Good Buffer, Bad Buffer

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Abstract

Bank regulators and academics have long conjectured the beneficial effects of preemptive loan loss provisioning (i.e., making higher provisions during good times so as to avoid doing so during bad times) for bank lending and stability. In contrast, accounting regulators express concerns about its potential adverse impact on reporting transparency due to the ensuing income smoothing. Using the late 1990s emerging market crisis to capture an adverse supply shock to bank capital, we show, consistent with the bright-side, that ensuing contractions in bank lending are weaker for banks that built buffers by provisioning preemptively. These lending differences translate into positive real effects for the buffering banks' small borrowers. However, consistent with the dark-side, these benefits of preemptive provisioning are absent in banks with insider lending, suggesting opportunistic smoothing. Our inferences are robust to addressing the endogeneity of preemptive loan loss provisioning and to corroborating the emerging market evidence with large-sample tests using Federal Reserve data on lending supply and demand. Overall, our results highlight the tradeoff between bank stability and transparency inherent in preemptive provisioning – while proactive recognition of unrealized losses reduces bank transparency, it increases bank stability (if and) when losses materialize.

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"The rules governing banks' loan loss provisioning and reserves require a trade-off between the goals of bank regulators, who emphasize safety and soundness, and the goals of accounting standard setters, who emphasize the transparency of financial statements. A strengthening of accounting priorities in the decade prior to the financial crisis was associated with a decrease in the level of loan loss reserves in the banking system"

Federal Reserve Bank (FRB) of Richmond (2012)

1. Introduction

The Great Recession of 2007-09 and the ensuing decline in economic growth placed a renewed spotlight on bank reporting and loan loss provisioning (e.g., Laux and Leuz, 2009, 2010; Vyas, 2011; Huizinga and Laeven, 2012; GAO, 2013; Beatty and Liao, 2014; Acharya and Ryan, 2016). While bank regulators, standard setters, and academics broadly agree that early recognition of *expected* loan losses is beneficial (see GAO, 2013 report to Congress; FASB, 2016; Beatty and Liao, 2011, 2014; Bushman and Williams, 2012, 2015), there is less agreement on whether banks should proactively build reserves (buffers) for *unexpected* loan losses by booking higher provisions during good times (e.g., Laeven and Majnoni, 2003).[1] Bank regulators advocate for this practice, citing the "safety-and-soundness" principle (see quote above and Landau, 2009) as making provisions during downturns puts downward pressure on bank capital at precisely the moment when capital is scarce and costly, threatening the stability of the banking sector. At the same time, banks may feel compelled to sell assets at fire sale prices or pare lending – adversely affecting the rest of the economy (e.g., Kashyap, Rajan, and Stein, 2008). Accounting standard setters, on the other hand, discourage preemptive loan loss provisioning on transparency grounds as it results in income smoothing (e.g., Levitt, 1998). These countervailing opinions were best illustrated in the SunTrust Bank litigation case where the SEC forced SunTrust to reverse what it deemed "over-provisioning" (Balla and Rose, 2011; Beck and

[1] According to the Basel Committee on Banking Supervision (2004): "While it is never possible to know in advance the losses a bank will suffer in a particular year, a bank can forecast the average level of credit losses it can reasonably expect to experience. These losses are referred to as Expected Losses (EL)…Losses above expected levels are usually referred to as Unexpected Losses (UL) - institutions know they will occur now and then, but they cannot know in advance their timing or severity."

Narayanamoorthy, 2013; Ryan and Keeley, 2013), while bank regulators expressed their discontent with the SEC's ruling.

No study (of which we are aware) provides evidence on the tradeoff between the claimed benefits of preemptive provisioning (e.g., GAO, 2013; Landau, 2009) and the costs of greater opacity and reduced risk discipline (e.g., Bushman and Williams, 2012) in the context of mitigating bank lending pro-cyclicality. More generally, if banks smooth earnings due to agency conflicts (e.g., Leuz et al., 2003; Jin and Myers, 2006; Gopalan and Jayaraman, 2012) rather than to build buffers, then it is not clear that preemptive loan loss provisioning will deliver its intended benefits (e.g., Baek, Kang, and Park, 2004; Lang and Maffett, 2011; Ng, 2011).[2] Pointing to the discipline-mitigating role of bank opacity, Harvey Goldschmid (then General Counsel of the SEC) noted:

> "*If allowances are stretched thin in bad times and padded in good times, then the financial statements of financial institutions would not disclose and reflect actual credit quality and amount of losses in the institutions' loan portfolios on a timely basis…Market discipline can only work if market participants have access to timely and reliable information that enables them to assess a bank's activities and the risks inherent in those activities… serious consequences can result from the obstruction of market discipline and the resulting skepticism…these consequences included flight of capital and greater cost of capital*" (Goldschmid, 1999).

To convincingly document whether preemptive loan loss provisioning is beneficial, it is perhaps obvious that one needs a period of unexpected losses to the bank's lending portfolio. However, to claim a causal link from bank reporting to bank stability, it is crucial to isolate borrower demand for capital from intermediary capital supply (e.g., Bernanke and Lown, 1991; Berger and Udell, 1994; Chava and Purnanandam, 2011; Acharya and Ryan, 2016). In other words, it is imperative that the crisis emanate from the supply-side (i.e., a reduction in banks' willingness to lend) rather than the demand-side (i.e., a decline in borrowers' demand for financing).

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[2] We use preemptive loan loss provisioning, buffer building, and income smoothing interchangeably.

Following prior work on the international transmission of financial shocks (e.g., Peek and Rosengren 1997, 2000; Kho, Lee, and Stulz, 2000; Chava and Purnanandam, 2011; Lo, 2014), we focus on the emerging market crisis of the 1990s, where U.S. banks transmitted adverse capital shocks suffered on their *foreign* loan portfolio on to their *domestic* borrowers via reduced lending. These crises were not only unexpected as evidenced by significant market reactions (e.g., Kho et al., 2000; Gatev, Schuermann, and Strahan, 2007) but also decouple supply and demand effects. Because domestic borrowers did not suffer a concurrent decline in creditworthiness (which we confirm), contractions in crisis-period domestic lending result from a clean supply shock to bank capital rather than from differences in domestic borrowers' demand for financing. We then examine crisis-period lending behavior to assess whether preemptive provisioning acts as a buffer against lending contractions that banks subsequently face when hit with an unexpected inward supply shift.[3] Our identifying assumption is that banks' pre-crisis provisioning behavior is exogenous to the timing and severity of the ensuing crisis.[4]

Our empirical tests are motivated by the capital crunch literature (e.g., Bernanke and Lown, 1991; Berger and Udell, 1994; Beatty and Liao, 2011), which documents a heightened sensitivity of bank lending to capital during crises. We begin by documenting such a crunch around the emerging market crisis – we find that the difference in quarterly loan growth between poorly- and well-capitalized banks widens from -1.12% pre-crisis to -5.91% during the crisis, an average lending differential of $666 million per quarter for our sample of banks.

[3] Since financial reporting rules do not mandate preemptive loan loss provisioning, we exploit discretion under existing rules allowing banks to voluntarily engage in smoothing. This is consistent with empirical evidence in both the U.S. (e.g., Beatty et al., 1995) and internationally (e.g., Laeven and Majnoni, 2003; Bushman and Williams, 2012). An alternative strategy is to exploit the Spanish setting, where accounting rules allow for dynamic (i.e., forward-looking) provisioning. We discuss this setting in more detail in Section 2.

[4] We verify that preemptive loan loss provisioning is not merely capturing correlated bank-level factors. In addition, we use a shock to preemptive loan loss provisioning and extract an instrumented measure that is orthogonal to underlying bank characteristics (discussed in more detail below).

