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Earnings Smoothing and Systemic Risk in the Banking Industry*

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Abstract

This study examines the relation between earnings smoothing through loan loss provision (LLP smoothing) and systemic risk in the US banking sector. We find that LLP smoothing is negatively associated with a bank's contribution to systemic risk in general and in both boom and bust periods. We further find that this association stems from the counter-cyclical cushioning role of beneficial LLP smoothing as a reaction to common risk exposure but does not work through the mechanism of bank interconnectedness or bank-specific risk. Moreover, the effect of LLP smoothing on systemic risk becomes weaker for banks with more heterogeneous loans and for banks with male managers or managers who have strong risk-taking incentives. Finally, we find that the effect is more pronounced for banks under enhanced monitoring by long-term debtholders, financial analysts, and Big-Four auditors in connection with LLP smoothing.

Keywords: Loan Loss Provision, LLP Smoothing, Systemic Risk, Common Risk Exposure, Bank Interconnectedness

JEL Classifications: G01, G21, G28, M41

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I. Introduction

This study examines the relation between earnings smoothing through loan loss provision (hereinafter LLP smoothing) and a bank's contribution to systemic risk in the financial system in the United States. Recently, both academics and regulators have paid considerable attention to the economic connection between accounting practices and financial crisis or systemic risk in the banking sector (e.g. Huizinga and Laeven, 2012; Bushman and Williams, 2015). A high level of systemic risk could indicate that the capital intermediation capacity of the financial sector is impaired or the stability of the banking system is threatened. If severe enough, systemic risk can trigger the collapse of the financial system and impose negative externalities on the whole economy, such as persistent drops in output (Holmstrom and Tirole, 1997; Allen *et al.*, 2012; Rampini and Viswanathan, 2019).

LLP smoothing, which could be beneficial or opportunistic, is a prevalent discretionary accounting practice in the banking industry and has been widely explored in prior studies (e.g. Beatty *et al.*, 1995; Collins *et al.*, 1995; Laeven and Majnoni, 2003; Kanagaretnam *et al.*, 2004; Liu and Ryan, 2006; Bushman and Williams, 2012). However, little attention has been paid to the association between LLP smoothing and systemic risk, and the existing literature only suggests inconsistent directions for their relation. For example, Liu and Ryan (2006) show that profitable banks in the United States smooth income over business cycles by systematically accumulating reserves during economic booms to serve as a buffer against negative shocks during economic busts, which implies that LLP smoothing has the potential to reduce systemic risk in the banking industry. In contrast, in an international setting, Bushman and Williams (2012) report that LLP smoothing increases bank-specific risk by hiding bad earnings news and increasing information opacity, which impedes market discipline over imprudent bank risk-taking. If this effect also persists in the United States, LLP smoothing may increase systemic risk. Nevertheless, Demerijian, Donovan, and Lewis-Western (2020) demonstrate that the income smoothing of US banks increases earnings informativeness about credit risk and facilitates the monitoring of borrowers, which suggests that LLP smoothing could also have beneficial effects in mitigating bank-specific risk and systemic risk in the United States. Overall, inferences from previous studies about the relation between LLP smoothing and systemic risk are indirect and ambiguous, which makes it necessary to conduct a systematic examination of this issue.

Investigating the link between LLP smoothing and systemic risk is of particular significance to equity investors, securities regulators, banking regulators, and accounting standard setters. First, securities regulators such as the Securities and Exchange Commission (SEC) have actively undertaken regulatory reforms to diminish systemic risk in the equity market, as mandated by the Dodd-Frank Act (White, 2013). Second, the "contingent" capital regulation for banks is typically based on market value and is affected by systemic risk in the equity market; thus, exploring how LLP smoothing affects systemic risk provides a useful reference for banking regulators. In addition, banking regulators stress the role of LLP smoothing in accumulating cushions and attenuating the adverse impact of severe economic downturns on bank performance. For example, the Basel Committee on Banking Supervision (BCBS) (2010) proposes "dynamic provisioning" as a means to cope with financial crises. Dynamic provisioning encourages banks to accumulate reserves through loan loss allowance in good times and to release them in downturns, drawing on the counter-cyclical and cushioning functions of LLP smoothing. Lastly, the SEC, the Financial Accounting Standards Board (FASB), and accounting professionals also care about the possibility that excessive reserves via LLP smoothing may increase information opacity (SEC, 1999; Balla and McKenna, 2009), which potentially increases banks' risk-taking. Similarly, John Dugan, former Comptroller of the Currency for the US Department of the Treasury, argues in his 2009 remarks on earnings smoothing and cookie jar accounting to the Institute of International Bankers that "if distorted in this manner, the loan loss reserve would indeed impair transparency and reduce market discipline, and would be unacceptable."[4]

We are motivated by the above background to examine the link between LLP smoothing and systemic risk. We predict that, due to its counter-cyclical cushioning property, LLP smoothing is negatively associated with systemic risk through the mechanism of common risk exposure. Prior literature shows that LLP smoothing on average counter-cyclically accumulates reserves in good times that could act as cushions to draw on in bad times (Beidleman, 1973; Laeven and Majnoni, 2003; Liu and Ryan, 1995, 2006). In particular, Beidleman (1973, p. 654) argues that LLP smoothing "represents an overt attempt to counter the cyclical nature of reported earnings" by expediting higher LLP during expansions that buffers against negative shocks in recessions. Laeven and Majnoni (2003) find that more profitable banks use higher levels of LLP smoothing. Liu and Ryan (1995, 2006) report that in the pre-1990 bust, weak banks managed income upward through LLP, and during the 1990s boom, profitable banks smoothed income downward via LLP, anticipating larger loan loss in a future bust. These studies suggest that banks mainly smooth earnings over business cycles in a beneficial way and that LLP smoothing has an inherent counter-cyclical cushioning property. One may argue that some banks may opportunistically smooth LLP and weaken LLP's counter-cyclical cushioning feature. However, there is evidence suggesting that this should not be a big concern, especially for the United States. For example, Demerijian, Lewis-Western, and McVay (2020) report that capable managers in general conduct beneficial smoothing among US banks, implying that beneficial LLP smoothing may dominate opportunistic LLP smoothing in the US banking system.

The counter-cyclical cushioning function of LLP smoothing could be a reaction to the common risk exposure of the banking industry. Specifically, in booms and good economic times, credit expands and expected future bank loan losses increase, and thus the common

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[4] https://www.occ.gov/news-issuances/speeches/2009/pub-speech-2009-16.pdf

risk exposure of the financial system is usually high. Meanwhile, a significant portion (if not all) of banks are profitable, and as a response to the increase in common risk exposure, these banks tend to be systematically involved in higher levels of earnings smoothing to accumulate reserves. This in turn increases bank capital sufficiency, helps cushion future loan losses and other losses in bad times, prevents bank risk accumulation over time, and thus reduces systemic risk. Therefore, banks' application of LLP smoothing to increase cushions implies a negative link between LLP smoothing and systemic risk in the banking industry, for which common macroeconomic risk exposure is an important mechanism (Adrian and Brunnermeier, 2016). Moreover, as common risk and imbalance are usually built up during booms and materialise and become low in crisis times (Hartmann *et al.*, 2009; Adrian and Brunnermeier, 2016), the link between LLP smoothing and systemic risk is likely to be more pronounced in good times when high-level LLP smoothing prevails among banks when they react to heightened common risk exposure.[5]

Adrian and Brunnermeier (2016) suggest that, in addition to common risk exposure, bank interconnectedness is another potential mechanism for systemic risk. However, no prior evidence implies that LLP smoothing is related to bank interconnectedness. If interconnectedness plays a role in the negative relation between LLP smoothing and systemic risk, then the relation should strengthen for more interconnected banks. We leave this to empirical validation.

To test the above conjectures, we use bank-quarters of US commercial banks to conduct empirical analyses because commercial banks play a more important role in transmitting negative shocks compared to non-depository institutions (Billio *et al.*, 2012). We mainly use two sets of LLP smoothing measures. The first measure is the percentile ranking of the coefficient of pre-LLP earnings in a LLP prediction model extending Beatty *et al.* (1995), Ahmed *et al.* (1999), Liu and Ryan (2006), and Bushman and Williams (2012). This bank-specific measure spans a long time period and is time invariant, which is appropriate for this study because we focus on LLP smoothing over long-run business cycles. Moreover, LLP smoothing is largely determined by the characteristics of bank managers and business models and is relatively stable over time but varies in the cross-section (Ge *et al.*, 2011; Demerjian *et al.*, 2013; Bouwman, 2014). The second LLP smoothing measure is bank specific and time variant and is measured as the percentile ranking of the product of the pre-LLP earnings and its estimated coefficient from a LLP prediction model which incorporates different magnitudes of pre-LLP earnings ratios in the time series.

We estimate systemic risk measures using stock return data, mainly because systemic

[5] The counter-cyclical cushioning nature of LLP smoothing can also constrain risk spillovers among banks via mitigating capital inadequacy and insolvency concerns of investors. When a bank with high-level LLP smoothing experiences loan losses, the accumulated reserves signify sufficient cushions to cover the losses. This boosts investors' belief in the bank and also in the whole financial system if banks share similar LLP smoothing activities, thus preventing risk spillover from one bank to others and reducing systemic risk.

risk and risk contagion in the equity markets are especially detrimental to bank shareholders whose investments are not protected by deposit insurance policies designed for the creditors of banks. In addition, equity value reflects investors' expectations about banks' capital sufficiency (Bushman and Williams, 2015). Specifically, extending Bushman and Williams (2015) and Adrian and Brunnermeier (2016), we measure a bank's contribution to systemic risk as the percentile ranking of negative one times the difference in the q% (1% or 5%) value at risk (VaR) of stock returns in the banking industry, conditional on a bank's stock return being at its q% VaR level versus being in its median state. This systemic risk measure aims to reflect the contribution of the stock price plummet of an individual bank to that in the financial sector.

Our main findings are as follows. OLS regressions show that, consistent with our predictions, LLP smoothing is significantly negatively related with a bank's contribution to systemic risk for our full 1993–2009 sample and also for the crisis and non-crisis periods, despite a relatively stronger relation for the non-crisis periods. The relation is more prominent in the subsample with higher GDP growth but exhibits no significant difference in the subsamples with high versus low bank interconnectedness. The evidence suggests that LLP smoothing is more likely linked to systemic risk through the common risk exposure mechanism but is unlikely linked through bank interconnectedness. To further investigate whether and how the counter-cyclical cushioning function of LLP smoothing accounts for its negative relation with systemic risk, we regress LLP smoothing on GDP growth, regress capital sufficiency on LLP smoothing, and also perform relevant portfolio analyses. We find that LLP smoothing is significantly positively associated with GDP growth and also improves capital sufficiency. These results support the notion that LLP smoothing, as a reaction to heightened common risk exposure during the period leading to a crisis, facilitates the enhancement of reserves accumulation and capital sufficiency, which ultimately contributes to the negative relation between LLP smoothing and systemic risk.

We next explore whether types of LLP smoothing (i.e. LLP smoothing on heterogeneous loans and LLP smoothing on homogeneous loans) and managerial characteristics (i.e. manager gender and suboptimal managerial risk-taking incentives) affect the relation between LLP smoothing and systemic risk. Heterogeneous loans leave more room for opportunistic managerial discretions than homogeneous loans, in that homogeneous loans better facilitate profitable banks to perform beneficial LLP smoothing to accumulate cushions against losses and mitigate overestimation of earnings before a crisis (Liu and Ryan, 2006). Therefore, LLP smoothing on homogeneous (heterogeneous) loans holds the potential to strengthen (weaken) the reducing effect of LLP smoothing on systemic risk. Regarding managerial features, female executives are more sensitive to firms' risk exposures and tend to choose more conservative policies (Levi *et al.*, 2014; Huang and Kisgen, 2013; Francis *et al.*, 2015). Thus, we expect that female bank managers react more strongly to increases in common risk exposure by applying high-level LLP smoothing, thus leading to a more pronounced negative relation between LLP smoothing and systemic risk. Moreover, managers with strong risk-taking incentives (e.g. with high-vega stock option holdings) are more inclined to use earnings smoothing to inflate earnings and hide losses (Bergstresser and Philippon, 2006; Grant *et al.*, 2009) than to use it to accumulate cushions in reaction to an increase in common risk exposure. We expect this suboptimal usage of LLP smoothing could weaken the negative relation between LLP smoothing and systemic risk. Our findings are consistent with these expectations: The negative LLP smoothing-systemic risk relation is stronger for banks with more LLP smoothing on homogeneous loans and for banks whose managers are female or have lower risk-taking incentives.

We take one step further to examine whether external monitoring mechanisms help mitigate the detrimental effect of suboptimal LLP smoothing on its association with systemic risk. Following prior studies, we consider three monitoring schemes: (1) debtholder monitoring measured by long-term debt ratio; (2) analyst coverage (e.g. Yu, 2008); and (3) Big-Four auditors (e.g. Kanagaretnam *et al.*, 2010). We expect these mechanisms constrain managers' suboptimal LLP smoothing practice and thus reinforce the link between LLP smoothing and systemic risk. We find supporting evidence that the negative LLP smoothing-systemic risk relation is accentuated in the subsample of firms that are subject to stronger monitoring by debtholders, financial analysts, or Big-Four auditors.

