustness check results for the associations between discretionary LCOs, non-discretionary LCOs, and a bank's contribution to systemic risk, using Equation (6). Models 1 and 2 present the results using the following alternative measures for discretionary and non-discretionary LCOs: the asset-based *LCODT* and *LCONT* and the loan-based *LCODL* and *LCONL*, respectively. Models 3 and 4 present the results for additional controls for discretionary accounting practices over LLP, including earnings management through LLP *LLPEMGMT*, earnings smoothing through LLP *LLPSMOOTH*, and LLP untimeliness *LLPDELR*. Model 5 presents the result using stock illiquidity measure *Amihud* as an additional control. Variable definitions are available in Appendix A. ***, **, and * indicate statistical significance at 1, 5, and 10 percent levels, respectively.

Table 7
Controlling for loan type and cross-section analysis on loan types

Independent variables	Model 1 *(Full sample)*		Model 2 (*Above-median homogeneous loans*)		Model 3 (*Below-median homogeneous loans*)	
	Coefficient	*t*-stat	Coefficient	*t*-stat	Coefficient	*t*-stat
Intercept	0.075	(2.94) **	0.152	(6.08) ***	0.025	(1.71) *
LCOD	**-0.025**	**(-3.14)** ***	**-0.057**	**(-4.62)** ***	**0.004**	**(0.12)**
LCON	**0.003**	**(2.32)** **	**0.006**	**(3.85)** ***	**0.0002**	**(0.21)**
Size	0.076	(5.73) ***	0.090	(6.85) ***	0.052	(1.16)
MB	0.031	(2.84) ***	0.012	(1.00)	0.042	(3.70) ***
ROA	1.738	(4.09) ***	2.541	(6.39) ***	1.140	(2.38) **
Sigma	0.004	(1.04)	0.006	(1.25)	0.003	(0.82)
Beta	0.027	(3.35) ***	0.026	(3.29) ***	0.028	(3.42) ***
Short-termDebt	0.125	(3.62) ***	0.192	(5.28) ***	0.085	(2.19) **
Mismatch	0.059	(3.25) ***	0.057	(2.33) **	0.052	(3.62) ***
NonInterestIncome	0.0001	(2.25) **	0.0001	(2.26) **	0.0001	(2.24) **
BankConnectedness	0.033	(1.76) *	-0.000	(-0.01)	0.059	(2.27) **
Loan	0.058	(3.94) ***	0.065	(6.18) ***	0.042	(2.78) ***
Momentum	-0.049	(-6.24) ***	-0.042	(-6.15) ***	-0.053	(-6.35) ***
Cokurt	0.005	(1.12)	0.004	(1.01)	0.005	(1.15)
Crisis	0.032	(4.62) ***	0.023	(2.31) **	0.037	(4.21) ***
Homo	0.028	(3.24) ***				
Hetero	-0.010	(-8.50) ***				
Time fixed effect	Yes		Yes		Yes	
Obs.	21,416		10,216		11,200	
Adj. R^2	0.362		0.386		0.342	
Test of equality for LCOD			$Chi^2(1)$ =8.23 Prob =0.0041			

This table presents regression results for examining the robustness of the main result after controlling for additional loan type control variables and cross-section analysis on loan types. In model 1, we report the OLS estimation results for relations between a bank's contribution to systemic risks and LCO components controlling for homogeneous loans and heterogeneous loans. Sample size is limited to the availability of bank level loan data. We measure homogeneous loans as the sum of consumer loans, family residential mortgages, loan to financial institutions and acceptance of other banks, scaled by total loans and heterogeneous loans as the commercial and industrial loans and direct lease financing, scaled by total loans. In models 2 and 3, we report the OLS estimation results for relations between a bank's contribution to systemic risks and LCO components for banks with above-median homogeneous loans ownership and below-median ownerships. We partition our sample based on the ratio of homogeneous loans to total loans. Appendix A provides detailed variable definitions for all variables we use in the analysis. ***, **, and * indicate statistical significance at 1, 5, and 10 percent levels, respectively.

References

Acharya, V. V., R. Engle, and M. Richardson. 2012. Capital shortfall: a new approach to ranking and regulating systemic risks. *The American Economic Review* 102 (3), 59–64.

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson. 2011. Quantifying systemic risk: how to calculate systemic risk surcharges. In: Haubrich, Joseph G., Lo, Andrew W. (Eds.), Quantifying Systemic Risk, *National Bureau of Economic Research*.

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson. 2017. Measuring systemic risk. *Review of Financial Studies* 30 (1), 2-47.