To guide our empirical execution, we consider two predictions. The "safety-and-soundness" hypothesis predicts that the capital crunch will be weaker for banks that engage in preemptive provisioning, as proactive loan loss provisioning (during non-crisis periods) reduces the need to take a hit to capital during a crisis, thereby mitigating lending contractions. Alternatively, the "opacity" hypothesis predicts that any potential beneficial effects of preemptive provisioning should be weaker in banks that smooth earnings for opportunistic reasons, since the ensuing opacity enables greater risk-taking or tunneling (e.g., Jin and Myers, 2006; Bushman and Williams, 2012; Gopalan and Jayaraman, 2012). This prediction aligns with accounting regulators' concerns about the adverse effects of reporting opacity.

Our empirical evidence supports the safety-and-soundness hypothesis. In particular, the sensitivity of crisis-period lending to capital levels is attenuated for banks with greater preemptive loan loss provisioning. We fail to detect such a difference in the pre-crisis period (in support of the parallel-trends assumption). We also find that banks with preemptive loan loss provisioning suffer larger decreases in stock liquidity and build less capital during the crisis, consistent with the role of opacity in aggravating adverse selection concerns. This evidence indicates that the weaker crunch we observe is not on account of banks' ability to raise fresh financing during the crisis.

Since discussions of bank pro-cyclicality often allude to its dampening effects on the industrial sector (e.g., Peek and Rosengren, 2000; GAO, 2013), we examine whether preemptive provisioning translates into real effects for these banks' borrowers. This analysis follows a more general inference by Gibson (1995), Peek and Rosengren (1997), and Chava and Purnanandam (2011) that adverse shocks to banks negatively affect underlying borrowers (as long as borrowers cannot perfectly substitute between financing sources). Indeed, we find that lending differences across preemptive and non-preemptive provisioners translate into positive valuation and investment effects for the banks' small borrowers. This highlights the broader role of preemptive loan loss provisioning in mitigating the transmission of banking shocks to the industrial sector.

Not all preemptive provisioning is beneficial, however. Consistent with the opacity hypothesis, we find that the beneficial effects of preemptive provisioning are absent in the subset of banks with insider-lending (i.e., lending to affiliated parties such as executives, directors, major shareholders and related entities), where preemptive loan loss provisioning is likely driven by opportunistic considerations rather than to build buffers. Our use of insider lending by banks as a proxy for a larger pattern of wealth-destroying behavior due to agency considerations is consistent with recent evidence (e.g., Goetz et al., 2013). It is also consistent with a broader body of work that documents the association between income smoothing and managerial rent-extraction in industrial firms (e.g., Leuz et al., 2003; Gopalan and Jayaraman, 2012).

Our subsequent analyses probe deeper into the mechanisms through which preemptive loan loss provisioning reduces bank lending pro-cyclicality. Banking regulators often contend that banks proactively provisioning during good times exhibit less aggressive lending and risk-taking (e.g., GAO, 2013; Jiménez et al., 2012). The early 1990s saw U.S. banks partaking of the growth in the Russian banking sector as well as the Asian economies. Bank lending spreads in those markets increased rapidly, as did GDP growth in the Tiger economies. By reducing capital levels, preemptive loan loss provisioning was argued to provide a much needed dampener to the risk-taking appetite of U.S. banks in these markets and thereby mitigate the euphoria of business cycles (e.g., Rajan, 2009). Consistent with this contention, we find that banks engaging in preemptive loan loss provisioning make fewer bad loans and experience slower loan growth in the pre-crisis years. This evidence, while exploratory, suggests that banks that provision preemptively exhibit safer lending during good times. These associations however raise the concern that it is the lower risk-taking during good times and not preemptive provisioning that makes these banks resilient to crises.

We address this concern in two ways. First, we show that conditioning on these (pre-crisis) characteristics does not generate the same inferences as preemptive loan loss provisioning. Second, we use the SEC litigation against SunTrust Bank in 1998 as a shock to banks' preemptive loan loss provisioning behavior. We hypothesize that publicly-listed banks respond to the SEC's strengthening of accounting priorities (over regulatory preferences) by reducing preemptive provisioning more than privately held banks (e.g., Balla and Rose, 2011). Even within public banks, we expect variation in banks' responses based on the expected level of SEC enforcement. Following prior work (e.g., Kedia and Rajgopal, 2011), we predict that banks closer in proximity to the SEC reduce preemptive provisioning more than those farther away.[5] We use the bank's listing status and its distance from the nearest SEC office as instruments to obtain a measure of preemptive loan loss provisioning that is orthogonal to underlying bank characteristics.

Because the SunTrust case occurred after the emerging market crisis, we use changes in aggregate bank lending standards from the Senior Loan Officer Opinion Survey (SLOOS) on Bank Lending collected quarterly by the Federal Reserve. These surveys are commonly used to represent changes in bank loan supply (e.g., Lown and Morgan, 2002, 2006; Leary, 2009; Maddaloni and Peydró, 2011; Axelson et al., 2013; Bassett et al., 2014; Ciccarelli, Maddaloni, and Peydro, 2015; Bergbrant, Bradley, and Hunter, 2016). An additional feature of these surveys is that they contain data on borrower demand that allow us to disentangle supply and demand. Results from this alternative setting provide reassuringly similar inferences to those from the

[5] See Eisenbach, Lucca, and Townsend, 2016 for evidence on resource constraints in bank supervision.

emerging market crisis. In particular, preemptive loan loss provisioning mitigates the contractionary effect of reduced bank supply on bank lending, but is uncorrelated with bank lending during periods of lower borrower demand. Further, these inferences are robust to using the instrumented measure of preemptive loan loss provisioning. Overall, we interpret these results as suggesting that the potential endogeneity of preemptive loan loss provisioning does not confound our findings.[6]

Our inferences are insensitive to additional robustness tests. First, they are not driven by the differential severity of the emerging market crisis (from the demand side) on preemptive provisioners versus others. Second, they are robust to alternative use of fixed effects and clustering of standard errors. Finally, we verify that inferences for preemptive loan loss provisioning are distinct from that of loan loss reporting timeliness (Jiang, Levine, and Lin, 2016; Beatty and Liao, 2011; Bushman and Williams, 2012). Reporting timeliness captures loan loss provisions' ability to incorporate *expected* loan losses as reflected in the change in loan quality (i.e., non-performing loans) in the contemporaneous and future quarter/year. Our measure of preemptive provisioning or smoothing, on the other hand, links loan loss provisions to the amount of pre-provision earnings, which is decoupled from loan-specific information and is a mechanism through which banks can provide for *unexpected* loan losses. Because major economic crises that threaten the financial system are often unforeseen, many hold the view that preemptive provisioning for "unexpected" losses is important for ensuring banking sector stability. Furthermore, while both timeliness and smoothing can be viewed as "forward-looking" in nature, they have starkly divergent implications for bank opacity, with smoothing exacerbating and timeliness ameliorating opacity and financing frictions (Bushman and Williams, 2012).

[6] In untabulated tests, we find (consistent with the emerging market results) that the beneficial effect of preemptive loan loss provisioning within this larger sample is again absent in banks with insider lending.

Therefore, the two measures involve very different cost-and-benefit tradeoffs when it comes to mitigating the capital crunch.