In the last set of analyses, we check whether the relation between LLP smoothing and systemic risk functions through bank-specific risk. Bushman and Williams (2015) show that delays in LLP provision increase systemic risk during financial crises via increasing bank-specific risk. Bushman and Williams (2012) argue that LLP smoothing hides bad earnings news and hinders market discipline over bank risk-taking in an international setting. We find that in the US setting, however, LLP smoothing does not significantly affect bank-specific risk. This difference is plausibly because in the US banking system, LLP smoothing has stronger connotations of enhancing cushions against losses and risks and improving earnings informativeness that facilitates disciplining excessive risk-taking. These beneficial effects of LLP smoothing can cancel out, but are not strong enough to dominate, the harmful effects of opportunistic LLP smoothing on banks' risk profile, leading to an insignificant relation between LLP smoothing and bank-specific risk.[6] The evidence also suggests that bank-specific risk is unlikely to be a mechanism for the link between LLP smoothing and systemic risk in the US banking industry, as documented in this paper. Finally, our main results are robust to alternative measures for LLP smoothing and systemic risk and also to controlling

[6] The explanation is also supported by prior evidence that LLP smoothing in the United States on average signals future performance and enhances earnings informativeness (e.g. Beidleman, 1973; Barnea *et al.*, 1975; Greenwalt and Sinkey, 1988; Tucker and Zarowin, 2006). Our untabulated results also reveal that LLP smoothing in the US banking industry does significantly enhance earnings response coefficients (results are available on demand), suggesting that LLP smoothing improves informativeness that facilitates the monitoring of bank risk-taking.

for opportunistic earnings management through LLP and LLP untimeliness.

Our work makes several contributions to the literature. First, this study adds to the literature on discretionary accounting choice, systemic risk, and financial crisis by documenting original evidence that LLP smoothing is negatively associated with systemic risk in the US banking industry through its function of counter-cyclically accumulating loan loss reserves, increasing capital sufficiency, and helping buffer against future losses. We also show that the main mechanism for the relation is the common risk exposure of the banking industry rather than bank interconnectedness and that loan types and certain managerial characteristics play an important role in moderating the relation.

Our paper extends, but differs fundamentally from, bank accounting studies on the links of opportunistic earnings management, through LLP and delay in LLP, with bank risk-taking, systemic risk, and financial crisis. For example, Cohen *et al.* (2014) report a positive relation between earnings management via LLP and stock price crash risk for the financial crisis period of the late 2000s, and Ma and Song (2016) document that opportunistic earnings management through LLP increases systemic risk in a non-crisis period. Unlike these studies about the information opacity effect of opportunistic earnings management on crash risk and systemic risk, our paper focuses on LLP smoothing that could be either beneficial or harmful and explores how LLP smoothing's beneficial property of counter-cyclically accumulating loan loss reserves in response to common risk exposure links to systemic risk. We find that our key evidence about the LLP smoothing-systemic risk relation is robust to controlling for opportunistic earnings management. Moreover, in contrast to Bushman and Williams (2015) who examine LLP untimeliness in incorporating future non-performing loans, we target the correlation between LLP and earnings (i.e. LLP smoothing) and show that its negative linkage with systemic risk remains even after we control for LLP untimeliness. Our findings also echo Ahmed and McMartin's (2014) evidence for non-financial firms that earnings smoothing improves stock returns during crisis times by alleviating investors' perceived risk. However, different from Ahmed and McMartin (2014), we study financial firms and focus on the counter-cyclical cushioning property of LLP smoothing and its association with sector-wide systemic risk in both crisis and non-crisis periods.

Second, this paper contributes to the literature on earnings smoothing and bank-specific risk. Our finding that higher managerial risk-taking incentives weaken the negative relation between LLP smoothing and systemic risk is in line with Bushman and Williams' (2012) evidence that, in an international setting, opportunistic LLP smoothing increases bank risk-taking by increasing information opacity. However, different from Bushman and Williams (2012), we find that in the US setting, LLP smoothing is insignificantly associated with bank-specific risk. The different findings in the two studies may be due to the different natures of LLP smoothing in the United States and the international setting, as explained above. Our results also imply that LLP smoothing in the United States may have less opportunistic connotations and exhibit more beneficial features that help counteract the harmful effects of opportunistic LLP smoothing on bank risk.

Third, our research is relevant to a broad literature on the link between governance mechanism and financial crisis. Prior studies find that countries and firms with strong corporate governance (better protection of minority shareholders, better accounting quality, more outside ownership, etc.) suffered less in the 1997–1998 "Asian Crisis" (Johnson *et al.*, 2000; Mitton, 2002), and firms with high financial reporting transparency had low liquidity risk in the 2008–2009 global financial crisis (Lang and Muffet, 2012). Extending these studies, we show that external monitoring mechanisms by debtholders, financial analysts, and Big-Four auditors enhance the effects of LLP smoothing in reducing systemic risk.

Finally, our study has important policy implications for economic policymakers, the SEC, and accounting standard setters. Our findings that a negative link between LLP smoothing and systemic risk persists in both crisis and non-crisis times but is stronger in non-crisis times suggest that LLP smoothing accumulates precautionary cushions that help restrain risk build-up in the financial system over time and is important in preventing the occurrence of financial crisis. This is consistent with Adrian and Brunnermeier (2016, p. 1730), who state: "During financial crises or periods of financial intermediary distress, tail events tend to spill across financial institutions. Such spillovers are preceded by a risk-buildup phase. Both elements are important contributors to financial system risk." Moreover, our results suggest that although beneficial LLP smoothing works to dampen systemic risk during crises, such effect is not as strong as in non-crisis periods. This is understandable and no surprise—as a discretionary accounting choice, LLP smoothing has its limits in addressing a severe financial crisis. Relatedly, this evidence implies that during crisis times, policymakers should rely more on radical and powerful interventions to constrain the spread of financial distress. Overall, our results showing that LLP smoothing does not increase bank-specific risk and can also helps constrain systemic risk suggest that for the US banking sector, LLP smoothing on average exhibits a beneficial effect in stabilising the financial system.

The remainder of this paper is organised as follows: Section II describes the research design, section III presents the main empirical results, section IV presents further analyses and robustness checks, and section V concludes the paper. Appendix A provides detailed definitions of the variables, and Appendix B reports the validity check of our LLP smoothing measures.

II. Research Design

2.1 Measurement for Earnings Smoothing via LLP

Our measures for LLP smoothing draw on the relation between LLP and pre-LLP earnings expressed in the LLP prediction model below, which extends the LLP models in

Ahmed *et al.* (1999), Liu and Ryan (2006), Nichols *et al.* (2009), and Bushman and Williams (2012):

$$LLP_{it} = \alpha_{0i} + \alpha_{1i}EBLLP_{it} + \alpha_{2i}NPL_{it} + \alpha_{3i}DNPL_{it+1} + \alpha_{4i}CAP_{it-1} + \alpha_{5i}LLA_{it-1} + \alpha_{6i}NCO_{it} + \alpha_{7i}DLOAN_{it} + \alpha_{8i}Q4_{it} + \varepsilon_{it}, \quad (1)$$

where, for bank *i* and fiscal quarter *t*, LLP_{it} refers to the ratio of LLP in the quarter to quarter-beginning total loans, and $EBLLP_{it}$ is pre-LLP earnings and is measured as the ratio of income before tax and LLP in the quarter to quarter-beginning total loans, following Ahmed *et al.* (1999) and Bushman and Williams (2012). NPL_{it} and $DNPL_{it+1}$ refer to non-performing loans (NPL) at the end of fiscal quarter *t* and their changes from fiscal quarters *t* to *t+1*, respectively, with both scaled by total loans at the beginning of quarter *t*. These two variables reflect current credit risk and its future change that need to be covered by LLP, and they are expected to be positively associated with LLP (Ahmed *et al.,* 1999; Liu and Ryan, 2006; Bushman and Williams, 2012). $DNPL_{it+1}$ also captures the forward-looking portion of LLP, and its coefficient reflects the degree of timeliness with which current provisions anticipate future credit risk (Nichols *et al.,* 2009; Beatty and Liao, 2011; Bhat *et al.*, 2019; Bushman and Williams, 2012, 2015). Tier-one risk-adjusted capital ratio of the previous quarter-end, denoted by CAP_{it-1}, controls for the effect of regulatory capital on LLP, and its coefficient should be positive (Ahmed *et al.,* 1999; Liu and Ryan, 2006; Bushman and Williams, 2012). Following Laeven and Majnoni (2003) and Nichols *et al.* (2009), we also include the following variables as additional LLP determinants: the ratio of loan loss allowance to quarter-beginning total loans LLA_{it-1}, the ratio of net loan charge-offs to quarter-beginning total loans NCO_{it}, and loan growth $DLOAN_{it}$. $Q4_{it}$ is an indicator variable for the fourth fiscal quarter that captures the special change in discretionary LLP at fiscal year-end due to financial statement auditing (Liu *et al.*, 1997). All input variables are winsorised by the 1st and 99th percentiles of their full sample empirical distributions. We require at least fifteen quarters' observations for each bank and use OLS regression with fixed effects to estimate Model (1) for each bank.

Our first LLP smoothing measure is the bank-specific coefficient on *EBLLP*. It should be positive if banks smooth their income via LLP because with an increase in earnings before LLP, banks are more likely to increase LLP to deflate reported earnings. This coefficient-based smoothing measure is widely used in prior research (e.g. Moyer, 1990; Beatty *et al.,* 1995; Collins *et al.,* 1995; Ahmed *et al.,* 1999; Laeven and Majnoni, 2003; Liu and Ryan, 2006; Bushman and Williams, 2012). To filter out potential measurement errors and model misspecifications such as nonlinearities, we use the percentile ranking of the *EBLLP* coefficient, *Ellp*, as the main smoothing proxy.

Since *Ellp* is estimated from OLS regressions in the full sampling period, it keeps constant over time for a particular bank but differs in the cross-section. The rationale for adopting this classical measure is that our focus is LLP smoothing over a long period of time and across business cycles. In addition, the LLP smoothing practice of a given bank is relatively stable over time, mainly because the ability and style of its CEO and CFO remain relatively constant throughout their incumbency, which can translate into a stable pattern of earnings smoothing practice (see Ge *et al.*, 2011; Demerjian *et al.*, 2013; Bouwman, 2014).[7] Moreover, the business model of a bank, which is sticky in the time series, also shapes the time-invariant nature of its earnings smoothing. Lastly, the consistency principle of the GAAP rule requires a relatively consistent LLP accounting policy over time.

Table 1 Statistics of Loan Loss Provision Model Inputs and Estimates

Panel A: Descriptive statistics for variable inputs in Model (1)

Variable	Mean	Median	STD	Q1	Q3
LLP	0.0013	0.0007	0.0022	0.0003	0.0013
EBLLP	0.0069	0.0068	0.0046	0.0032	0.0135
NPL	0.0131	0.0080	0.0160	0.0042	0.0152
DNPL	0.0005	0.0000	0.0046	-0.0009	0.0013
CAP	0.1110	0.1060	0.0300	0.0880	0.1270
LLA	0.0146	0.0134	0.0070	0.0107	0.0168
*NCO(*100)*	0.0942	0.0386	0.1873	0.0039	0.1037
DLOAN	0.0318	0.0214	0.0645	0.0019	0.0451

Panel B: Descriptive statistics for estimates from OLS regression in Model (1)

Intercept and Coefficients	Mean	Median	STD	Q1	Q3	Q3-Q1
Intercept	0.001	0.001	0.004	0.000	0.002	0.002
t-stat	(7.26)***					(17.20)***
Ellp(Raw)	0.019	0.019	0.223	-0.038	0.106	0.144
t-stat	(2.14)**					(11.65)***
NPL	0.050	0.041	0.077	0.008	0.085	0.077
t-stat	(16.01)***					(19.15)***
DNPL	0.027	0.015	0.091	-0.018	0.060	0.078
t-stat	(7.33)***					(19.73)***
CAP	-0.003	-0.001	0.040	-0.001	0.007	0.008
t-stat	(-1.88)*					(8.08)***
LLA	-0.090	-0.055	0.176	-0.145	0.003	0.148
t-stat	(-12.50)***					(18.02)***
*NCO(*100)*	0.005	0.005	0.006	0.001	0.008	0.007
t-stat	(-19.41)***					(17.90)***
DLOAN	0.002	0.001	0.008	-0.001	0.003	0.004
t-stat	(4.89)***					(11.73)***
Q4(/100)	0.009	0.001	0.071	-0.013	0.022	0.035
t-stat	(3.11)***					(15.94)***
Avg. R-sqr	0.739	0.782	0.188	0.605	0.892	0.194

[7] In particular, Demerjian *et al.* (2013) report that more capable managers are associated with higher earnings quality. Ge *et al.* (2011) directly link CFO personal traits (e.g. age and education) to earnings smoothing, and Bouwman (2014) shows that optimistic CEOs smooth earnings more than rational CEOs. We notice, however, that management characteristics may at the same time affect a bank's contribution to systemic risk. Therefore, in a later part of this paper, we specifically examine management characteristics in our analyses of the LLP smoothing-systemic risk relation.