Adrian, T., and M. K. Brunnermeier. 2016. CoVaR. *American Economic Review* 106 (7), 1705-1741.

Afonso, G., J.Santos, and J. Traina. 2014. Do 'too-big-to-fail' banks take on more risk? *Economic Policy Review* 20 (2), 41-58.

Allen, F., A. Babus, and E. Carletti. 2012a. Asset commonality, debt maturity, and systemic risk. *Journal of Financial Economics* 104 (3), 519–534.

Allen, L., T. G. Bali, and Y. Tang. 2012b. Does systemic risk in the banking industry predict future economic downturns? *Review of Financial Studies* 25 (10), 3000–3036.

Allen, F., and D. Gale. 1998. Optimal financial crises. *The Journal of Finance* 53 (4), 1245–1284.

Allen, F., and D. Gale. 2004. Financial intermediaries and markets. *Econometrica* 72 (4), 1023–1061.

Amihud, Y., Mendelson, H., and L. H. Pedersen. 2006. Liquidity and asset prices. Now Publishers Inc.

Ang, A., J. Chen, and Y. Xing. 2006. Downside risk. *Review of Financial Studies* 19 (4), 1191–1239.

Basel Committee on Banking Supervision (BASEL). 2010a. Basel III Press release: group of governors and heads of supervision announces higher global minimum capital standards. *Bank for International Settlements*. September 2010. Basel: Switzerland.

Basel Committee on Banking Supervision (BASEL). 2010b. BASEL III: a global regulatory framework for more resilient banks and banking systems. *Bank for International Settlements*. December 2010. Basel: Switzerland.

Beaver, W. H., C. Eger, S. Ryan, and M. Wolfson. 1989. Financial reporting, supplemental disclosures, and the structure of bank share prices. *Journal of Accounting Research* 27 (2), 157–178.

Beaver, W. H., and E. E. Engel. 1996. Discretionary behavior with respect to allowances for loan losses and the behavior of security prices. *Journal of Accounting and Economics* 22 (1), 177–206.

Beltratti, A., and R. M. Stulz. 2012. The credit crisis around the globe: why did some banks perform better? *Journal of Financial Economics* 105 (1), 1–17.

Benoit, S., G. Colletaz, C. Hurlin, and C. A. Perignon. 2013. Theoretical and empirical comparison of systemic risk measures. *Working paper*.

Benson, K., Clarkson, P. M., Smith, T., and Tutticci, I. (2015). A review of accounting research in the Asia Pacific region. *Australian Journal of Management*, 40 (1), 36-88.

Benson, K., Faff, R., and Smith, T. (2014). Fifty years of finance research in the Asia Pacific Basin. *Accounting & Finance*, 54(2), 335-363.

Bernal, O., J-Y Gnabo, and G. Guilmin. 2014. Assessing the contribution of banks, insurance and other financial services to systemic risk. *Journal of Banking and Finance* 47 (complete), 270–282.

Bernanke, B. S. 1983. Nonmonetary effects of the financial crisis in the propagation of the Great Depression. *The American Economic Review* 73 (3), 257–276.

Berger, A. N., and C. H. S. Bouwman. 2013. How does capital affect bank performance during financial crises? *Journal of Financial Economics* 109 (1), 146–176.

Berger, A. N., R. DeYoung, M. J. Flannery, D. Lee, and O. Oztekin. 2008. How do large banking organizations manage their capital ratios? *Journal of Financial Services Research* 34 (2), 123–149.

Berger, A. N., and G. F. Udell. 2004. The institutional memory hypothesis and the procyclicality of bank lending behavior. *Journal of Financial Intermediation* 13 (4), 458–495.

Bhat, G., R. Frankel, and X. Martin. 2011. Feedback in bank mortgage-backed security holdings and fair value accounting. *Journal of Accounting and Economics* 52 (2-3), 153–173.

Billio M., M. Getmansky, A. Lo, and L. Pelizzon. 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics* 104 (3), 535–559.

Bouvard, M., P. Chaigneau, and A. D. Motta. 2015. Transparency in the financial system: rollover risk and crises. *The Journal of Finance* 70 (4), 1805–1837.

Brunnermeier, M. K., Dong, G., and D. Palia. 2012. Banks' non-interest income and systemic risk. *Working paper*.

Brunnermeier, M., and L. Pedersen. 2009. Market liquidity and funding liquidity. *Review of Financial Studies*, 22, 2201-2238.

Bushman, R. M. (2014). Thoughts on financial accounting and the banking industry. *Journal of Accounting and Economics*, 58(2-3), 384-395.