We make several contributions. First, consistent with a beneficial effect of preemptive loan loss provisioning, we show that crisis-period lending contractions are weaker for banks provisioning preemptively pre-crisis using a supply-shock that is not confounded by borrower demand for financing.[7] In addition, we provide suggestive evidence that these banks grew lending less aggressively (in both volume and risk) in the pre-crisis period, consistent with bank regulators' contentions that preemptive loan loss provisioning promotes bank stability by curbing banks' risk-taking appetite during expansionary periods (GAO, 2013). This evidence is important, as it sheds light on the role of bank reporting in the economic consequences of banking crises. It is also pertinent to the distinct roles that BASEL attributes to bank capital and loan loss provisions – the former as a buffer for unexpected losses and the latter as a means to recognize expected losses (e.g., Laeven and Majnoni, 2003). Effects of preemptive loan loss provisioning on bank stability are also policy-relevant. In particular, if preemptive provisions are indeed beneficial in mitigating banking crises, it suggests that observed levels of bank capital could be a lower bound for true economic capital used to cushion against unexpected shocks.[8]

Second, consistent with accounting regulators' concerns about income smoothing reducing market discipline, we find that the benefits of preemptive provisioning are absent in banks presumably smoothing earnings for opportunistic reasons. These results reinforce the point made in accounting research (e.g., Dechow, Ge, and Schrand, 2010) that the costs and benefits of earnings quality are context-specific. Our banking setting provides a context where "low

[7] Other studies also examine bank pro-cyclicality but study different aspects of bank reporting, such as fair value accounting for investment securities (Xie, 2016) and timely reporting of expected losses (Beatty and Liao, 2011).
[8] See Admati et al. (2013) and Admati and Hellwig (2014) for a discussion of the need to increase bank capital and Thakor (2014) for a summary of the link between bank capital and bank fragility.

earnings quality" in the sense of informational (in)efficiency provides other benefits to banks, such as greater stability during a crisis.[9]

Third, we document how preemptive loan loss provisioning translates into real effects in the industrial sector. Crisis-period lending differences between preemptive and non-preemptive provisioners result in sizeable valuation and investment effects for small borrowers. This evidence extends prior work on the link between bank health and both borrower performance (Peek and Rosengren, 1997, 2000; Gibson, 1995; Chava and Purnanandam, 2011) and disclosure (Lo, 2014).

Finally, in their recent survey, Acharya and Ryan (2016) emphasize the importance of disentangling capital demand and supply effects for drawing valid inferences. We answer their call by relying on the emerging market crisis to provide a clean supply shock to bank capital and tracing its effects on lending. In addition, we use time-series data on bank supply and borrower demand collected by the Federal Reserve in conjunction with large sample data to corroborate inferences from our emerging market crisis setting. Our inferences reiterate the importance of disentangling bank supply from borrower demand while making inferences about bank reporting behavior.

2. Related literature

Loan loss provisions represent one of the largest accounting expenses for a bank and reduce both bank earnings and regulatory capital. Prior research suggests that loan loss provisions can involve significant managerial discretion. Wahlen (1994) estimates discretionary loan loss provisions by controlling for underlying loan quality as reflected in non-performing

[9] It is important to note that our inferences do not allow for normative prescriptions about optimal bank reporting as we do not assess the overall adverse effects of preemptive loan loss provisioning on reporting transparency. In our view, our study contributes a piece of evidence to the debate regarding preemptive loan loss provisioning but is not intended to be a comprehensive assessment of its overall desirability.

loans and loan charge-offs and shows that discretionary (non-discretionary) loan loss provisions signal good (bad) news about bank future cash flows. Liu and Ryan (1995) find evidence suggesting that the degree of managerial discretion in loan loss provisions varies across different types of loans. Ahmed, Takeda, and Thomas (1999) exploit changes in capital adequacy regulations to show that banks use loan loss provisions for capital management. Relatedly, Liu and Ryan (2006) find that profitable banks use loan loss provisions to smooth earnings.

A number of recent studies focus on the timeliness of loan loss provisions (or conversely, delayed loan loss recognition) and its relation to bank risk exposure and lending. Bushman and Williams (2012; 2015) document that delayed loan loss recognition reduces bank risk-taking discipline and increases risk exposures. Beatty and Liao (2011) find exacerbated capital crunch effects during recessions for banks that delay loan loss provisioning. Gallemore (2016) finds that delayed loan loss provisioning inhibits effective regulatory oversight and is associated with regulatory forbearance. The overarching theme in these studies is that delayed loan loss recognition increases bank opacity, resulting in various negative consequences.

There are several important differences between loan loss provision timeliness and preemptive provisioning (smoothing) even though both can be viewed as “forward-looking” in nature. Timeliness captures loan loss provisions’ ability to anticipate changes in non-performing loans in the contemporaneous and the next quarter (or year). This reflects the extent to which provisions incorporate *expected* loan losses from the near future and is grounded in loan-specific information. Smoothing, on the other hand, captures banks’ use of loan loss provisions to dampen earnings volatility and is conditional exclusively on pre-provision earnings without explicit consideration of loan-specific information. This allows smoothing to serve as a mechanism through which banks can provide for *unexpected* loan losses. Furthermore, the two measures have starkly different implications for bank transparency and risk-taking discipline, with timely provisioning (which anchors in loan-specific information) enhancing risk discipline and smoothing (which disregards loan-specific information) impairing it (Bushman and Williams, 2012).

The unanswered question in the literature is whether income smoothing via provisions that are not conditioned on loan-specific information can produce the positive effects conjectured by banking regulators in mitigating pro-cyclicality. As Bushman and Williams (2012, p.2) note, "…the banking literature posits that smoothing is implicitly forward-looking in nature and can mitigate pro-cyclicality. The idea is that smoothing allows a buildup in reserves when earnings are high and current losses are low, and a reserve draw down in future periods when earnings are low and current loan losses are high." They further observe that "…the claim that smoothing mitigates pro-cyclicality has not been empirically established." This is the focus of our study.

Our analysis is comparable to Beatty and Liao (2011) in that both studies consider the capital crunch effect during recessions. The distinction lies in the different reporting metrics examined – provision timeliness in Beatty and Liao (2011) and preemptive provisioning (i.e., smoothing) in our case. In addition, we use the emerging market crisis to isolate a supply shock that is distinct from a borrower (i.e., demand) shock to achieve better identification, which, as stressed by Acharya and Ryan (2016), is important for drawing sharper inferences (see Peek and Rosengren, 1997; 2000 and Chava and Purnanandam, 2011 for other studies that disentangle supply and demand shocks, with the latter employing the same emerging market crisis setting).

When considering the effects of preemptive loan loss provisioning, examining Spanish banks can be instructive as Spanish reporting rules require dynamic (forward-looking) provisions. Here, provisions combine specific provisions based on loan-specific information and general provisions derived from historical loan loss experience over a full credit cycle. Jiménez et al. (2012) use Spain's mandatory adoption of dynamic provisioning in 2000 (combined with firm-bank lending data) and find that mandatory dynamic provisioning resulted in greater lending during crises, which in turn benefited borrowers. In contrast, our study speaks to *discretionary* provisioning (as U.S. reporting rules do not mandate dynamic provisioning) via income smoothing. Our setting also allows for a contrast between the beneficial effects of preemptive provisioning on bank stability and the detrimental effects on managerial rent-extraction. Our evidence on both the dark and bright sides of preemptive provisioning suggests that the benefits of preemptive provisioning in Jiménez et al. likely depend on the extent of agency problems within banks.[10]

Finally, Fillat and Montoriol-Garriga (2010) apply the Spanish dynamic provisioning model to U.S. banks. They find that had U.S. banks applied the Spanish model, banks would have reported lower provisions and higher income during the 2007-09 crisis, although the loan loss allowance buffer still would have been insufficient to fully absorb actual losses during the crisis. This evidence also suggests that dynamic provisioning can have a stabilizing effect on the banking sector during a crisis. However, since they focus on the recent crisis which comingles borrower demand and bank supply effects, it does not provide clear evidence of the role of bank reporting. Further, they do not investigate how bank lending is affected by (or varies with) dynamic provisioning nor do they investigate the potential dark side of preemptive loan loss provisioning.