Notes:
Panel A reports the descriptive statistics for the input variables used in the LLP expectation model specified in Model (1) below. Panel B presents the average coefficient estimates and R-Squared (*Avg. R-sqr*) from OLS regressions of *LLP* on income before LLP and tax *EBLLP* and other controls using Model (1), as well as their distributional statistics. In Panel B, *Ellp(Raw)* refers to the coefficient on *EBLLP*. The sample includes 21,174 bank-quarters for 601 US commercial banks for all fiscal quarters from 1993 to 2009.

$$LLP_{it} = \alpha_{0i} + \alpha_{1i}EBLLP_{it} + \alpha_{2i}NPL_{it} + \alpha_{3i}DNPL_{it+1} + \alpha_{4i}CAP_{it-1} + \alpha_{5i}LLA_{it-1} + \alpha_{6i}NCO_{it} + \alpha_{7i}DLOAN_{it} + \alpha_{8i}Q4_{it} + \varepsilon_{it}, \quad (1)$$

where NPL_{it} and $DNPL_{it+1}$ denote non-performing loans for bank i at the end of fiscal quarter t and its future change over the fiscal quarter $t+1$, respectively. CAP_{it-1} is tier-one capital ratio, and LLA_{it-1} is loan loss allowance in the previous quarter $t-1$. NCO_{it} is net loan charge-offs, and $DLOAN_{it}$ denotes loan growth. $Q4_{it}$ is a dummy variable for the fourth fiscal quarter.

Nevertheless, in order to show that our results are not sensitive to the time-invariant LLP smoothing measure, we also adopt a time-varying proxy for LLP smoothing in our main tests, *Ellp_bank*, which is measured as the percentile ranking of the product of pre-LLP and pre-tax earnings *EBLLP* and its estimated coefficient in Model (1). This time-varying measure captures the different magnitudes of cushions created through LLP smoothing over time and acts as a supplement to the time-invariant measure.

Table 1 reports the descriptive statistics of model inputs and the OLS estimation results (i.e. intercepts and coefficients) for the LLP model specified in Model (1) using 21,174 bank-quarters for 601 banks in the United States from 1993 to 2009, with Panel A presenting the descriptive statistics of the variables used in the model and Panel B reporting the results for estimating Model (1) using income before LLP and tax (*EBLLP*) as earnings input. Consistent with Ahmed *et al.* (1999), Liu and Ryan (2006), and Bushman and Williams (2012), Panel A shows that banks on average have positive LLP and positive pre-LLP earnings. As revealed in Panel B, the mean raw value of the coefficients on *EBLLP*, *Ellp(Raw)*, is 0.019 and statistically significant, which is comparable to the result in Ahmed *et al.* (1999), who report a mean coefficient of 0.036 on *EBLLP* from a simpler LLP model for the sample period of 1986 to 1995. The mean coefficient on subsequent NPL changes, *DNPL*, is 0.027, suggesting that banks provision LLP for potential loan losses from future credit risk deterioration and confirming the forward-looking nature of LLP in incorporating future credit risk documented in prior studies (Nichols *et al.,* 2009; Beatty and Liao, 2011; Bushman and Williams, 2012). In line with Liu and Ryan (2006) and Bushman and Williams (2012), the mean coefficient on tier-one capital ratio *CAP* is -0.003.

In robustness checks, we adopt several other metrics to measure LLP smoothing. The first one is the percentile ranking of coefficient-based LLP smoothing measure, *Ellp2*, estimated from Model (1) that uses the ratio of net income after tax but before LLP to total loans to measure *EBLLP*, following Liu and Ryan (2006).[8] The second one is the percentile ranking of incremental R-Squared, *IncRsqr*, computed by taking the difference in R-Squared

8 This measure draws on the rationale that banks normally manage bottom-line after-tax earnings. We note, however, that this measurement also captures earnings management driven by tax-related incentives, which adds noise to our research purpose.

between Model (1) above and Model (2) below which removes *EBLLP* from Model (1). This measure follows the rationale of Beatty and Liao (2011) and reflects the incremental explanatory power of pre-LLP earnings for (discretionary) LLP behaviours, with a higher value indicating more LLP smoothing.

$$LLP_{it} = \beta_{0i} + \beta_{1i}NPL_{it} + \beta_{2i}DNPL_{it+1} + \beta_{3i}CAP_{it-1} + \beta_{4i}LLA_{it-1} + \beta_{5i}NCO_{it} + \beta_{6i}DLOAN_{it} + \beta_{7i}Q4_{it} + \zeta_{it} \quad (2)$$

The third and fourth alternative LLP smoothing metrics used in the robustness checks are also based on the coefficient of income before tax and before LLP but follow the LLP prediction model in Bushman and Williams (2015). The Bushman-Williams LLP prediction model is more appropriate for estimating the delay of LLP in incorporating future non-performing loans rather than LLP smoothing *per se*. We denote the percentile ranking of this measure by *Ellp_BW* and its corresponding time-varying version by *Ellp_bank_BW*. The last LLP smoothing measure we adopt is the percentile ranking of quarterly changes of income before tax and before LLP, denoted by *DeltaEbllp*, following Kanagaretnam *et al.*'s (2004) intuition that banks with higher earnings variations have stronger incentives to smooth earnings.

2.2 Measurement for Systemic Risk

We measure a bank's contribution to systemic risk on the basis of the *CoVaR* concept in Adrian and Brunnermeier (2016), which captures systemic risk in the financial industry conditional on a particular financial institution being in distress. In the existing bank risk literature and practice, the distress risk of a bank is indicated as the q% (e.g. 1% or 5%) VaR of its total asset return, meaning that with q% probability, total asset return is equal to or below $\text{VaR}_{q\%}$ over a given time horizon. On the basis of the *CoVaR* concept and the VaR-based bank risk measure, Adrian and Brunnermeier (2016) develop a proxy for a bank's contribution to systemic risk (i.e. $\Delta CoVaR$), which is measured by the difference between the $\text{VaR}_{q\%}$ of total asset return in the banking industry conditional on (1) the bank's total asset return being at its q% VaR and (2) the bank's total asset return being in its median state. This systemic risk measure is well recognised in the literature (e.g. Boyson *et al.*, 2010; Gauthier *et al.*, 2012). To effectively examine systemic risk in equity markets, we extend the *CoVaR* framework to develop a measure for a bank's contribution to systemic risk based on the 1% VaR of stock returns for an individual bank and the financial industry, following Bushman and Williams (2015). Specifically, we define bank i's contribution to systemic risk at the end of fiscal quarter t, denoted by $\Delta CoVaR(Raw)_{it}$, as negative one times the difference of the 1% VaR of stock return in the financial sector when bank i's stock return is at its 1% VaR and in its median state.

Our systemic risk measure is suited to the purpose of this study. First, in order to examine systemic risk in equity markets, we use stock returns to gauge a bank's contribution to systemic risk, a way that is consistent with Bushman and Williams (2015). Second, our measure is forward looking by projecting current bank characteristics (e.g. bank size, leverage, and maturity mismatch) to future risk contagion, and it incorporates the effects of macroeconomic factors on stock returns. Finally, and more importantly, our *CoVaR*-based measure facilitates examining the two potential mechanisms of systemic risk: common risk exposure and bank interconnectedness.

$\Delta CoVaR$ can be estimated in multiple ways. Following Boyson *et al.* (2010), Bushman and Williams (2015), and Adrian and Brunnermeier (2016), we use the quantile regression method to estimate the conditional VaR of stock market return in the banking sector for a given probability (quantile) $q\%$ when a bank's stock return is at its $p\%$ VaR ($p\%$ = 50% corresponds to the median state). Quantile regressions make no distributional assumptions, are estimable for a large range of possible quantiles, and allow heteroskedasticity (Boyson *et al.*, 2010). Specifically, we first run 1% quantile regressions of weekly stock returns for individual banks and the financial sector over a rolling window of one hundred weeks using Models (3) and (4) below:

$$R_w^i = \alpha^i{}_{1\%} + \beta^i{}_{1\%} Z_{w-1} + \varepsilon_w^i \tag{3}$$

$$R_w^{system} = \alpha^{system|i}{}_{1\%} + \beta_1^{system|i}{}_{1\%} Z_{w-1} + \beta_2^{system|i}{}_{1\%} R_w^i + \varepsilon_w^{system|i}, \tag{4}$$

where R_w^i is stock return for bank i in week w, and R_w^{system} is the corresponding value-weighted average equity return of the financial system. Z_{w-1} is a vector of state variables including the following macroeconomic and financial variables lagged by one week: market return, equity volatility, short-term liquidity risk, interest rate risk, term structure, default risk, and real estate return.[9]

We then use the predicted values from both models to obtain the 1% VaR of stock return for bank i in week w and the corresponding 1% *CoVaR* for the financial industry, as shown below:

$$VaR_{w1\%}^i = \hat{\alpha}_{1\%}^i + \hat{\beta}_{1\%}^i Z_{w-1} \tag{5}$$

$$CoVaR_{w1\%}^i = \hat{\alpha}^{system|i}{}_{1\%} + \hat{\beta}_1^{system|i}{}_{1\%} Z_{w-1} + \hat{\beta}_2^{system|i}{}_{1\%} VaR_{w1\%}^i, \tag{6}$$

where $CoVaR_{w1\%}^i$ indicates the 1% VaR of value-weighted stock return of the banking sector in week w conditional on bank i's stock return being at its 1% VaR. Similarly, we estimate 1% VaR of stock return in the banking sector when bank i's return is in its median state and denote

[9] We use weekly value-weighted return for all common stocks to proxy for aggregate market return. Equity volatility is the standard deviation of the natural logarithm of one plus daily stock returns over the previous three months. Short-term liquidity risk is the difference between the three-month LIBOR and the three-month US T-bill rate. Interest rate risk is the quarterly change in the three-month US T-bill rate. We use yield spread between the 10-year US T-bond rate and the three-month US T-bill rate to proxy for term structure. Default risk is computed as the difference between the 10-year BAA corporate bond rate and the 10-year US T-bond rate. Weekly real estate return is calculated on the basis of the FEDERAL HOUSING FINANCE AGENCY (FHFA) house price index.

it $CoVaR^{i}_{w50\%}$. Then, bank i's contribution to systemic risk in week w is the difference between the two *CoVaR*s:

$$\Delta CoVaR^{i}_{w1\%} = CoVaR^{i}_{w1\%} - CoVaR^{i}_{w50\%} \tag{7}$$

We measure bank i's contribution to systemic risk in fiscal quarter t as the sum of weekly $\Delta CoVaR^{i}_{w1\%}$ across the quarter multiplied by negative one, such that a higher value indicates a higher contribution to systemic risk. We take the percentile ranking of the value as the main measure for bank i's contribution to systemic risk and denote it $\Delta CoVaR_{it}$. To check whether the measure is sensitive to different probability levels of VaR, we also adopt another ranked metric, $\Delta CoVaR5_{it}$, based on the 5% VaR of stock return for robustness check. In Appendix B, we provide a detailed validation check for systemic risk measures in this paper and prior studies.

2.3 Baseline Regression Model

We use the following model to examine the lead-lag relation between LLP smoothing and a bank's contribution to systemic risk:

$$\Delta CoVaR_{it} = \varphi_0 + \varphi_1 SMOOTH_{it-1} + Controls_{it-1} + \mu_{it}, \tag{8}$$

where $\Delta CoVaR_{it}$ refers to measures for bank i's contribution to systemic risk in quarter t. $SMOOTH_{it-1}$ denotes LLP smoothing measures in the previous quarter: the time-invariant *Ellp* and the time-varying *Ellp_bank*, or other smoothing measures used in robustness checks. Following Bushman and Williams (2015), Adrian and Brunnermeier (2016), and Brunnermeier *et al.* (2020), we include a set of control variables $Controls_{it-1}$ at the end of quarter t-1: the market-to-book ratio (*MB*), return on assets in the prior quarter (*ROA*) and in the current quarter (*ROA2*), market beta (*Beta*), equity return volatility (*Sigma*), the natural logarithm of market value (*Size*) and its square (*Size_sqr*), maturity mismatch (*Mismatch*), tier-one capital ratio (*CAP*), and bank business model (*Niir*) measured as the ratio of non-interest income to total income. We also control for market-based variables such as return momentum (*Mom*), relative skewness of stock return to the market (*Coskew*), and relative kurtosis of stock return to the market (*Cokurt*). Appendix A provides detailed definitions of these variables. If earnings smoothing in general exhibits a negative relation with a bank's contribution to systemic risk, we expect to observe $\varphi_1 < 0$. To estimate Model (8), we use OLS regressions with t-statistics adjusted for bank and time (year and quarter) clusters.