Bushman, R. M., and C. Williams. 2015. Delayed expected loss recognition and the risk profile of banks. *Journal of Accounting Research* 53 (3), 511–553.

Caballero, R. J., and A. Krishnamurthy. 2008. Collective risk management in flight to quality episode. *The Journal of Finance* 63 (5), 2195–2230.

Chen, W., Hribar, P., and S. Melessa. 2018. Incorrect inferences when using residuals as dependent variables. *Journal of Accounting Research*, 56 (3), 751-796.

Collins, J., D. Shackelford, and J. Whalen. 1995. Bank differences in the coordination of regulatory capital, earnings, and taxes. *Journal of Accounting Research* 33 (2), 263–291.

Cready, W. M., and U. G. Gurun. 2010. Aggregate market reaction to earnings announcements. *Journal of Accounting Research* 48 (2), 289–334.

Dugan, J. C. 2009. Loan loss provisioning and pro-cyclicality. Remarks by Comptroller of the Currency Dugan before the Institute of International Bankers (March 2).

Elsinger, H., A. Lehar, and M. Summer. 2006. Risk assessment for banking systems. *Management Science* 52 (9), 1301–1314.

Fahlenbrach, R., R. Prilmeier, and R. M. Stulz. 2012. This time is the same: using bank performance in 1998 to explain bank performance during the recent financial crisis. *The Journal of Finance* 67 (6), 2139–2185.

Financial Stability Forum. 2009. Report of the financial stability forum on addressing procyclicality in the financial system.

Gertler, M., N. Kiyotaki, and A. Queralto. 2011. Financial crises, bank risk exposure and government financial policy. *Working paper*.

Goldstein, I., and A. Razin. 2013. Three branches of theories of financial crises. Working paper, *National Bureau of Economic Research* (No. 18670).
Goyenko, R., C. W. Holden, and C. A. Trzcinka. 2009. Do liquidity measures measure liquidity? *Journal of Financial Economics* 22 (2), 153–181.
Granger, C. W. J. 1969. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica* 37 (3), 424–43.
Hart, O., and L. Zingales. 2011. A new capital regulation for large financial institutions. *American Law and Economics Review* 13 (2), 453–490.
He, Z., and A. Manela. 2016. Information acquisition in rumor-based bank runs. *The Journal of Finance* 71 (3), 1113–1158.
Hirshleifer, D., K. Hou, and S. H. Teoh. 2009. Accruals, cash flows, and aggregate stock returns. *Journal of Financial Economics* 91 (3), 389–406.
Hovakimian, A., E. J. Kane, and L. Laeven. 2012. Variation in systemic risk at U.S. banks during 1974–2010. Working paper, *National Bureau of Economic Research* (No. 18043).
Hribar, P., S. J. Melessa, R. C. Small, and J. H. Wilde. 2017. Does managerial sentiment affect accrual estimates? Evidence from the banking industry. *Journal of Accounting and Economics* 63 (1), 26-50.
Huizinga, H., and L. Laeven. 2012. Bank valuation and accounting discretion during a financial crisis. *Journal of Financial Economics* 106 (3), 614–634.
International Monetary Fund. 2008. Global financial stability report: containing systemic risks and restoring financial soundness.
Iyer, R., and J. Peydro. 2011. Interbank contagion at work: evidence from a natural experiment. *Review of Financial Studies* 24 (4), 1337–1377.
Jackson, A. B. (2018), Discretionary accruals: earnings management … or not? *Abacus*, 54 (2), 136-153.
Joslin, S, M. Priebsch, and K. J. Singleton. 2014. Risk premiums in dynamic term structure models with unspanned macro risks. *The Journal of Finance* 69 (3), 1197–1233.
Kannan, P., and F. Kohler-Geib. 2009. The uncertainty channel of contagion. *World Bank Policy Research*, working paper No. 4995.
Kashyap, A. K. and J. C. Stein. 1995. The impact of monetary policy on bank balance sheets. Carnegie-Rochester Conference Series on Public Policy 42, 151-195.
Keeton, W., and C. Morris. 1987. Why do banks loan losses differ? *Economic Review* 7 (5), 3–21.
Khandani, A. E., A. W. Lo, and R. C. Merton. 2013. Systemic risk and the refinancing ratchet effect. *Journal of Financial Economics* 108 (1), 29–45.
Kim J-B, L. Li, M. Ma and F. Wu. 2016. Earnings smoothing and systemic risk in the banking industry. Working paper, University of Waterloo.
Konchitchki, Y. 2011. Inflation and nominal financial reporting: implications for performance and stock prices. *The Accounting Review* 86 (3), 1045–1085.
Kothari, S. P., J. Lewellen, and J. B. Warner. 2006. Stock returns, aggregate earnings surprises, and behavioral finance. *Journal of Financial Economics* 79 (3), 537–568.
Laeven, L., and G. Majnoni. 2003. Loan loss provisioning and economic slowdowns: too much, too late? *Journal of Financial Intermediation* 12 (2), 178–197.
Lang, M., and M. Maffett. 2011. Transparency and liquidity uncertainty in crisis periods. *Journal of Accounting and Economics*, 52 (2-3), 101-125.