[10] It is also pertinent to note that the key element of dynamic provisioning, i.e., general provisions, is still based on historical loan data, albeit over a longer period that includes an entire credit cycle. This is different from the smoothing measure commonly seen in the literature (and which we adopt), which is decoupled from loan-specific information.

3. Hypothesis development

The consensus among academics and banking regulators is that bank loan loss provisions are pro-cyclical, i.e., provisions are lower during upswings and higher (often sharply) in downturns (e.g., Borio et al., 2001; Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005). Making large provisions during an economic downturn diminishes bank capital at exactly the moment when capital is scarce and difficult to replenish (Kashyap and Stein, 2004).[11] To maintain capital adequacy, banks often resort to selling assets and/or paring lending, particularly banks with low capital – giving rise to a "capital crunch" or "credit crunch" (Bernanke and Lown, 1991).[12]

The fact that banks tend to accelerate loan loss provisions as economic conditions deteriorate suggests the possibility of lax lending standards and delayed recognition of the hidden dangers from questionable loans extended during the preceding period of prosperity. While the delay in loan loss recognition may be partly attributed to bank complacency in risk assessment during booms, it is often noted that current U.S. accounting rules regarding credit losses put constraints on timely loan loss provisioning.[13] For example, the U.S. Government and Accountability Office's (GAO) report on bank failures during the recent financial crisis points to the incurred loss model as a source of loan loss provision pro-cyclicality (GAO, 2013). The same report recognizes the FASB's recent work to introduce an expected loss model but also notes it is

[11] In the post-BASEL regime, loan loss provisions always reduce Tier 1 capital and reduce Tier 2 capital when the loan loss allowance is greater 1.25% of risk-weighted assets (see Beatty and Liao, 2014).

[12] Syron (1991) was the first to differentiate between a "credit crunch" and a "capital crunch" where the former refers to contractions in lending due to a drying up of deposits, while the latter refers to reduced lending due to a decline in bank equity. We use the two terms interchangeably in our setting.

[13] Specifically, current U.S. GAAP rules require application of the "incurred loss model" for estimating credit losses, where loss provisions primarily rely on historical information and a loss must be "probable" and estimable to be recognized in the financial statements. The FASB recently reached a decision to move to an "expected loss model" by 2020 (2021) for public (private) banks, where credit losses are assessed based on "information about past events, current conditions and reasonable and supportable forecasts."
http://www.fasb.org/jsp/FASB/FASBContent_C/ProjectUpdatePage&cid=1176159268094#decisions

unclear if an expected loss model would have made much difference during the recent financial crisis, given that the timing and severity of the crisis were unexpected.

Despite general agreement that making provisions for "expected" losses is beneficial (as indicated by the recent FASB move to such a model), an interesting question is whether banks should go one step further in provisioning to guard against "unexpected" losses. This involves making preemptive provisions during booms when bank earnings are high, which consequently requires lower provisions during downturns. Because major economic crises that threaten the safety and soundness of the financial system are often unforeseen, many view preemptive provisioning for "unexpected" losses as important for ensuring banking sector stability. In 2009 remarks before the Institute of International Bankers, Mr. Dugan, then Comptroller of the Currency, argues that with preemptive loan loss provisioning "…banks can be realistic about recognizing and dealing with credit problems early, when times are good, by building up a large 'war chest' of loan loss reserves. Later, when the loan losses crystallize, the fortified reserve can absorb the losses without impairing capital, keeping the bank safe, sound, and able to continue extending credit." Several academic studies offer similar conjectures about the benefits of preemptive loan loss provisioning (e.g., Borio et al., 2001; Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005). However, Bushman and Williams (2012) note that these conjectured advantages are not empirically established. We test the relation between preemptive loan loss provisioning and the severity of the capital crunch (i.e., the heightened dependence of lending on bank equity) that banks experience during a crisis. Under banking regulators' view that preemptive loan loss provisioning promotes bank safety and soundness, we expect banks that provision preemptively to experience a weaker capital crunch during a crisis. We refer to this as the "Safety-and-Soundness Hypothesis."

Hypothesis 1 (*Safety-and-Soundness Hypothesis*): The severity of the capital crunch during a crisis is *weaker* in banks with preemptive loan loss provisioning.

In contrast, a case against preemptive loan loss provisioning can be made on the grounds that it results in income smoothing. Creating reserves when income is high amounts to building a "cookie jar reserve" that can be used for the purpose of earnings management. This potentially reduces financial reporting transparency and weakens bank accountability (Levitt, 1998; Petersen, 1998). Consistent with this, Bushman and Williams (2012) find that preemptive provisioning (i.e., bank income smoothing through loan loss provisions) is associated with reduced discipline over bank risk-taking. This is also consistent with a larger literature on industrial firms that finds that income smoothing results in opacity that facilitates rent-extraction by insiders (e.g., Leuz et al., 2003; Jin and Myers, 2006; Gopalan and Jayaraman, 2012).

In addition, studies show that opacity-related adverse selection concerns are heightened during crises. For example, Lang and Maffett (2011) and Ng (2011) show that lower reporting transparency is associated with higher liquidity risk for industrial firms. The idea is that opaque firms have less firm-specific information, which makes them more susceptible to market-wide liquidity and return movements. The illiquidity impact of opacity is especially pronounced during a crisis when there is a "flight to quality (transparency)," as opacity (i.e., information asymmetry) hinders the ability of market participants to differentiate healthy firms from vulnerable ones. Bushman and Williams (2015) examine this feature within the banking sector and show that delayed loan loss recognition (which is distinct from income smoothing but similarly exacerbates bank opacity) is associated with greater bank risk exposure. As a result, banks that smooth income for opportunistic reasons should face greater financing frictions during a crisis.

Based on these arguments, we expect the beneficial effect of preemptive loan loss provisioning that we hypothesize above to be weaker in banks that smooth earnings for opportunistic reasons. We refer to this as the "Opacity Hypothesis."

> Hypothesis 2 (*Opacity Hypothesis*): The impact of preemptive loan loss provisioning in mitigating the capital crunch is weaker in banks that smooth for opportunistic reasons.

4. Data and research design

4.1. Data sources

We collect consolidated financial information covering balance sheet and income statements for bank holding companies (BHCs) available from FR Y-9C reports filed with the Federal Reserve System on a calendar-quarter basis.[14] We include both public and private BHCs in our sample as FR Y-9C reports are required for both public and private entities. As a result, our data covers a more comprehensive sample than Bank Compustat data, which covers only publicly-listed financial institutions.