III. Main Empirical Results

3.1 Data Sources, Sampling, and Descriptive Statistics

Our sample consists of bank-quarters for publicly traded commercial banks in the US stock markets of NYSE, NASDAQ, and AMEX from 1993 to 2009. We retrieve financial statement data from quarterly Compustat, the Report of Condition and Income ("Call Report"), or the FR Y-9C report filed with the Federal Reserve Board by a commercial bank or a bank holding company. We obtain stock return data from CRSP, CEO stock option compensation data from ExecuComp, and gender information for executives from the Institutional Shareholder Services (ISS) database. We first estimate LLP smoothing measures for each bank, as well as measures for a bank's contribution to systemic risk. We then match both types of measures with the control variables used in main empirical analyses. We omit observations with missing main measures for LLP smoothing and systemic risk and missing values for control variables, and winsorise all variables at the 1st and 99th percentiles of their empirical distributions. The final sample contains an unbalanced panel of 601 unique banks and 21,174 bank-quarters.

Table 2 Descriptive Statistics and Correlation Matrix for Variables Used in Empirical Analysis

Panel A: Statistical summary for variables used in the main tests

Variable	N	Mean	Median	STD	Q1	Q3
ΔCoVaR(Raw, %)	21174	23.297	20.538	18.990	10.768	32.059
ΔCoVaR	21174	0.544	0.567	0.286	0.308	0.790
Ellp(Raw)	21174	0.027	0.021	0.191	-0.036	0.106
Ellp	21174	0.514	0.527	0.282	0.273	0.762
Ellp_bank(Raw, %)	20934	0.024	0.012	0.139	-0.022	0.074
Ellp_bank	20934	0.517	0.530	0.287	0.271	0.766
Ellp2	21174	0.515	0.538	0.280	0.274	0.746
IncRsqr	21174	0.490	0.485	0.285	0.232	0.739
Ellp_BW	21124	0.494	0.497	0.279	0.248	0.737
Ellp_bank_BW	19967	0.506	0.513	0.284	0.259	0.753
MB	21174	1.685	1.579	0.751	1.173	2.080
ROA(%)	21174	0.237	0.269	0.312	0.184	0.341
Sigma(%)	21174	0.371	0.310	0.235	0.229	0.432
Beta	21174	0.532	0.381	0.532	0.117	0.871
Mismatch	21174	-0.060	-0.047	0.046	-0.075	-0.030
Size	21174	5.502	5.129	1.833	4.165	6.535
Size_sqr	21174	33.635	26.305	23.374	17.350	42.701
CAP	21174	11.177	10.700	3.631	8.860	12.760
Niir	21174	0.879	0.729	14.533	0.477	0.997
Mom	21174	0.056	0.049	0.204	-0.061	0.173
Coskew	21174	-0.055	-0.039	0.191	-0.149	0.064
Cokurt	21174	1.221	0.947	1.289	0.251	1.941
RGDP	21174	2.604	2.900	2.062	1.600	4.200
IncInfo	21004	0.178	0.146	0.965	-0.229	0.544

Panel B: Correlation matrix for LLP smoothing and systemic risk measures

	ΔCoVaR	*Ellp*	*Ellp_bank*	*Ellp2*	*IncRsqr*	*Ellp_BW*	*Ellp_bank_BW*
ΔCoVaR	1						
Ellp	-0.114***	1					
Ellp_bank	-0.104***	0.934***	1				
Ellp2	-0.156***	0.677***	0.639***	1			
IncRsqr	-0.147***	0.275***	0.276***	0.090***	1		
Ellp_BW	-0.067***	0.587***	0.551***	0.426***	0.226***	1	
Ellp_bank_BW	-0.048***	0.552***	0.579***	0.398***	0.228***	0.942***	1

Notes:
Panel A reports the descriptive statistics for the measures of LLP smoothing (*Ellp*, *Ellp(Raw)*, *Ellp_bank*, *Ellp_bank(Raw)*, *Ellp2*, *IncRsqr*, *Ellp_BW*, *Ellp_bank_BW*) and systemic risk ($\Delta CoVaR$, $\Delta CoVaR(Raw)$), as well as other variables used in the main empirical tests. Panel B reports the Pearson correlations among the ranked LLP smoothing and systemic risk measures. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively. Detailed definitions of each variable are provided in Appendix A.

Table 2 provides the descriptive statistics for the variables included in our empirical analyses, with a statistical summary for the testing and control variables in Panel A and the Pearson correlations among the testing variables (e.g. contribution to systemic risk and LLP smoothing measures) in Panel B. As shown in Panel A, the mean values of the two main LLP smoothing measures before rank transformation, *Ellp(Raw)* and *Ellp_bank(Raw)* (in percentage), are 0.027 and 0.024, respectively.[10] The corresponding ranked measures *Ellp* and *Ellp_bank* share similar means (0.514 and 0.517, respectively), as well as similar standard deviations and quantiles, implying that they refer to similar relative levels of earnings smoothing via LLP. Panel B shows that all the ranked LLP smoothing metrics are significantly positively correlated with each other, although with various correlation levels. More importantly, the ranked measure for a bank's contribution to systemic risk $\Delta CoVaR$ possesses significantly negative correlations with all LLP smoothing proxies, with their correlation coefficients ranging from -0.048 to -0.156. Though only suggestive of the underlying relation, these correlations imply that LLP smoothing is negatively linked to systemic risk in the stock market. Nonetheless, the result can be spurious without controlling for other determinants of systemic risk. Therefore, we conduct multivariate regression analyses in the next section and in the robustness checks to better evaluate the association between LLP smoothing and a bank's contribution to systemic risk.

3.2 The Relation between LLP Smoothing and a Bank's Contribution to Systemic Risk

Table 3 presents the OLS regression results for testing the link between earnings smoothing via LLP and a bank's contribution to systemic risk using Model (8). The full-sample regression results in Panel A show that both the time-invariant and time-varying LLP smoothing measures, *Ellp* and *Ellp_bank*, are significantly negatively associated with a bank's contribution to systemic risk measure $\Delta CoVaR$, with the coefficients (*t*-statistics) on *Ellp* and *Ellp_bank* being -0.072 (-2.32) and -0.062 (-2.16), respectively. These results imply that a one percentile increase in LLP smoothing measures *Ellp* and *Ellp_bank* corresponds to a decrease in $\Delta CoVaR$ of 0.072 percentile and 0.062 percentile, respectively. The evidence suggests that,

[10] Note that the statistics for *Ellp(Raw)* reported here are different from those in Table 1. The reason is that the statistics for the LLP smoothing measures reported in Table 2 are computed from a pooled sample of all bank-quarters, whereas those in Table 1 are calculated across banks. An untabulated analysis shows that when Table 1 reports the statistics for estimated coefficients in Panel B for all bank-quarters rather than for each bank, the statistics for *Ellp(Raw)* would be the same as those reported in Table 2.

Table 3 Relation between LLP Smoothing and a Bank's Contribution to Systemic Risk

Panel A: OLS regression results for the full sample

	Dependent Variable: $\Delta CoVaR$		Dependent Variable: $\Delta CoVaR$	
	coef	*t*-stat	coef	*t*-stat
Intercept	-0.218	(-2.92)***	-0.225	(-3.02)***
Ellp	**-0.072**	**(-2.32)****		
Ellp_bank			**-0.062**	**(-2.16)****
MB	0.012	(1.21)	0.012	(1.16)
ROA	-0.004	(-0.51)	-0.006	(-0.74)
ROA2	-0.005	(-0.68)	-0.009	(-1.06)
Sigma	0.086	(3.57)***	0.087	(3.61)***
Beta	0.023	(1.84)*	0.023	(1.80)*
Mismatch	-0.010	(-0.08)	-0.019	(-0.14)
Size	0.157	(7.73)***	0.160	(7.89)***
Size_sqr	-0.007	(-4.66)***	-0.007	(-4.83)***
CAP	0.000	(0.14)	0.000	-0.16
Niir	0.000	(1.79)*	0.000	(2.12)**
Mom	-0.067	(-5.77)***	-0.066	(-5.62)***
Coskew	0.005	(0.23)	0.006	(0.26)
Cokurt	0.010	(2.30)**	0.010	(2.30)**
Years & Quarters	Yes		Yes	
Obs.	21,174		20,934	
Adjusted R-sqr	0.358		0.356	

Panel B: OLS regression results for subsamples split by business cycle

	Dependent Variable: $\Delta CoVaR$				Dependent Variable: $\Delta CoVaR$			
	BOOM Subsample		BUST Subsample		BOOM Subsample		BUST Subsample	
	Coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
Intercept	-0.085	(-1.12)	-0.129	(-1.27)	-0.102	(-1.35)	-0.114	(-1.15)
Ellp	**-0.076**	**(-2.47)****	**-0.062**	**(-1.67)***				
Ellp_bank					**-0.065**	**(-2.25)****	**-0.058**	**(-1.65)***
MB	0.014	(1.35)	-0.004	(-0.29)	0.014	(1.30)	-0.003	(-0.25)
ROA	0.003	(0.28)	-0.016	(-1.95)*	0.000	(0.02)	-0.015	(-1.81)*
ROA2	-0.008	(-0.65)	-0.004	(-0.57)	-0.011	(-0.86)	-0.010	(-1.29)
Sigma	0.052	(1.51)	0.055	(2.00)**	0.053	(1.52)	0.062	(2.19)**
Beta	0.022	(1.71)*	0.050	(2.12)**	0.022	(1.67)*	0.052	(2.24)**
Mismatch	-0.028	(-0.20)	0.062	(0.33)	-0.035	(-0.25)	0.041	(0.22)
Size	0.148	(7.14)***	0.195	(6.78)***	0.152	(7.32)***	0.181	(6.08)***
Size_sqr	-0.006	(-4.09)***	-0.010	(-5.43)***	-0.006	(-4.26)***	-0.010	(-4.80)***
CAP	0.001	(0.31)	-0.003	(-0.98)	0.001	(0.34)	-0.003	(-1.02)
Niir	0.000	(0.25)	0.000	(2.11)**	0.000	(0.20)	0.000	(2.60)***
Mom	-0.045	(-3.41)***	-0.112	(-3.73)***	-0.044	(-3.30)***	-0.100	(-3.34)***
Coskew	-0.004	(-0.17)	0.082	(1.73)*	-0.003	(-0.15)	0.074	(1.50)
Cokurt	0.009	(1.89)*	0.015	(1.59)	0.009	(1.85)*	0.015	(1.57)
Years & Quarters	Yes		Yes		Yes		Yes	
Obs.	18,167		3,007		17,949		2,985	
Adjusted R-sqr	0.343		0.356		0.341		0.353	

Notes:

This table presents the OLS estimation results for regressing a bank's contribution to systemic risk on LLP smoothing and other control variables using Model (8) below, with Panel A reporting results for the full sample and Panel B reporting results for the subsamples partitioned by the boom (BOOM) versus bust (BUST) times of the business cycle.

$$\Delta CoVaR_{it} = \varphi_0 + \varphi_1 SMOOTH_{it-1} + Controls_{it-1} + \mu_{it}, \quad (8)$$

where $\Delta CoVaR$ refers to the percentile ranked measure for a bank's contribution to systemic risk $\Delta CoVaR$. *SMOOTH* refers to LLP smoothing measure *Ellp* or *Ellp_bank*. *Controls* includes the market-to-book ratio

(*MB*), lagged return on assets (*ROA*) and its contemporaneous value (*ROA2*), stock return beta (*Beta*), maturity mismatch variable (*Mismatch)*, equity return volatility (*Sigma*), bank size (*Size*) and its square (*Size_sqr*), tier-one capital ratio (*CAP*), business model (*Niir*), momentum (*Mom*), the relative skewness of stock return to the market (*Coskew*), and the relative kurtosis of stock return to the market (*Cokurt*). Variable definitions are provided in Appendix A. *t*-statistics are adjusted for time clusters, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

in general, banks with higher-level LLP smoothing are associated with less contribution to systemic risk. To test the sensitivity of the above results to the ranking scheme used for measuring earnings smoothing and a bank's contribution to systemic risk, we alternatively use the unranked values of LLP smoothing and systemic risk measures. Untabulated analyses show that the results remain qualitatively unchanged.

The results for the control variables in Panel A are generally consistent with those in Bushman and Williams (2015), Adrian and Brunnermeier (2016), and Brunnermeier *et al.* (2020). Specifically, bank size, beta, equity return volatility (*Sigma*), co-kurtosis, and bank business model (*Niir*) are significantly positively associated with a bank's contribution to systemic risk, whereas return momentum and squared size are significantly negatively associated with it. Other control variables do not have consistent and significant coefficients. The positive coefficient on bank size suggests that stock price crashes of large banks contribute more to sector-wide systemic risk, consistent with the "too-big-to-fail" argument. Though the coefficient on squared bank size is negative, its magnitude is small, implying that the "too-big-to-fail" phenomenon overwhelmingly persists.