Levine, R., L. Chen, and W. Xie. 2016. Spare tire? Stock markets, banking crises, and economic recoveries. *Journal of Financial Economics*, forthcoming.
Liu, C., and S. Ryan. 2006. Income smoothing over the business cycle: changes in banks coordinated management of provisions for loan losses and loan charge-offs from the pre-1990 bust to the 1990s boom. *The Accounting Review* 81 (2), 421–441.
Lopez-Espinosa, G., A. Moreno, A. Rubia, and L. Valderrama. 2014. Short-term wholesale funding and systemic risk: a global CoVaR approach. *Journal of Banking and Finance* 36 (12), 3150–3162.
Ma, M. and V. Song. 2016. Discretionary Loan Loss Provisions and Systemic Risk in the Banking Industry. *Accounting Perspective* 15 (2), 89–130.
Morgan, D. P. 2002. Rating banks: risk and uncertainty in an opaque industry. *The American Economic Review* 92 (4), 874–888.
Moyer, S. E. 1990. Capital adequacy ratio regulations and accounting choices in commercial banks. *Journal of Accounting and Economics* 13 (2), 123–154.
Ng, J., and S. Roychowdhury. 2014. Do loan loss reserves behave like capital? Evidence from recent bank failures. *Review of Accounting Studies* 19 (3), 1234–1279.
Nichols, D. C., Wahlen, J. M., and M. M. Wieland. 2009. Publicly traded versus privately held: implications for conditional conservatism in bank accounting. *Review of Accounting Studies* 14 (1), 88–122.
Petersen, M. A. 2009. Estimating standard errors in finance panel data sets: comparing approaches. *Review of Financial Studies* 22 (1), 435–480.
Reinhart, C. M., and K. S. Rogoff. 2011. From financial crash to debt crisis. *The American Economic Review* 101(5), 1676–1706.
Rose, A. K., and M. M. Spiegel. 2009a. The causes and consequences of the 2008 crisis: early warning. Working paper, *National Bureau of Economic Research* (No. 15357).
Rose, A. K., and M. M. Spiegel. 2009b. The causes and consequences of the 2008 crisis: international linkages and American exposure. Working paper, *National Bureau of Economic Research* (No. 15358).
Securities and Exchange Commission. 2008. Report and recommendations pursuant to section 133 of the Emergency Economic Stabilization Act of 2008: study on mark-to-market accounting.
Shivakumar, L. 2007. Aggregate earnings, stock market returns and macroeconomic activity: a discussion of 'Does earnings guidance affect market returns? The nature and information content of aggregate earnings guidance.' *Journal of Accounting and Economics* 44 (1-2), 64–73.
Trapp, M., and C. Wewel. 2013. Transatlantic systemic risk. *Journal of Banking and Finance* 37 (11), 4241–4255.
Van de Leur, M.C.W., A. Lucas, and N. J. Seeger. 2017. Network, market, and book-based systemic risk rankings. *Journal of Banking and Finance* 78 (May), 84–90.
Van den Heuvel, S. 2009. The Bank Capital Channel of Monetary Policy. Board of Governors of the Federal Reserve. Available at https://ideas.repec.org/p/red/sed006/512.html.
Vyas, D. 2011. The timeliness of accounting write-downs by U.S. financial institutions during the financial crisis of 2007–2008. *Journal of Accounting Research* 49 (3), 823–860.
Wahlen, J. M. 1994. The nature of information in commercial bank loan loss disclosures. *The Accounting Review* 69 (3), 455–478.

White, M. J. 2013. Testimony on mitigating systemic risk in the financial markets through wall street reforms. *U.S. Securities and Exchange Commission*.
Yellen, J. L. 2008. The financial markets, housing, and the economy. *FRBSF Economic Letter* (Apr., 18), Federal Reserve Bank of San Francisco.