4.2. Emerging markets crisis (EM_CRISIS)

The purpose of our study is to provide evidence on the role of preemptive loan loss provisioning in crisis-period bank lending. To isolate this effect, we exploit a shock to bank capital that is reasonably exogenous to borrowers' demand (Kho, Lee, and Stulz, 2000; Chava and Purnanandam, 2011), as differences in lending should emanate from the supply side rather than from variation in the demand for financing from borrowers. Specifically, we focus on

[14] These reports are required beginning in June 1986 for U.S. BHCs with assets exceeding a filing threshold of $150 million prior to 2006 and exceeding $500 million thereafter. The threshold for required filing was increased to reflect inflation, normal growth in assets, and industry consolidation of bank holding companies. The filing threshold subsequently increased to $1 billion in 2015 after our sample period.

financial crises affecting emerging economies in the late 1990s, which we label the emerging market crisis (*EM_CRISIS*).[15]

We follow prior studies that examine the effect of these crises on bank-reliant borrowers' performance (Chava and Purnanandam, 2011) and disclosure (Lo, 2014). These studies note that as events unfolded in emerging markets, certain U.S. banks faced large losses due to their exposure to sovereign debt and to private business loans in these countries. Palmer (2000, p. 91) notes that over the 1997–1999 period, a handful of large money center banks accounting for more than 40% of the total assets of all U.S. banks "consistently accounted for about 80% of total claims on counterparties in emerging markets" by U.S. banks. For these large banks, emerging market claims as a percentage of risk-adjusted capital exceeded 200% just prior to the start of the emerging market crisis (Palmer, 2000). As a result of the large loss potential on these emerging market claims, stock prices for exposed banks fell by more than a quarter in the aftermath of the events in Russia and did not recover until the early 2000s (Kho, Lee, and Stulz, 2000; Gatev, Schuermann, and Strahan, 2007). The FDIC's quarterly report for the third-quarter of 1998 shows that during the quarter of the Russian devaluation, banks recorded significantly higher charge-offs and incurred losses on their foreign operations (FDIC, 1998).

For our tests, it is important that the loss exposure of banks on emerging market loans directly affected exposed banks' willingness and ability to lend in the U.S. domestic market via a reduction in the supply of lendable capital (i.e., via an adverse shock to capital ratios). Consistent with this idea, Chava and Purnanandam (2011) show that, relative to the two years before the

[15] In July 1997, the Bank of Thailand announced its decision not to defend the Thai baht's peg to the U.S. dollar. Net capital outflows from the country ensued, and the Thai stock market fell significantly (Lo, 2014). On 27 October 1997, the Dow Jones industrial plunged 554 points, or 7.2%, amid ongoing worries about the Asian economies, and the New York Stock Exchange briefly suspended trading. In the following months, similar crises hit other Asian countries, including Indonesia, Malaysia, the Philippines, and South Korea. The crisis deepened in August 1998, as Russia devalued its currency and unilaterally suspended debt payments. Eventually the crisis spread to Latin America, resulting in a devaluation of the Brazilian real in January 1999.

Russian devaluation in 1998, exposed U.S. banks decreased (increased) domestic loan volume (loan spreads) significantly more than unaffected U.S. banks in the years following the crisis.

To measure banks affected by the emerging market crisis, we follow Chava and Purnanandam (2011) to construct an indicator, *TREAT*, based on quarterly charge-offs made during the fourth-quarter of 1997 through the third-quarter of 1999 on loans and leases made to foreign banks and governments.[16] These charge-offs were near zero between 1996Q1 and 1997Q3, as represented graphically in Figure 1.[17] As a result, these charge-offs capture the adverse shock as a result of the emerging markets crisis in a nearly discrete fashion. In addition, we define a control group of unaffected banks (i.e., *TREAT* = 0) that also made foreign loans but did not record charge-offs against these loans during the crisis period. The advantage of requiring control banks to also have foreign loans is that it selects banks similar to the affected banks in terms of lending. The disadvantage is that the control sample shrinks to 40 banks. However, since our primary results focus on the sample of affected banks and differentiate between preemptive- and non-preemptive provisioners *within* this sample, the choice of the control group is less critical in our setting.

Appendix A details our final sample of 57 banks with data available for our sample period between 1996Q1 and 1999Q3 and also for estimating preemptive loan loss provisioning in the period from 1993 to 1996. Of these 57 banks, 17 banks are affected by the emerging market crisis (*TREAT* = 1) as reflected in their charge-offs on loans to foreign banks and

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[16] Chava and Purnanandam (2011) use two additional measures to identify affected banks: (i) losses on investments in foreign debt and equity securities and (ii) banks reporting exposure to affected countries in their annual reports following Kho, Lee, and Stulz (2000), who in turn identify 78 large banks covered in Datastream based on exposures to affected emerging market countries. In contrast to these studies, we focus on foreign loan charge-offs made by BHCs in order to include private banks in the sample. Chava and Purnanandam (2011) find a high correlation among the three measures of identifying affected banks (in the range of 70% to 80%).
[17] We start our sample period from 1996Q1 since this post-dates the Mexican crisis, with the devaluation of the peso in December 1994. Our results are robust to starting our sample from 1994Q4.

governments and the remaining 40 are unaffected (*TREAT* = 0).[18] Consistent with Palmer (2000), Figure 2 shows that our sample accounts for a substantial portion of total lending by the U.S. banking sector, covering around 60% of all loans extended by banks filing FR Y-9C reports, on average.

4.3. Measure of preemptive loan loss provisioning (SMOOTH)

Our primary independent variable of interest is the extent of preemptive loan loss provisioning. To estimate this, we measure the relation between quarterly loan loss provisions and contemporaneous pre-provision earnings during the years leading up to the crisis. Specifically, we require BHCs to file a minimum of 10 quarterly FR Y-9C reports over a three-year period ending in calendar year 1996, prior to the start of the emerging market crisis beginning in 1997. We follow Beatty and Liao (2011) and eliminate BHCs with non-loan asset growth exceeding 10% to address issues related to mergers and acquisitions. Our estimate of preemptive provisioning is β_1, which we label *SMOOTH*, from the following model estimated separately for each BHC:

$$LLP_{iq} = \alpha + \beta_1 EBLLP_{iq} + \beta_2 CAP_{iq-1} + \beta_3 SIZE_{iq-1} + \beta_4 \Delta GDP_q + \beta_5 \Delta NPL_{iq-1} + \beta_6 \Delta NPL_{iq} + \beta_7 \Delta NPL_{iq+1} + \varepsilon_{iq} \quad (1)$$

where *LLP* is the quarterly loan loss provision scaled by lagged loans and leases net of unearned income; *EBLLP* is earnings before *LLP* calculated as quarterly pre-tax income plus *LLP* scaled by lagged loans; *CAP* is equity capital as of the beginning of the quarter scaled by beginning of quarter total assets; *SIZE* is the natural log of beginning of quarter total assets; *ΔGDP* indicates quarterly growth in real per capita gross domestic product. Appendix B provides detailed data

[18] We exclude Bank of America and NationsBank from our sample because the acquisition of the former (previously called BankAmerica) by the latter happened in 1998, which overlaps with the crisis-period. In addition, while neither BankAmerica nor NationsBank made charge-offs on foreign bank and government loans, the combined entity did, causing ambiguity in assigning a treatment classification. In an earlier version, we had defined Bank of America as unaffected, and continued to find similar results as reported here.

sources and definitions. The next three variables viz., lagged, current and future non-performing loans (ΔNPL_{iq-1}, ΔNPL_{iq} and ΔNPL_{iq+1}), control for the non-discretionary component of provisioning. Subscripts are included for BHC (*i*) and quarter (*q*). All continuous variables including coefficient estimates for *SMOOTH* are winsorized at the 1% tails.

Appendix C presents results of estimating eq. (1) above. Model (1) presents the condensed model without current and future changes in NPL, while model (2) includes these. The positive coefficient on *EBLLP* indicates preemptive loan loss provisioning on average, where banks provide more during periods when pre-provision earnings are higher. The positive and significant coefficient of 0.189 on *EBLLP* in model (2) suggests that banks, on average, provision 19 cents per dollar of pre-provision earnings. This estimate is similar to the 0.174 estimate that Laeven and Majnoni (2003) document for large U.S. banks over a similar time period. The coefficient on *EBLLP* is similar in magnitude (0.166) in model (2) that includes current and future *ΔNPL* as controls for the non-discretionary component of *LLP*.