We next explore whether the LLP smoothing-systemic risk association has different realisations in different macroeconomic conditions characterised by business cycle stages (i.e. over bust versus boom periods). Specifically, we partition the full sample into bust period (*BUST*) and boom period (*BOOM*) subsamples. We use the NBER business cycle classifications to assign quarterly observations into the *BUST* subsample if they are within the contraction periods and into the *BOOM* subsample otherwise.[11] We then re-estimate Model (8) for each subsample. The results reported in Panel B of Table 3 show that for both subsamples, the LLP smoothing measures *Ellp* and *Ellp_bank* are significantly negatively associated with a bank's contribution to systemic risk, *ΔCoVaR*, consistent with the full-sample results. Notably, however, the LLP smoothing and systemic risk relation is relatively stronger in the *BOOM* subsample, with magnitudes and *t*-statistics for the LLP smoothing coefficients larger than those in the *BUST* subsample. For example, *Ellp* has a coefficient of -0.076 and a *t*-statistic of -2.47 in the *BOOM* subsample, while in the *BUST* subsample, the coefficient reduces (in magnitude) to -0.062 and the *t*-statistic also decreases. Therefore, consistent with the implication of the counter-cyclical cushioning role of earnings smoothing,

[11] Contraction periods refer to the periods between peak dates and subsequent trough dates, which in our sample fall into the second to the fourth quarter in 2001, all quarters in 2008, and the first two quarters in 2009. Also, we understand that the notation of *BOOM* actually refers to the non-*BUST* (or non-crisis) period, including the expansion period and the period leading up to the bust.

Panel B reveals that the negative LLP smoothing-systemic risk relation is manifested more during non-crisis times, although the relation is qualitatively unchanged in bust periods.

3.3 Mechanisms for the Relation between LLP Smoothing and Systemic Risk: Common Risk Exposure and Bank Interconnectedness

Adrian and Brunnermeier (2016) suggest that systemic risk operates through two mechanisms: common risk exposure of the banking industry and bank interconnectedness. In this section, we explore whether and how LLP smoothing is linked to systemic risk through these mechanisms. We expect that the counter-cyclical cushioning property of LLP smoothing hinges more on common risk exposure. We use real GDP growth in a quarter, *RGDP*, to measure common risk exposure, with the top (bottom) *RGDP* tertile indicating high (low) exposure level. We measure the interconnectedness of an individual bank, denoted by *OUT*, as the number of banks that are significantly Granger-caused by the bank in a quarter, calculated on the basis of the principal component analysis (PCA) and Granger-causality networks of monthly stock returns of all commercial banks in our sample using a rolling window of 36 months, extending Billio *et al.* (2012). The top (bottom) tertile indicates a high (low) level of bank interconnectedness. We estimate the baseline model for two sets of paired subsamples: (1) subsamples with the top tertile real GDP growth *High RGDP* versus the bottom tertile *Low RGDP*; (2) subsamples with the top tertile bank interconnectedness *High OUT* versus the bottom tertile *Low OUT*. Table 4 reports the results.

Table 4 Mechanisms for the Relation between LLP Smoothing and Systemic Risk: Common Risk Exposure and Bank Interconnectedness

Panel A: OLS regression results for subsamples of common risk exposure

	Dependent Variable: $\Delta CoVaR$				Dependent Variable: $\Delta CoVaR$			
	High RGDP Subsample		Low RGDP Subsample		High RGDP Subsample		Low RGDP Subsample	
	Coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
Intercept	-0.171	(-1.82)*	-0.121	(-1.28)	-0.150	(-1.68)*	-0.006	(-0.05)
Ellp	**-0.097**	**(-2.68)*****	-0.049	(-1.31)				
Ellp_bank					**-0.085**	**(-2.55)****	-0.045	(-1.30)
MB	0.009	(0.67)	0.004	(0.35)	0.009	(0.63)	0.004	(0.34)
ROA	0.005	(0.25)	-0.007	(-0.90)	-0.001	(-0.07)	-0.007	(-0.94)
ROA2	0.018	(0.86)	-0.011	(-1.57)	0.022	(1.01)	-0.013	(-1.79)*
Sigma	-0.016	(-0.36)	0.110	(4.76)***	-0.016	(-0.35)	0.111	(4.82)***
Beta	0.014	(0.61)	0.020	(1.02)	0.012	(0.51)	0.020	(1.02)
Mismatch	-0.026	(-0.14)	0.096	(0.59)	-0.030	(-0.16)	0.087	(0.53)
Size	0.141	(5.64)***	0.166	(5.91)***	0.144	(5.79)***	0.166	(5.86)***
Size_sqr	-0.005	(-2.69)***	-0.008	(-4.21)***	-0.005	(-2.82)***	-0.008	(-4.20)***
CAP	0.002	(0.88)	-0.003	(-1.11)	0.003	(1.00)	-0.003	(-1.13)
Niir	0.002	(1.79)*	0.000	(2.32)**	0.002	(1.70)*	0.000	(2.71)***
Mom	-0.051	(-2.52)**	-0.124	(-6.69)***	-0.051	(-2.48)**	-0.123	(-6.62)***
Coskew	-0.016	(-0.44)	0.011	(0.33)	-0.014	(-0.39)	0.011	(0.32)
Cokurt	0.001	(0.11)	0.024	(2.97)***	0.001	(0.20)	0.025	(3.02)***
Years & Quarters	Yes		Yes		Yes		Yes	
Obs.	7,359		6,673		7,276		6,637	
Adjusted R-sqr	0.346		0.347		0.345		0.345	

Panel B: OLS regression results for subsamples of bank interconnectedness

	Dependent Variable: $\Delta CoVaR$				Dependent Variable: $\Delta CoVaR$			
	High OUT Subsample		Low OUT Subsample		High OUT Subsample		Low OUT Subsample	
	Coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
Intercept	-0.245	(-3.15)***	-0.009	(-0.09)	-0.243	(-3.08)***	-0.026	(-0.29)
Ellp	**-0.061**	**(-1.92)***	**-0.083**	**(-2.32)****				
Ellp_bank					**-0.053**	**(-1.78)***	**-0.072**	**(-2.14)****
MB	0.023	(2.01)**	0.002	(0.14)	0.022	(1.95)*	0.001	(0.11)
ROA	-0.007	(-0.85)	-0.002	(-0.14)	-0.009	(-1.09)	-0.004	(-0.26)
ROA2	-0.003	(-0.49)	-0.011	(-0.74)	-0.007	(-0.93)	-0.014	(-0.83)
Sigma	0.087	(3.46)***	0.074	(2.08)**	0.087	(3.49)***	0.075	(2.09)**
Beta	0.011	(0.69)	0.033	(2.25)**	0.012	(0.71)	0.032	(2.18)**
Mismatch	-0.004	(-0.03)	-0.026	(-0.17)	-0.006	(-0.04)	-0.042	(-0.28)
Size	0.160	(7.23)***	0.153	(6.41)***	0.163	(7.31)***	0.157	(6.57)***
Size_sqr	-0.007	(-4.55)***	-0.006	(-3.63)***	-0.007	(-4.66)***	-0.006	(-3.78)***
CAP	-0.000	(-0.10)	0.001	(0.28)	-0.000	(-0.10)	0.001	(0.31)
Niir	0.000	(2.59)***	0.000	(1.29)	0.000	(3.14)***	0.000	(1.20)
Mom	-0.071	(-4.90)***	-0.056	(-2.96)***	-0.069	(-4.74)***	-0.056	(-2.93)***
Coskew	-0.009	(-0.36)	0.028	(0.90)	-0.007	(-0.28)	0.026	(0.83)
Cokurt	0.009	(1.57)	0.012	(2.11)**	0.009	(1.58)	0.011	(2.04)**
Years & Quarters	Yes		Yes		Yes		Yes	
Obs.	10,488		10,686		10,347		10,587	
Adjusted R-sqr	0.371		0.313		0.369		0.311	

Notes:
This table presents paired top and bottom tertile subsample results for exploring whether the link between LLP smoothing and systemic risk operates via two well-documented mechanisms, common risk exposure and bank interconnectedness, using Model (8) as described in Table 3. We use quarterly real GDP growth (*RGDP*) to proxy for common risk exposure of the banking industry and use stock return interconnectedness *OUT* in Billo *et al.* (2012) to proxy for bank interconnectedness. Panel A reports results for paired subsamples with high versus low quarterly real GDP growth (*High RGDP* versus *Low RGDP*), whereas Panel B reports results for paired subsamples with high versus low stock return interconnectedness (*High OUT* versus *Low OUT*). Variable definitions are provided in Appendix A. *t*-statistics are adjusted for time clusters, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

Panel A of Table 4 shows that the negative relation between LLP smoothing (measured by *Ellp* or *Ellp_bank*) is much stronger and more significant in the high GPD growth subsample. Specifically, for both LLP smoothing measures, the magnitudes of the LLP smoothing coefficient and *t*-statistic in the *High RGDP* subsample are almost double the corresponding values in the *Low RGDP* subsample (-0.097 vs. -0.049 for the coefficient and -2.68 vs. -1.31 for the *t*-statistic in the *Ellp* case; -0.085 vs. -0.045 for the coefficient and -2.55 vs. -1.30 for the *t*-statistic in the *Ellp_bank* case). This evidence supports the notion that common risk exposure may be a potential mechanism for the relation between LLP smoothing and systemic risk and is consistent with the counter-cyclical cushioning property of LLP smoothing while banks accumulate more loan loss reserves when common risk exposure is high during economic booms.

Panel B presents the interconnectedness subsample results. It appears that the negative LLP smoothing-systemic risk association manifests more in the low interconnectedness than in the high interconnectedness subsample. For example, using *Ellp* to measure LLP smoothing, we document a LLP smoothing coefficient of -0.083 for the *Low OUT* subsample, as compared with the coefficient of -0.061 for the *High OUT* subsample. Similar observations are obtained for the *Ellp_bank* case. However, untabulated Z-tests show that the difference in coefficient between the *Low OUT* and the *High OUT* subsamples is statistically insignificant. Therefore, the evidence suggests that bank interconnectedness is unlikely to be a mechanism for the link between LLP smoothing and systemic risk.

3.4 Counter-Cyclicality of LLP Smoothing and the Common Risk Exposure Mechanism

To further explore the mechanism of common risk exposure for the association between LLP smoothing and systemic risk, we conduct several additional analyses to check whether the counter-cyclicality of LLP smoothing is a reaction to common risk exposure and how it affects banks' capital sufficiency. Specifically, we first perform portfolio analyses of average LLP smoothing levels in the top and bottom GDP growth tertile portfolios. The results reported in Panel A of Table 5 show that the level of earnings smoothing via LLP is substantially higher when the GDP growth rate is higher. The unranked raw value of the LLP smoothing measure, *Ellp(raw)*, is, on average, more than doubled in the High *RGDP* subsample (0.036 vs. 0.016), and the difference in *Ellp(raw)* between the high and low GDP growth subsamples is statistically significant.

Table 5 Further Exploring the Common Risk Exposure Mechanism for the Link between LLP Smoothing and Systemic Risk

Panel A: Portfolio analysis of LLP smoothing based on real GDP growth

	Ellp(Raw)	*Ellp_bank(Raw)*
High *RGDP*	0.036	0.029
Low *RGDP*	0.016	0.022
High – Low	0.020	0.007
(*t*-stat)	(5.72)***	(2.62)***

Panel B: Portfolio analysis of capital sufficiency based on LLP smoothing

	CAP		*CAP*
High *Ellp*	11.128	High *Ellp_bank*	11.389
Low *Ellp*	10.930	Low *Ellp_bank*	11.161
High - Low	0.198	High - Low	0.227
(*t*-stat)	(3.74)***	(*t*-stat)	(3.88)***

Panel C: Regression analysis of LLP smoothing as a reaction to common risk exposure

	Dependent Variable: *Ellp*			
	Coef	*t*-stat	coef	*t*-stat
Intercept	0.501	(164.66)***	0.496	(99.85)***
RGDP	0.003	(3.65)***		
BOOM			0.017	(3.21)***
Obs.	24,898		25,652	
R-sqr	0.001		0.000	

Panel D: Regression analysis of the impact of LLP smoothing on capital sufficiency				
	Dependent Variable: *CAP*			
	coef	*t*-stat	coef	*t*-stat
Intercept	11.022	(178.19)***	10.849	(179.66)***
Ellp	**0.237**	**(2.61)*** **		
Ellp_bank			**0.588**	**(6.73)*** **
RGDP	0.031	(2.53)**	0.020	(1.65)*
Obs.	22,222		21,661	
R-sqr	0.001		0.002	

Notes:
This table reports the results for further exploring the common risk exposure mechanism for the link between LLP smoothing and systemic risk. Specifically, panels A and B report the portfolio analysis of LLP smoothing based on real GDP growth *RGDP* and the portfolio analysis of capital sufficiency *CAP* based on LLP smoothing, respectively. Panel C reports the OLS estimation results for the regression of earnings smoothing via LLP (*Ellp* or *Ellp_bank*) on GDP growth rate (*RGDP*) or an indicator of a boom period (*BOOM*). Panel D reports the OLS estimation results for the regression of capital sufficiency (*CAP*) on LLP smoothing (*Ellp* or *Ellp_bank*), after controlling for GDP growth rate (*RGDP*). Variable definitions are provided in Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

We next explore whether and how the counter-cyclical cushioning function of LLP smoothing helps improve banks' capital sufficiency. We first perform portfolio analyses of banks' average capital sufficiency levels *CAP* (i.e. the tier-one risk-adjusted capital ratio) on the basis of tertile LLP smoothing portfolios; the results are reported in Panel B of Table 5. We find that the capital sufficiency level increases with LLP smoothing. Specifically, *CAP* is 11.128% in the High *Ellp* group (i.e. top tertile) and 10.930% in the Low *Ellp* group (i.e. bottom tertile), and 11.389% in the High *Ellp_bank* group and 11.161% in the Low *Ellp_bank* group, with the differences in both cases being statistically significant. Evidence from both panels A and B suggests that banks tend to provision more loan loss reserves by applying higher level of LLP smoothing in good economic conditions when their common risk exposure is high, and as a result, banks also have a high level of capital sufficiency. Therefore, these results support the role of common risk exposure in the link between counter-cyclical LLP smoothing and systemic risk.