4.4. Descriptive statistics

Table 1, Panel A presents descriptive statistics for combined pre-crisis and crisis periods for our sample. Banks show significant variation in preemptive loan loss provisioning, reflected in the distribution of *SMOOTH*. Mean *SMOOTH* of 0.104 indicates that the average bank provisions 10 cents from every dollar of pre-provision earnings.[19] Loan growth (*ΔLOANS*) is positive (0.039), denoting average quarterly growth of 3.9%. Total equity capital to assets (*CAP*) averages 8% of total assets for our sample of large banks (median total assets of $20.8 billion [$e^{9.945}$]).

[19] This differs from the mean coefficient of 0.166 on *EBLLP* in Appendix C because the latter is estimated from a bank-specific regression while the latter is based on a pooled sample with bank and year fixed effects.

Panel B of Table 1 compares affected and unaffected banks along key pre-crisis characteristics. Affected banks are almost indistinguishable from their unaffected counterparts in terms of preemptive provisioning (mean *SMOOTH* of 0.099 for affected banks versus 0.090 for unaffected banks). Affected banks also show statistically similar pre-crisis loan growth (0.046 versus 0.038). Affected banks are less capitalized (0.076 versus 0.082) and larger ($24 billion versus $14 billion). These univariate comparisons should be interpreted cautiously, however.

Panel C confirms the crisis-induced supply-shock for affected banks by tabulating charge-offs on loans to foreign governments/banks (*CO_FOR_GB*) and to foreign corporate borrowers (*CO_FOR_CI*) before and during the crisis. Both types of charge-offs increased more for affected banks (0.027 to 0.503 for sovereign/government loans and 0.484 to 1.977 for commercial loans) than unaffected banks (0.007 to 0.000 and 0.060 to 0.217, respectively).[20]

Panel C also validates the absence of a demand shock by showing that charge-offs on *domestic* loans (*CO_DOM*) did not increase statistically (or economically) around the crisis for either affected banks (17.713 to 17.517) or unaffected banks (18.167 to 16.430). These trends are depicted graphically in Figure 3 (Panels A and B).

5. Results

5.1. Bank lending during the crisis

To examine the effect of the emerging market crisis on bank lending, we estimate the following regression:

$$\begin{aligned}\Delta LOANS_{iq} = {} & \alpha_i + \beta_1 CAP_{iq-1} + \beta_2 EM\_CRISIS_{iq} + \beta_3 CAP_{iq-1} * EM\_CRISIS_{iq} * \\ & + \beta_4 TREAT_i + \beta_5 CAP_{iq-1} * TREAT_i + \beta_6 EM\_CRISIS_{iq} * TREAT_i + \\ & \beta_7 CAP_{iq-1} * EM\_CRISIS_{iq} * TREAT_i + \varepsilon_{iq} \qquad (2)\end{aligned}$$

[20] Charge-offs are scaled by lagged total loans and multiplied by 10^4 for exposition.

where $\Delta LOANS_{iq}$ denotes loan growth between quarter q and q-1 for bank i; *CAP* is the equity capital ratio as of quarter q-1;[21] *TREAT* is an indicator set to one for banks affected by the emerging market crisis and to zero for unaffected banks; *EM_CRISIS* is an indicator set to one for the emerging market crisis periods (1997Q4 to 1999Q3) and to zero in the pre-crisis period (1996Q1 to 1997Q3); and α_i denotes bank fixed effects. We cluster standard errors in two ways – (i) by bank and (ii) by bank and year. Our results are robust to both methods.

The capital crunch of Bernanke and Lown (1991) predicts a positive coefficient on β_7 (i.e., a heightened dependence of bank lending on capital levels during the crisis for affected banks). Because regulatory restrictions on lending are tied to bank capital ratios, banks with low capital curtail lending more than those with high capital. Table 2 presents results of estimating eq. (2). Model (1) omits bank fixed effects while model (2) includes them. Model (3) clusters standard errors by bank and year. Consistent with the capital crunch hypothesis, the coefficient on *CAP*EM_CRISIS*TREAT* (i.e., β_7) is positive and significant at the 1% significance level in all three models.[22] To interpret the economic magnitude of the capital crunch, we perform a difference-in-differences comparison similar to Berger and Udell (1994). In particular, we first compare the difference in lending growth between poorly- and well-capitalized banks (first-difference) and then compare how this difference varies between crisis and non-crisis periods (second-difference). Using the bottom quartile (0.069) and the top quartile (0.087) of *CAP* to capture poorly- versus well-capitalized banks, we find a lending growth difference of -1.12%

[21] We rely on total capital because Tier 1 capital is unavailable prior to 1996, resulting in insufficient data to cover the pre-crisis period.
[22] In contrast, unaffected banks do not experience a capital crunch during the crisis, as seen by the negative coefficient on *CAP*EM_CRISIS* in all three models. This coefficient is insignificant when bank fixed effects are included.

during non-crisis periods.[23] Consistent with the constraining role of bank capital on crisis-period lending, the difference in lending growth between poorly- versus well-capitalized banks increases to -5.91% during the emerging market crisis. This difference-in-difference estimate of 4.79% (i.e., 5.91 – 1.12) represents the capital crunch, and translates into a lending differential of \$666 million each quarter (given average pre-period assets of $e^{10.083}$ times the average loan ratio of 0.58).

5.2. Role of preemptive loan loss provisioning

We examine our primary hypothesis by considering how preemptive loan loss provisioning affects the crisis-induced capital crunch suffered by affected banks. To avoid using four-way interaction terms, we estimate the following model for affected banks by interacting *SMOOTH* with the capital-crunch specification of eq. (2):[24]

$$\begin{aligned}\Delta LOANS_{iq} = \; & \alpha_i + \beta_1 CAP_{iq-1} + \beta_2 EM\_CRISIS_{iq} + \beta_3 CAP_{iq-1} * EM\_CRISIS_{iq} + \\ & \beta_4 CAP_{iq-1} * SMOOTH_i + \beta_5 EM\_CRISIS_{iq} * SMOOTH_i + \beta_6 CAP_{iq-1} * \\ & EM\_CRISIS_{iq} * SMOOTH_i + \varepsilon_{iq} \end{aligned} \quad (3)$$

where *SMOOTH* is the estimate of preemptive loan loss provisioning. We include bank fixed effects that subsume the coefficient on *SMOOTH*. The *Safety-and-Soundness* hypothesis predicts the capital crunch will be weaker for banks provisioning preemptively ($\beta_6 < 0$), while the *Opacity* hypothesis predicts that this mitigating effect will be weaker in banks that smooth for opportunistic reasons.

Table 3, Model (1) presents results of estimating eq. (3). The coefficient on *CAP*EM_CRISIS*SMOOTH* (i.e., β_6) is negative and significant at a 5% significance level. This

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[23] We compute these by comparing lending growth during non-crisis periods (sum of the coefficients on *CAP*, *TREAT* and *CAP*TREAT*) with the crisis-period (sum of *CAP*, *EM_CRISIS*, *CAP*EM_CRISIS*, *TREAT*, *CAP*TREAT*, *EM_CRISIS*TREAT* and *CAP*EM_CRISIS*TREAT*), and by substituting *CAP*=0.069 and 0.087 for poorly- and well- capitalized banks, respectively.

[24] We show, in tests described below, that the effect of preemptive loan loss provisioning on the capital crunch is not found amongst unaffected banks that did not suffer a capital crunch.

supports the *Safety-and-Soundness* hypothesis and suggests that preemptive loan loss provisioning is associated with a weaker capital crunch during the emerging market crisis. In terms of economic significance, the difference in lending between poorly- and well-capitalized banks in the bottom decile of preemptive loan loss provisioning is -9.77% or $1.36 billion every quarter. In contrast, this difference is -0.35% or $49 million for banks in the top decile of preemptive provisioning.