The above results are further confirmed by the regression analyses presented in panels C and D of Table 5. In Panel C, we regress *Ellp* on *RGDP* and find they are significantly positively related (*t*-statistic = 3.65).[12] In Panel D, we regress subsequent capital sufficiency *CAP* on *Ellp* or *Ellp_bank* (after controlling for *RGDP*) and find that *CAP* is significantly positively associated with both LLP smoothing measures, consistent with the portfolio analysis in Panel B. In sum, the overall findings in this section lend consistent support to the notion that the counter-cyclicality of LLP smoothing is a reaction to common risk exposure

[12] In addition, using the alternative LLP smoothing measure *Ellp_bank* delivers similar results, which are not reported due to space limitations. The above results are also unchanged if we use an indicator variable for *BOOM* period, as defined before, to replace *RGDP* (i.e. we find that LLP smoothing level is significantly higher during the boom period).

and increases capital sufficiency, which at least partially accounts for the negative association between LLP smoothing and a bank's contribution to systemic risk.

3.5 Suboptimal LLP Smoothing, Managerial Characteristics, and the Relation between LLP Smoothing and Systemic Risk

The tenet of our argument hinges on the beneficial function of LLP smoothing. To provide further support to this rationale, we examine whether the suboptimal type of LLP smoothing weakens the above-documented relation between LLP smoothing and systemic risk. Specifically, we classify LLP smoothing into LLP smoothing on homogeneous loans and LLP smoothing on heterogeneous loans. Our analysis of homogeneous versus heterogeneous loans is motived by two considerations that are pertinent to the main research purpose of our paper. First, in relation to the cushioning function of LLP, Liu and Ryan (2006) report that during a boom period, profitable banks smooth income downward by accelerating LLP mainly on homogenous loans. Moreover, profitable banks are more likely to attract and retain capable managers, and Demerijian, Lewis-Western, and McVay (2020) find that more capable managers conduct smoothing in a way that is beneficial rather than harmful to financial stability in the United States. Second, prior literature (e.g. Liu and Ryan, 1995, 2006; Kanagaretnam *et al.*, 2003) suggests that LLPs for homogeneous loans, relative to those for heterogeneous loans, are more informative than opportunistic because homogeneous loans allow bank managers narrower latitude for discretion in LLP estimation (i.e. they provide management with less flexibility in opportunistically estimating LLP than do heterogeneous loans). The combination of the above two arguments suggests that LLP smoothing on homogenous loans tends to be more beneficial in terms of reducing a bank's contribution to systemic risk. In contrast, to the extent that heterogeneous loans provide more room for managerial discretion, financially weak banks tend to use it to smooth earnings upwards in bust periods (Liu and Ryan 2006) because weak banks host weak managers (Demerijian, Lewis-Western, and McVay, 2020) who are more likely to conduct opportunistic and harmful LLP smoothing on heterogeneous loans. This rationale points to a weakened relation between LLP smoothing on heterogeneous loans and systemic risk.

To test our prediction, we classify observations in our sample into a HETEROGENOUS subsample if heterogeneous loans take more than 50% of the total loans in a bank-quarter and classify other bank-quarters into a HOMOGENEOUS subsample.[13] We then re-estimate Model (8) for the paired subsamples separately and report the results in Panel A of Table 6.

[13] Following Liu and Ryan (2006), we calculate homogeneous loans as the sum of consumer loans, one-to-four family residential mortgages, loans to financial institutions, and acceptances to other banks; we measure heterogeneous loans as the sum of industrial, commercial, and other real estate loans. Total loans are the sum of homogeneous and heterogeneous loans. Accordingly, we classify LLP smoothing as LLP smoothing relating to homogeneous loans if a bank-quarter has more homogeneous loans than heterogeneous loans and as LLP smoothing relating to heterogeneous loans if a bank-quarter has more heterogeneous loans than homogeneous loans.

Table 6 Suboptimal LLP Smoothing, Managerial Characteristics, and the Relation between LLP Smoothing and Systemic Risk

Panel A: OLS regression results for subsamples of LLP smoothing on heterogeneous loans versus LLP smoothing on homogeneous loans

	Dependent Variable: $\Delta CoVaR$				Dependent Variable: $\Delta CoVaR$			
	HETEROGENEOUS Subsample		HOMOGENEOUS Subsample		HETEROGENEOUS Subsample		HOMOGENEOUS Subsample	
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
Intercept	-0.455	(-2.22)**	-0.160	(-2.11)**	-0.437	(-2.13)**	-0.196	(-2.24)**
Ellp	-0.082	(-1.36)	**-0.072**	**(-2.11)****				
Ellp_bank					-0.068	(-1.29)	**-0.064**	**(-1.98)****
Other Controls	Yes		Yes		Yes		Yes	
Obs.	3,198		17,976		3,143		17,791	
Adjusted R-sqr	0.435		0.296		0.427		0.294	

Panel B: OLS regression results for subsamples with versus without female executives

	Dependent Variable: $\Delta CoVaR$				Dependent Variable: $\Delta CoVaR$			
	NON-FEMALE Subsample		FEMALE Subsample		NON-FEMALE Subsample		FEMALE Subsample	
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
Intercept	0.778	(1.61)	0.606	(1.78)*	0.701	(1.44)	0.613	(1.71)*
Ellp	-0.030	(-0.58)	**-0.127**	**(-1.95)***				
Ellp_bank					-0.019	(-0.43)	**-0.106**	**(-1.89)***
Other Controls	Yes		Yes		Yes		Yes	
Obs.	932		2,690		925		2,684	
Adjusted R-sqr	0.294		0.317		0.296		0.314	

Panel C: OLS regression results for subsamples of high versus low managerial risk-taking incentives

	Dependent Variable: $\Delta CoVaR$				Dependent Variable: $\Delta CoVaR$			
	High VEGA Subsample		Low VEGA Subsample		High VEGA Subsample		Low VEGA Subsample	
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
Intercept	0.234	(0.56)	0.632	(2.51)**	0.360	(0.88)	0.523	(2.19)**
Ellp	-0.075	(-1.25)	**-0.122**	**(-2.17)****				
Ellp_bank					-0.057	(-1.11)	**-0.090**	**(-1.84)***
Other Controls	Yes		Yes		Yes		Yes	
Obs.	2,377		2,377		2,345		2,353	
Adjusted R-sqr	0.294		0.360		0.286		0.356	

Notes:
This table reports the subsample OLS estimation results for regressing a bank's contribution to systemic risk on LLP smoothing and other control variables using Model (8) as described in Table 3, for subsamples based on LLP smoothing subcategories and managerial characteristics. Panel A presents results for subsamples classified by the dominance of LLP smoothing on homogeneous loans or on heterogeneous loans in a bank-quarter (*HOMOGENEOUS* versus *HETEROGENEOUS*). Panel B presents the results for subsamples categorised by the gender of the CEO, director, or CFO (*FEMALE* versus *NON-FEMALE*). Panel C reports the results for the subsamples based on high versus low managerial risk-taking incentives proxied by the vega of executive stock option holdings (*High VEGA* versus *Low VEGA*). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

The results show that, for the HETEROGENEOUS subsample, there is no statistically significant relation between both measures of LLP smoothing and systemic risk. Consistent with our prediction, the evidence implies that LLP smoothing on heterogeneous loans is more likely to be opportunistic and harmful for accumulating cushions for a crisis, and it cancels out the beneficial systemic risk effect by LLP smoothing over homogeneous loans in these bank-quarters. In contrast, as we predicted, LLP smoothing on homogeneous loans remains significantly and negatively related with systemic risk. We further explain that homogeneous loans across different banks share more commonalities in business operations and risk exposures. The much larger HOMOGENEOUS subsample also indicates the prevalence of homogeneous loans and related beneficial LLP smoothing in the US banking system, and thus our main findings reflect the dominant theme of LLP smoothing and its effect on a bank's contribution to systemic risk.

We further examine the impacts of managerial features on the LLP smoothing-systemic risk relation. Earnings smoothing via LLP is executed by bank managers and thus influenced by their characteristics, risk appetite, and incentives. For example, relative to male managers, female managers are more risk averse and prone to more conservative accounting, financing, or investment practices (Levi *et al.,* 2014; Huang and Kisgen, 2013; Francis *et al.,* 2015). As a result, they may be more sensitive to the common risk exposure of the banking industry and apply the cushioning function of LLP smoothing more actively. Therefore, for banks with female managers, we expect a more negative relation between LLP smoothing and systemic risk than for banks with male managers. To examine this issue, we run regressions for the baseline model for a subsample of banks with a female top manager (e.g. female CEO, director, or CFO), denoted *FEMALE*, versus a subsample of other banks with a male top manager (*NON-FEMALE*). The results in Panel B of Table 6 show that the LLP smoothing-systemic risk relation is significantly negative only in the *FEMALE* subsample, lending support to our conjecture.

We next consider another managerial characteristic which could also lead to suboptimal LLP smoothing and a weakened cushioning function: bank managers' risk-taking incentives. Risk-taking incentives are proxied by the vega of managerial stock option holdings. High-vega options give managers incentives to increase firm's excessive risk-taking, and in turn they are inclined to use earnings smoothing to inflate earnings level and hide losses (Bergstresser and Philippon, 2006; Grant *et al.,* 2009), which has been shown to increase bank risk in an international setting by Bushman and Williams (2012). This practice, when applied systematically by most bank managers with strong risk-taking incentives, tends to destabilise the whole financial sector, thus weakening the negative LLP smoothing-systemic risk relation. The results in Panel C of Table 6 are consistent with this expectation: The coefficients on both LLP smoothing measures *Ellp* and *Ellp_bank* lose statistical significance in the *High VEGA* (i.e. upper half) subsample, while they remain significantly negative in the *Low VEGA* (lower half) subsample. This evidence points to the notion that suboptimal LLP smoothing driven by managerial risk-taking incentives attenuates the negative association between LLP smoothing and systemic risk. In the next section, we analyse how some monitoring mechanisms that constrain the suboptimal smoothing activities help enhance the LLP smoothing's relation with systemic risk.

3.6 Monitoring Mechanisms and the Relation between LLP Smoothing and Systemic Risk

We consider three external monitoring mechanisms that can potentially strengthen the negative link between LLP smoothing and systemic risk: monitoring by long-term creditors, monitoring by financial analysts, and monitoring by external auditors. We use leverage (long-term debt ratio), analyst coverage, and Big-Four/non-Big-Four auditor type to measure these monitoring schemes, respectively. High leverage, more analyst coverage, and Big-Four auditor represent the situation with stronger external monitoring and less room for suboptimal LLP smoothing, and we expect to observe a stronger (i.e. more negative) LLP smoothing-systemic risk relation.