Model (2) tests the validity of the parallel-trends assumption, i.e., whether pre-crisis loan growth is similar for preemptive provisioners and non-preemptive provisioners. We create an indicator variable, *PRE_CRISIS*, to denote the quarter immediately preceding the start of the crisis period and interact this indicator with *CAP*, *SMOOTH* and *CAP*SMOOTH*. While the coefficient on *CAP*EM_CRISIS*SMOOTH* remains negative and significant, indicating a weaker crisis-period capital crunch for smoothers, the coefficient on *CAP*PRE_CRISIS*SMOOTH* is insignificant. In other words, we fail to detect systematic differences in pre-crisis lending between preemptive provisioners and other affected banks. Model (3) clusters standard errors along both firm and time dimensions and reports similar results. Finally, model (4) estimates eq. (3) for unaffected banks. In contrast to affected banks, the coefficient on *CAP*EM_CRISIS_SMOOTH* is positive (coeff. = 0.331) and insignificant, suggesting that preemptive loan loss provisioning is not associated with the capital crunch in unaffected banks. These results mitigate concerns that preemptive loan loss provisioning is merely capturing some omitted bank characteristic, because in such a case, one should detect a similar effect for both affected and unaffected banks.

We conduct several robustness tests and report these results in Table 4. First, we transform *SMOOTH* into ranks ranging from 0 to 1 to mitigate concerns about outliers in the first-stage estimation and re-run model (3) of Table 3. Model (1) of Table 4 presents only the main coefficient of interest (*CAP*EM_CRISIS*SMOOTH*) although the specification includes all control variables. The coefficient *CAP*EM_CRISIS*SMOOTH* remains negative and significant (now at the 1% level), indicating that our results are unlikely to be driven by outliers in our estimate of *SMOOTH*.

Second, we ensure that our results are not due to differential severity of the crisis from the demand side. In other words, if foreign borrowers of preemptive loan loss provisioners were less adversely affected by the crisis than those of non-preemptive provisioners, then we could observe a weaker capital crunch for these banks. We include the change in foreign non-performing loans (Δ*NPL_FOR*) in the model and continue to find a negative and significant *CAP*EM_CRISIS*SMOOTH* coefficient in model (2) of Table 4.

Finally, we ensure that preemptive loan loss provisioning has an independent effect from loan loss reporting timeliness, which has also been shown to alleviate the credit crunch (Beatty and Liao, 2011). We include *TIMELY* (defined as the increase in adjusted r-squared from including current and future *ΔNPL* in the loan loss provision model) and its associated interactions with *CAP* and *EM_CRISIS*. Model (3) of Table 4 continues to show a negative and significant (at the 1% level) coefficient on *CAP*EM_CRISIS*SMOOTH*, indicating that the preemptive provisioning results are not subsumed by loan loss reporting timeliness.[25]

5.3. Real effects of preemptive loan loss provisioning on the industrial sector

We now turn to how the observed differences in bank lending translate into real effects for the industrial sector. Chava and Purnanandam (2011) show that supply shocks to bank lending are transmitted to the industrial sector and in particular to bank-dependent borrowers.

[25] We are unable to detect significance on the loan loss timeliness interactions. This could be due to estimation error in the first stage model for our sample of banks with foreign lending.

Along these lines, we investigate whether differences in crisis-period lending between preemptive provisioners and other banks translates into valuation and investment-based real effects for borrowers. We match our sample banks to borrowers using syndicated loan data on DealScan.[26] We then use the link file provided by Chava and Roberts (2008) to obtain financial information for these borrowers from COMPUSTAT. We require data on capital expenditure, market capitalization, book values of total assets and long-term debt, and information to compute return on assets. Imposing these requirements leaves us with a sample of 7,865 firm-bank-quarter observations.[27]

We predict that borrowers of affected banks experience negative shocks to their investment and valuations, and that these negative shocks are mitigated for those borrowing from preemptive loan loss provisioners. We first verify that the emerging market crisis does indeed propagate to borrowers of affected banks in our sample. We run the following model:

$$\begin{aligned} Q_{iq} = {} & \alpha_i + \beta_1 TREAT_{iq} + \beta_2 EM\_CRISIS_{iq} + \beta_3 TREAT_{iq} * EM\_CRISIS_{iq} + \\ & \beta_4 MVE_{iq} + \beta_5 ROA_{iq} + \beta_6 LEV_{iq} + \varepsilon_{iq} \end{aligned} \tag{4}$$

where *Q* is the borrowing firm's Tobin's Q; *TREAT* is an indicator for whether the borrower obtains a syndicated loan from an affected bank; and *EM_CRISIS* is the crisis-period indicator. We also control for *MVE* (natural log of the borrower's market cap); *ROA* (return on assets), and *LEV* (financial leverage). Measurement details for each variable are provided in Appendix B.

Table 5, Panel A presents descriptive statistics for the borrower sample of 7,865 firm-quarter observations. The mean *MVE* of 6.558 corresponds to $705 million, with the smallest

[26] In matching banks between the regulatory and the DealScan databases, we require an exact name match. We identify the total amount of lending from each bank to each borrower based on each lender's share of the total syndicate. We then aggregate total quarterly borrowing at the firm-bank level.
[27] We retain multiple lender observations for each firm-quarter in order to estimate the firm's *average* sensitivity to its lenders' preemptive provisioning behavior. To address any potential overstating of statistical significance, we verify that clustering by firm rather than (and in addition to) by bank provides similar inferences. We also find similar inferences when we collapse the sample to one observation per firm-quarter by retaining only the largest lender.

firm at $11 million and the largest at $70 billion. The typical firm is profitable as seen by the median *ROA* of 0.01. The mean *INV* (i.e., capital expenditures) for the sample is 0.024.[28]

Panel B of Table 5 presents results of eq. (4). Models (1) through (3) present results for the entire set of borrowers. Inconsistent with an overall value implication for borrowers of affected banks, the coefficient on *TREAT*EM_CRISIS* is insignificant. Following Chava and Purnanandam (2011), we split our sample of borrowers into small and large (at median total assets). Consistent with smaller firms with limited access to additional capital sources experiencing adverse value implications of a decrease in bank lending, model (4) shows a negative and significant coefficient on *TREAT*EM_CRISIS* of -0.19 (*p*-value < .01) – a decrease of 17% relative to average *Q* for our sample. In contrast, this coefficient is insignificant for large borrowers in model (5).

To provide evidence on the role of preemptive loan loss provisioning in the propagation of capital shocks to borrowers, we run a regression model similar to equation (4) but allow for the borrower outcomes to vary depending on whether the lending bank is a preemptive provisioner. In particular, we estimate the following model:

$$Outcome_{iq} = \alpha_i + \beta_1 SMOOTH_i + \beta_2 EM\_CRISIS_{iq} + \beta_3 SMOOTH_i * EM\_CRISIS_{iq} + \beta_4 MVE_{iq} + \beta_5 ROA_{iq} + \beta_6 LEV_{iq} + \varepsilon_{iq} \quad (5)$$

where *Outcome* is either Tobin's Q (*Q*) or capital expenditure (*INV*); *SMOOTH* indicates preemptive provisioning; and remaining variables are defined following equation (4) above.