Table 7 Impact of Monitoring Mechanisms on the Relation between LLP Smoothing and Systemic Risk

Panel A: OLS regression results for subsamples of strong versus weak debtholder monitoring

	Dependent Variable: $\Delta CoVaR$				Dependent Variable: $\Delta CoVaR$			
	HLEVEREGE Subsample		LLEVEREGE Subsample		HLEVEREGE Subsample		LLEVEREGE Subsample	
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
Intercept	-0.171	(-1.69)*	-0.207	(-1.99)**	-0.102	(-1.19)	-0.337	(-3.51)***
Ellp	**-0.092**	**(-2.42)****	-0.054	(-1.42)				
Ellp_bank					**-0.088**	**(-2.47)****	-0.043	(-1.23)
Other Controls	Yes		Yes		Yes		Yes	
Obs.	10,587		10,587		10,477		10,457	
Adjusted R-sqr	0.380		0.340		0.378		0.338	

Panel B: OLS regression results for subsamples of strong versus weak analyst monitoring

	Dependent Variable: $\Delta CoVaR$				Dependent Variable: $\Delta CoVaR$			
	HANALYST Subsample		LANALYST Subsample		HANALYST Subsample		LANALYST Subsample	
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
Intercept	0.056	(0.43)	-0.164	(-1.54)	0.059	(0.46)	-0.175	(-1.65)
Ellp	**-0.095**	**(-2.54)****	-0.058	(-1.44)				
Ellp_bank					**-0.082**	**(-2.37)****	-0.049	(-1.28)
Other Controls	Yes		Yes		Yes		Yes	
Obs.	8,626		12,548		8,574		12,360	
Adjusted R-sqr	0.298		0.215		0.297		0.213	

Panel C: OLS regression results for subsamples with and without Big-Four auditors

	Dependent Variable: $\Delta CoVaR$				Dependent Variable: $\Delta CoVaR$			
	BIG4 Subsample		NONBIG4 Subsample		BIG4 Subsample		NONBIG4 Subsample	
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
Intercept	-0.146	(-1.26)	-0.216	(-1.24)	-0.258	(-2.27)**	-0.119	(-0.71)
Ellp	**-0.078**	**(-1.86)***	-0.043	(-0.82)				
Ellp_bank					**-0.067**	**(-1.76)***	-0.037	(-0.73)
Other Controls	Yes		Yes		Yes		Yes	
Obs.	6,398		6,033		6,385		5,998	
Adjusted R-sqr	0.395		0.283		0.394		0.282	

Notes:
This table reports the OLS estimation results for regressing a bank's contribution to systemic risk on earnings smoothing and other control variables using Model (8), as described in Table 3, for paired subsamples based on monitoring mechanisms. Specifically, Panel A reports results for top and bottom tertile subsamples categorised by strong versus weak debtholders' monitoring, proxied by high leverage ratio *HLEVERAGE* and low leverage ratio *LLEVERAGE*, respectively. Panel B reports results for the top and bottom tertile subsamples of strong versus weak financial analyst monitoring, measured by high analyst following level *HANALYST* and low analyst following level *LANALYST*, respectively. Panel C reports the results for the subsamples categorised by strong versus weak auditors' monitoring, proxied by Big-Four auditors (*BIG4*) and Non-Big-Four auditors (*NONBIG4*), respectively. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

We conduct subsample regression analyses by partitioning the full sample into tertile portfolios according to the creditor or analyst monitoring mechanism measure and report the results for subsamples of banks with the top tertile leverage (*HLEVERAGE*) versus the bottom tertile leverage (*LLEVERAGE*), and with the top tertile analyst coverage (*HANALYST*) versus the bottom tertile analyst coverage (*LANALYST*). For the auditor monitoring mechanism, we design two subsamples including banks audited by a Big-Four auditor (*BIG4*) versus a non-Big-Four auditor (*NONBIG4*). The results in Table 7 consistently reveal that for the *HLEVERAGE*, *HANALYST*, and *BIG4* subsamples, both LLP smoothing measures *Ellp* and *Ellp_bank* are significantly negatively related with a bank's contribution to systemic risk *ΔCoVaR*, with coefficients (*t*-statistics) ranging from -0.067 to -0.095 (-1.76 to -2.54). In contrast, for the *LLEVERAGE*, *LANALYST*, and *NONBIG4* subsamples, the relation between LLP smoothing and systemic risk becomes insignificant, although remaining negative. The evidence suggests that external monitoring by creditors, financial analysts, and auditors puts pressure on bank managers to constrain suboptimal LLP smoothing, which helps enhance the negative link between LLP smoothing and systemic risk. Meanwhile, for the purpose of mitigating systemic risk, the results also highlight the importance of scrutinising suboptimal managerial incentives for loan loss provisioning and LLP smoothing, especially in banks with weak monitoring schemes.

IV. Further Analyses and Robustness Checks

4.1 Bank-Specific Risk and the Relation between LLP Smoothing and Systemic Risk

After obtaining the basic results for the association between LLP smoothing and a bank's contribution to systemic risk, we now investigate whether and how LLP smoothing affects bank-specific risk and then how bank-specific risk impacts the relation between LLP smoothing and systemic risk.

Bushman and Williams (2012) show that LLP smoothing increases bank-specific risk in an international setting, and Bushman and Williams (2015) report that bank-specific risk also works as a channel for delay in recognising LLP to increase systemic risk. Using the US setting, we have shown that LLP smoothing is negatively associated with systemic risk through the common risk exposure mechanism. However, whether and how bank-specific risk could affect their association remains an open empirical question, and reconciliation with the findings of Bushman and Williams (2012) is also necessary.

Table 8 Bank-Specific Risk and the Relation between LLP Smoothing and Systemic Risk

	Dependent Variable: *VaR*				Dependent Variable: *ΔCoVaR*			
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
Intercept	0.099	(9.28)***	0.103	(9.53)***	-0.199	(-2.75)***	-0.215	(-2.99)***
Ellp	0.001	(0.34)			**-0.074**	**(-2.40)****		
Ellp_bank			0.001	(0.31)			**-0.064**	**(-2.24)****
VaR					0.278	(2.84)***	0.280	(2.84)***
Other Controls	Yes		Yes		Yes		Yes	
Obs.	20,604		20,377		20,604		20,377	
Adjusted R-sqr	0.564		0.565		0.364		0.362	

Notes:
This table reports the results for regressing *VaR* on LLP smoothing with the same controls as in Model (8). The table also presents results for regressing a bank's contribution to systemic risk on LLP smoothing, using Model (8) as described in Table 3 after additionally controlling for bank-specific risk *VaR*. Definitions of *VaR* and other variables are provided in Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

To this end, we use the 1% VaR based on the empirical distribution of a bank's daily stock returns over one year starting from the current quarter to proxy for bank-specific risk. We first examine whether LLP smoothing is linked to bank-specific risk and then analyse whether bank-specific risk changes LLP smoothing's relation with systemic risk. Table 8 reports the results and shows that in an OLS regression of bank-specific risk on LLP smoothing using the same set of controls as in Model (8), both LLP smoothing measures *Ellp* and *Ellp_bank* are insignificantly associated with the bank-specific risk measure *VaR*. This evidence suggests that, unlike the international evidence in Bushman and Williams' (2012) paper, LLP smoothing does not seem to increase bank-specific risk in the US banking sector. One potential explanation is that LLP smoothing in the United States may have less opportunistic connotations and be more beneficial; for example, LLP smoothing facilitates counter-cyclical cushioning against bank loss and risk build-up and improves earnings informativeness, which helps the monitoring of bank risk. Collectively, these effects of beneficial LLP smoothing offset the effects of harmful and opportunistic LLP smoothing, leading to the observed insignificant relation.

We next add *VaR* as an additional independent variable to the baseline model about the relation between LLP smoothing and systemic risk. The regression results reported in the right-hand part of Table 8 show that *VaR per se* is significantly positively associated with future $\Delta CoVaR$; meanwhile, the negative relation between LLP smoothing and systemic risk still holds. Overall, these findings suggest that the link between LLP smoothing and systemic risk does not work through bank-specific risk because LLP smoothing is not significantly associated with bank-specific risk and bank-specific risk does not subsume the LLP smoothing-systemic risk relation.

4.2 Alternative Measures and Additionally Controlling for Earnings Management and LLP Untimeliness

As robustness checks, we first examine whether the baseline regression results documented above still hold for the following five alternative proxies for LLP smoothing introduced in section 2: (1) *Ellp2*, the percentile ranking of the coefficient of *EBLLP* computed as the ratio of net income after tax but before LLP to total loans; (2) *IncRsqr*, the percentile ranking of the incremental R-Squared; (3) *Ellp_BW*, the coefficient-based measure estimated using the LLP model in Bushman and Williams (2015); (4) *Ellp_bank_BW*, the corresponding time-varying measure; (5) *DeltaEbllp*, the percentile ranking of quarterly changes of income before tax and before LLP. We re-estimate Model (8) using these measures and report the results in the left-hand section of Table 9. The results show that the coefficients on all these alternative LLP smoothing measures remain significantly negative, indicating that our main findings are insensitive to different measurement schemes for LLP smoothing.

Next, we further control for earnings management via LLP and LLP untimeliness in incorporating future non-performing loans in our baseline model. Ma and Song (2016) report that opportunistic earnings management via LLP increases systemic risk, and Bushman and Williams (2015) show that LLP untimeliness is positively linked to systemic risk. LLP smoothing in our study focuses on ironing away earnings volatility, which fundamentally differs from earnings management via LLP that focuses on manipulating reported earnings through discretions over LLP. It is also distinct from LLP untimeliness that focuses on recognition of future non-performing loans. Therefore, we expect that our baseline conclusion about the relation between LLP smoothing and systemic risk is robust to additionally controlling for earnings management and LLP untimeliness. To check this, we add Ma and Song's (2016) earnings management measure, *Emgmt*, and Bushman and Williams' (2015) LLP untimeliness measure, *Untimely*, as additional controls to re-estimate Model (8). The results reported in the left-hand section of Table 9 indicate that both main measures for LLP smoothing (i.e. *Ellp* and *Ellp_bank*) remain significantly negatively associated with systemic risk. In addition, *Emgmt* and *Untimely per se* are significantly positively associated with systemic risk, consistent with Ma and Song (2016) and Bushman and Williams (2015). The evidence thus supports our expectation.

Lastly, we check the robustness of our baseline regression results to different probability levels for the *CoVaR*-based systemic risk measure and report the results in the right-hand section of Table 9. For the dependent variable, we use the percentile ranking of the 5% *ΔCoVaR*-based measure computed following the same method as for the 1% *ΔCoVaR*-based case, and denote it *ΔCoVaR5*. The coefficients on *Ellp* and *Ellp_bank* remain significantly negative, although with lower magnitudes and different significance levels. This evidence suggests that using systemic risk measures based on a higher probability VaR (thus a less extreme risk) gives qualitatively similar yet weaker results. This may be due to the noisier measure for systemic risk conditional on a bank's less extreme loss conditions. In brief, our main results are also robust to alternative systemic risk measures.[14]

4.3 The impacts of FDICIA and SOX

The Federal Deposit Insurance Corporation Improvement Act of 1991 (FDICIA) requires bank auditors and examiners to evaluate the internal controls of banks with total assets over US$500 million (over US$1 billion after 2005). Altamuro and Beatty (2010) document that these FDICIA provisions lead to differences in financial reporting quality between large and small banks. FDICIA regulation may also make a difference in LLP practice and affect the LLP smoothing and systemic risk relation. To examine whether our results are robust to FDICIA regulation, we partition our sample into subsamples affected and not affected by FDICIA and replicate the baseline analysis. Untabulated results for both subsamples are qualitatively unchanged.

Similar to the FDICIA regulation, the Sarbanes-Oxley Act of 2002 (SOX) mandates managers and external auditors of listed firms to report the adequacy of internal control over financial reporting. To examine the possibility that SOX may affect our results, we re-examine Model (8) using the pre- and post-SOX subsamples; the findings (untabulated) are qualitatively similar to our baseline results.

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[14] As an additional effort, we also use the *MES* and *%SRISK* measures in Acharya *et al.* (2012) as alternative measures for systemic risk in untabulated robustness tests. Specifically, *MES* is measured 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. *%SRISK* is the average daily expected capital shortfall that a bank needs to cover in a quarter if there is a financial crisis to the aggregate expected capital shortfall in the financial sector. Unlike our main systemic risk measure, *MES* and *%SRISK* focus on the impact of the loss or stock price plummet of the banking sector on that of a specific bank. Nevertheless, during severe market downturns when the stock prices of many banks plummet simultaneously, one bank's expected loss or stock price plummet is correlated with its contribution to the loss or stock price plummet of the whole banking sector. In this case, *MES* and *%SRISK* can also capture risk contagion from one bank to other banks to some degree. An untabulated analysis shows that our main findings are insensitive to using both of these alternative systemic measures.

Table 9 Robustness Checks for the Relation between LLP Smoothing and Systemic Risk

	Dependent Variable: $\Delta CoVaR$														Dependent Variable: $\Delta CoVaR5$			
	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat	coef	*t*-stat
Intercept	-0.207	(-2.69)***	-0.211	(-2.77)***	-0.183	(-2.44)**	-0.183	(-2.38)**	-0.245	(-3.65)***	-0.230	(-2.85)***	-0.242	(-3.02)***	-0.470	(-8.66)***	-0.447	(-10.08)***
Ellp											**-0.090**	**(-2.59)*** **			**-0.039**	**(-1.71)***		
Ellp_bank													**-0.076**	**(-2.31)****			**-0.030**	**(-1.67)***
Ellp2	**-0.076**	**(-2.41)****																
IncRsqr			**-0.076**	**(-2.51)****														
Ellp_BW					**-0.073**	**(-2.41)****												
Ellp_bank_BW							**-0.065**	**(-2.28)****										
DeltaEbllp									**-0.316**	**(-1.74)***								
Emgmt											0.081	(3.18)***	0.082	(3.20)***				
Untimely											0.097	(2.75)***	0.096	(2.70)***				
Other Controls	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Obs.	21,174		21,174		22,296		21,029		23,223		15,154		15,139		21,174		20,934	
Adjusted R-sqr	0.358		0.358		0.351		0.353		0.350		0.390		0.388		0.503		0.500	

Notes:
This table presents the robustness check results for Model (8), as described in Table 3, by (1) using several alternative measures for LLP smoothing; (2) using an alternative measure for a bank's contribution to systemic risk; and (3) further controlling for earnings management via LLP *Emgmt* and delay in recognising LLP (*Untimely*). The alternative LLP smoothing measures include *Ellp2*, *IncRsqr*, *Ellp_BW*, *Ellp_bank_BW*, and *DeltaEbllp*. The alternative systemic risk measure is $\Delta CoVaR5$. Earnings management measure *Emgmt* follows Ma and Song (2016), and the delay in recognising LLP measure *Untimely* follows Bushman and Williams (2015). Detailed definitions are provided in Appendix A. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% confidence levels, respectively.

V. Conclusion

This study examines the link between a bank's earnings smoothing via LLP and its contribution to systemic risk in the banking industry in the equity market. We find that LLP smoothing is negatively related with systemic risk in general, and the relation holds for both boom and bust periods, despite being stronger in boom periods. The effect of LLP smoothing in mitigating systemic risk is found to work through the mechanism of common risk exposure wherein the counter-cyclical cushioning role of LLP smoothing acts as a reaction to the common risk exposure. However, there is no evidence that the LLP smoothing-systemic risk relation is entailed by bank interconnectedness or bank-specific risk. Moreover, we show that the link between LLP smoothing and systemic risk weakens for LLP smoothing on heterogeneous loans and for banks with male managers or managers with strong risk-taking incentives. Meanwhile, stronger external monitoring mechanisms over LLP smoothing by long-term debtholders, financial analysts, and Big-Four auditors enhance the negative relation between LLP smoothing and systemic risk.

Overall, the evidence in this paper provides a comprehensive description of the link between LLP smoothing and a bank's contribution to systemic risk in the banking industry, especially in the United States. Our study adds insights to the ongoing regulatory reform of the SEC aimed at mitigating systemic risk in capital markets and enlightens the debate between securities regulators and banking regulators regarding discretionary loan loss provisioning.

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Appendix A Variable Definitions

LLP Smoothing Measures

Ellp: the percentile ranking of the coefficient on income before tax and LLP in the LLP prediction model specified in Model (1) in the text. A higher value of *Ellp* indicates more earnings smoothing via LLP.

Ellp(Raw): the unranked value of *Ellp*.

Ellp_bank: the percentile ranking of the product of income before tax and LLP and its coefficient in the LLP prediction model specified in Model (1) in the text. A higher value of *Ellp_bank* indicates more earnings smoothing via LLP.

Ellp_bank(Raw): the unranked value of *Ellp_bank*.

Ellp2: the percentile ranking of the coefficient on net income before LLP in the LLP prediction model specified in Model (1). A higher value of *Ellp2* indicates more earnings smoothing via LLP.

IncRsqr: the percentile ranking of the incremental explanatory power of income before tax and LLP in the LLP prediction model specified in Model (1), with the incremental explanatory power calculated as the difference in R-Squared between Model (1) and Model (2) that removes only income before tax and LLP from Model (1). A higher value of *IncRsqr* indicates more earnings smoothing via LLP.

Ellp_BW: the percentile ranking of coefficient on income before tax and LLP in the LLP prediction model used in Bushman and Williams (2015). A higher value of *Ellp_BW* indicates more earnings smoothing via LLP.

Ellp_bank_BW: the percentile ranking of the product of income before tax and LLP and its coefficient in LLP prediction model used in Bushman and Williams (2015). A higher value of *Ellp_bank_BW* indicates more earnings smoothing via LLP.

DeltaEbllp: a proxy for LLP smoothing and measured as the percentile ranking of quarterly changes of income before tax and LLP, following Kanagaretnam *et al.* (2004). A higher value of *DeltaEbllp* indicates more earnings smoothing via LLP.

Measures for a Bank's Contribution to Systemic Risk

$\Delta CoVaR_{it}$: a proxy for bank *i*'s contribution to systemic risk in quarter *t* and calculated as the percentile ranking of negative one times the incremental change in 1% VaR of stock return in the financial sector when bank *i*'s stock return is at its 1% VaR and when it is in its median state. A higher value of $\Delta CoVaR_{it}$ indicates larger contribution of bank *i* to systemic risk in quarter *t*.

$\Delta CoVaR5_{it}$: a proxy for bank *i*'s contribution to systemic risk in quarter *t* and calculated as the percentile ranking of negative one times the incremental change in 5% VaR of stock return in the financial sector when bank *i*'s stock return is at its 5% VaR and when it is in its median state. A higher value of $\Delta CoVaR5_{it}$ indicates larger contribution of bank *i* to systemic risk in quarter *t*.

Control Variables and Conditioning Variables

$RGDP_t$: the quarterly growth rate of real GDP for quarter *t*.

OUT_{it}: the number of banks that are significantly Granger-caused by bank *i* in quarter *t*, calculated on the basis of the PCA and Granger-causality networks of monthly stock returns of all commercial banks using a rolling window of 36 months, extending Billio *et al.* (2012).

CAP_{it}: the tier-one risk-adjusted capital ratio for bank *i* at the end of fiscal quarter *t* as reported in Compustat.

MB_{it}: the market-to-book ratio for bank *i* at the end of fiscal quarter *t*.

ROA_{it}: the ratio (in percentage) of earnings before extraordinary items to total assets for bank *i* at the end of fiscal quarter *t*.

$Sigma_{it}$: the standard deviation (in percentage) of daily stock returns for bank *i* in fiscal quarter *t*.

$Beta_{it}$: the sensitivity of bank *i*'s stock return to CRSP value-weighted market return at the end of fiscal quarter *t*, calculated on the basis of daily returns over the previous fiscal year.

$Mismatch_{it}$: a proxy for debt maturity mismatch and measured as the ratio of the difference between short-term debt and cash to total liabilities for bank *i* at the end of fiscal quarter *t*.

$Size_{it}$: the natural logarithm of market value (in million USD) of bank *i* at the end of fiscal quarter *t*.

$Size\_sqr_{it}$: the square term of the natural logarithm of market value (in million US$) of bank *i* at the end of fiscal quarter *t*.

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

Mom_{it}: the buy-and-hold stock return of bank *i* over the 11-month period ending one month prior to the end of fiscal quarter *t*.

$Coskew_{it}$: skewness of daily stock returns of bank *i* relative to that of the market in fiscal quarter *t*.

$Cokurt_{it}$: kurtosis of daily stock returns of bank *i* relative to that of the market in fiscal quarter *t*.

VaR_{it}: a proxy for bank-specific risk of bank *i* and measured by the 1% VaR based on the empirical distribution of the bank's daily stock returns over one year starting from fiscal quarter *t*.

$Emgmt_{it}$: the measure for earnings management through LLP of bank *i* in fiscal quarter *t,* as used in Ma and Song (2016).

$Untimely_{it}$: the measure for LLP untimeliness in incorporating future non-performing loans of bank *i* in fiscal quarter *t,* as used in Bushman and Williams (2015).

Appendix B Validation Check for Systemic Risk Measures

We check the validation of our main systemic risk measure *ΔCoVaR* by comparing it with its unranked value *ΔCoVaR(Raw)* and the 5% ΔCoVaR-based *ΔCoVaR*5 and *ΔCoVaR5(Raw)*. We perform correlation analysis and PCA for these measures along with the *%SRISK* and *MES* measures in Acharya *et al.* (2012). Specifically, *MES* is measured as the average daily marginal expected shortfall for stock return of a bank in a quarter given that the market return is below its 2% percentile. *%SRISK* is the average daily expected capital shortfall that a bank needs to cover in a quarter if there is a financial crisis to the aggregate expected capital shortfall in the financial sector. In addition, we also compare our stock return- and ΔCoVaR-based systemic risk measures with the asset return- and ΔCoVaR-based systemic risk proxy used in Adrian and Brunnermeier (2016), which we denote by *ΔCoVaR_at*. Table B1 reports the results.

Panel A shows that the mean of a bank's contribution to systemic risk *ΔCoVaR(Raw)* is 23.297%. The mean of the asset return-based systemic risk measure *ΔCoVaR_at* is 19.475%, which is generally comparable to its weekly correspondence of 1.000% to 1.200% in Adrian and Brunnermeier (2016) and Brunnermeier *et al.* (2020) that translate into mean quarterly values of 17.000% to 21.086%.

Panel B reports Pearson correlations and shows that the stock return-based systemic risk measures under the ΔCoVaR scheme are significantly positively associated with each other, with all correlation coefficients significant at the 1% level, and most of their correlations with other systemic risk measures are above 0.334, except for those with *%SRISK*. Specifically, the correlation coefficient between *ΔCoVaR* and *ΔCoVaR(Raw)* is 0.899, but their correlations with *%SRISK* are merely 0.082 and 0.106, respectively. The correlation coefficients of *%SRISK* with all other systemic risk measures are similarly low and between 0.021 and 0.133. The above evidence collectively suggests that our measures possess convergent validity in general for gauging a bank's contribution to systemic risk. With regard to their discriminant validity, Panel B indicates that the stock return-based ΔCoVaR measures all exhibit positive correlations lower than 0.500 with *%SRISK* and *MES*, although the correlation coefficients among the ΔCoVaR-based measures themselves are higher than 0.500. In addition, the average variance extracted among all stock return-based ΔCoVaR measures is 0.621, higher than the critical value of 0.500 for discriminant validity (Fornell and Larcker, 1981).

Lastly, the PCA in Panel C indicates that *ΔCoVaR* and *ΔCoVaR(Raw)* have the highest weights of 0.907 and 0.930, respectively, for the first factor of the PCA, which are much higher than those for *MES* and *%SRISK*. The eigenvalue for the first factor is 4.131, well exceeding the eigenvalues for the second and third factors (1.009 and 0.768, respectively). This indicates that the first factor is the most effective one and, by inference, that *ΔCoVaR* and *ΔCoVaR(Raw)* (and their 5%-level correspondences) are effective systemic risk measures. Overall, analyses from different perspectives suggest that our stock return- and ΔCoVaR-based measures possess both convergent validity and discriminant validity in capturing systemic risk.

Table B1 Validation Check for Measures of Systemic Risk

Panel A: Statistical summary for systemic risk measures used in this paper and prior studies

Variable	Mean	Median	STD	Q1	Q3
ΔCoVaR	0.544	0.567	0.286	0.308	0.790
ΔCoVaR(Raw, %)	23.297	20.538	18.990	10.768	32.059
ΔCoVaR5	0.549	0.570	0.284	0.316	0.793
ΔCoVaR5(Raw, %)	14.922	12.568	11.490	7.231	19.847
ΔCoVaR_at(%)	19.475	16.311	19.613	7.379	28.772
%SRISK	0.291	0.000	3.419	0.000	0.010
MES	1.367	1.110	1.511	0.421	2.203

Panel B: Pearson correlations between systemic risk measures used in this paper and prior studies

Variable	*ΔCoVaR*	*ΔCoVaR(Raw)*	*ΔCoVaR5*	*ΔCoVaR5(Raw)*	*ΔCoVaR_at*	*%SRISK*	*MES*
ΔCoVaR	1						
ΔCoVaR(Raw)	0.899***	1					
ΔCoVaR5	0.819***	0.758***	1				
ΔCoVaR5(Raw)	0.741***	0.853***	0.869***	1			
ΔCoVaR_at	0.588***	0.612***	0.524***	0.537***	1		
%SRISK	0.082***	0.106***	0.092***	0.133***	0.021***	1	
MES	0.334***	0.363***	0.380***	0.410***	0.307***	0.118***	1

Panel C: PCA of systemic risk measures used in this paper and prior studies

Variable	First Factor	Second Factor	Third Factor
ΔCoVaR	0.907	-0.076	-0.159
ΔCoVaR(Raw)	0.930	-0.060	-0.126
ΔCoVaR5	0.898	-0.028	-0.080
ΔCoVaR5(Raw)	0.910	0.009	-0.040
ΔCoVaR_at	0.717	-0.147	-0.044
%SRISK	0.131	0.962	-0.222
MES	0.527	0.227	0.817
Eigenvalue	4.131	1.009	0.768
Variance Explained	4.131	1.009	0.768

Notes:
This table reports the validation check results for our systemic risk measures by contrasting them with the existent systemic risk measures in prior studies. Panel A presents their descriptive statistics, and Panel B reports their Pearson correlations, with *, **, and *** indicating statistical significance at the 10%, 5%, and 1% confidence levels, respectively. Panel C reports the results for the PCA of different systemic risk measures. Our systemic risk measures include *ΔCoVaR*, *ΔCoVaR(Raw)*, and their correspondences at the 5% VaR level (*ΔCoVaR5* and *ΔCoVaR5(Raw)*). Other existent systemic risk measures include *ΔCoVaR_at*, *%SRISK*, and *MES*. *ΔCoVaR_at* is an asset return- and ΔCoVaR-based measure that proxies for a bank's contribution to systemic distress risk in a quarter used in Adrian and Brunnermeier (2016). *%SRISK* measures the average daily expected capital shortfall that a bank needs to cover in a quarter if there is a financial crisis to the aggregate expected capital shortfall in the financial sector, following Acharya *et al.* (2012). *MES* is the average daily marginal expected shortfall for stock return of a bank in a quarter given that the market return is below its 2% percentile, following Acharya *et al.* (2012).