We estimate equation (5) separately for small and large borrowers following evidence in Panel B that only small borrowers experience declines in value when loan supply contracts. We

[28] Here and in Panel C of Table 5, we lose some observations due to missing values for capital expenditure.

continue to present results for large borrowers as a falsification test.[29] Results in Panel C show that preemptive provisioning limits the adverse impacts on both borrower value and investment. Specifically, the coefficient on *SMOOTH*EM_CRISIS* is significantly positive in model (1) (coefficient of 0.219, *p*-value < .1) and also in model (2) that includes firm fixed effects (coefficient of 0.049, *p*-value < .05).[30] The significantly positive coefficient on this interaction term suggests that preemptive provisioning limits the adverse value effects for small borrowers of these banks. Turning to large borrowers, we find an insignificant coefficient on *SMOOTH*EM_CRISIS* in both model (3) as well as model (4).

Models (5) and (6) present the investment results to shed light on the mechanism underlying the value shifts. To the extent borrowers are unable to obtain funding for positive net present value projects, firm value should decline. Consistent with this idea, Panel C shows that preemptive loan loss provisioning limits the reduction in investment around the crisis. The coefficient on the interaction term *SMOOTH*EM_CRISIS* is significantly positive in model (5) for small firms (coefficient of 0.423, *p*-value < .01).[31] Here again, we do not find a similar effect for large borrowers, with an insignificant coefficient on *SMOOTH*EM_CRISIS* in model (6). Overall, preemptive loan loss provisioning provides investment and valuation benefits to small borrowers around the crisis period.

5.4. Opportunistic smoothing

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[29] This design roughly corresponds to Mill's (1884) "Method of Difference" test for examining whether a causal relation exists. Acharya and Ryan (2016, p.285) note that researchers employing this method must show that the hypothesized effect is "absent when the hypothesized cause is absent."

[30] To estimate equation (5) with fixed effects by firm, we first demean all variables by borrowing firm before running two-way clustered OLS. This results in a lower explanatory power for the regression model relative to a typical fixed effects regression, as the fixed effects are adjusted out rather than included. We take this approach to allow for two-way clustering in Stata to function, as this program will not run with a large number of regressors.

[31] These regressions do not control for the borrowers' investment opportunity set. In untabulated tests, we find greater Investment-*Q* sensitivity (where *Q* is defined both at the firm and industry levels) for small borrowers of smoothing banks as compared to small borrowers of non-smoothing banks during the crisis period.

We examine next whether the beneficial effects of preemptive loan loss provisioning are weaker in banks that might be smoothing for opportunistic reasons, as predicted by the "opacity hypothesis". Following prior studies, we use the presence of insider-lending as the proxy for managerial opportunism.[32] For example, Goetz, Laeven, and Levine (2013) find that geographic diversity exacerbates agency problems and allows bank managers to destroy wealth by lending to insiders. The idea that income smoothing facilitates rent-extraction by insiders is also supported by a larger literature on industrial firms (e.g., Leuz et al., 2003; Gopalan and Jayaraman, 2012).

We split our sample into banks with and without insider lending (*INSIDE*) and estimate the capital crunch specification from eq. (3) within each group. Table 6 presents the results. Column (1) re-produces results for all affected banks (from Table 3) as a reference. The coefficient on *CAP*EM_CRISIS*SMOOTH* is negative (coeff. = -17.341) and significant at the 1% level in the sub-sample of banks without insider lending and is insignificant (coeff. = -2.530) for insider-lending banks. Differences in these coefficients are not only statistically different (at the 1% level) but are also economically meaningful. These results support the opacity hypothesis and indicate that while preemptive provisioning, in general, benefits banks by reducing vulnerability to crises, these benefits are absent in banks that presumably smooth earnings for opportunistic reasons.

5.5. Underlying mechanisms driving the weaker capital crunch

Having established the effect of preemptive provisioning on crisis-period lending, we now explore the two potential mechanisms that could be contributing to the weaker capital crunch observed in preemptively provisioning banks: (i) these banks are better able to raise new

[32] We do not maintain that bank managers smooth earnings exclusively for insider lending reasons. Rather, we view insider lending as an indicator of a larger pattern of self-serving behavior by managers, and expect insider lending to be positively correlated with other agency-related activities (such as empire-building and perquisite consumption).

financing, thereby alleviating binding capital constraints, and/or (ii) these banks engaged in more prudent lending (both in terms of volume and risk) during the pre-crisis period.

5.5.1. Crisis-period information asymmetry and capital building

Beatty and Liao (2011) find that banks with timelier reporting of expected loan losses suffer a weaker capital crunch during a crisis. They note that one contributing factor is the ability to raise fresh capital because expected loss reporting timeliness increases transparency, mitigating information asymmetry concerns. Even though preemptive loan loss provisioning is distinct from timely loss reporting both conceptually (as the latter conditions on expected losses while the former is unconditional) and empirically, it could be that proactive provisioning is all that matters and a distinction between expected and unexpected losses is irrelevant. In such a case, one would expect preemptive loan loss provisioning to similarly manifest in lower adverse selection concerns and a greater ability to raise equity capital.

In contrast, if preemptive loan loss provisioning does indeed increase opacity (due to the resulting income smoothing) then these banks should face higher adverse selection concerns, especially during the crisis period.[33] This rationale follows recent studies that document greater crisis-period stock illiquidity for firms that are opaque (see Ng, 2011 for U.S. evidence and Lang and Maffett, 2011 for international evidence). More relevant to banks, Bushman and Williams (2015) find that bank reporting opacity (captured by delayed reporting of expected loan losses) is associated with higher stock market illiquidity, especially during crisis periods.

To provide evidence on these opposing predictions, we examine how the emerging market crisis influenced preemptive provisioners' stock illiquidity and capital building behavior (differentially from other affected banks). Figure 4 and Table 7 present these results. Figure 4

[33] We rely on Jayaraman (2008) who documents a positive association between income smoothing and information asymmetry as evidence that income smoothing increases opacity.

illustrates changes in stock illiquidity around the crisis for publicly-listed affected and unaffected banks. We define stock illiquidity (*ILLIQ*) following Amihud (2002) as the natural log of the ratio of unsigned daily stock returns to dollar trading volume averaged over the quarter. Results in Panel A of Figure 4 show a sharp increase in *ILLIQ* for affected banks but no such change for unaffected banks. Panel B splits affected banks into smoothers (i.e., banks with *SMOOTH*>0) versus non-smoothers (*SMOOTH*<=0) and shows that the increases in illiquidity in Panel A are more pronounced for smoothers. This is consistent with our prediction that the opacity inherent in preemptive provisioning increases information asymmetry, especially during crisis periods.

Table 7 provides multivariate evidence for the sample of affected banks. The coefficient on *EM_CRISIS*SMOOTH* is positive and significant in models (1) and (2) where the outcome variable is *ILLIQ*, indicating that crisis-period stock illiquidity is positively associated with preemptive loan loss provisioning.[34] Similar to the illiquidity tests, we regress change in capital (Δ*CAP*) on *EM_CRISIS* and *SMOOTH*EM_CRISIS*.[35] The negative and significant coefficient on *SMOOTH*EM_CRISIS* indicates less crisis-period capital building in preemptive provisioners. This result is robust to controlling for expected loss reporting timeliness in model (4). Overall, we interpret these results as evidence that the channel through which preemptive loan loss provisioning affects the capital crunch is distinct from that of expected loss reporting timeliness (as shown by Beatty and Liao, 2011). While reporting timeliness is associated with lower information asymmetry, preemptive provisioning correlates positively with information asymmetry, particularly during the crisis.[36]

[34] In unreported tests, we verify that these increases in stock illiquidity are concentrated in banks with insider lending that are presumably smoothing for opportunistic reasons.

[35] We define the change in capital as increases in contributed capital net of dividend payouts.

[36] Our fixed effects design precludes examining whether preemptive provisioners raise more capital in the pre-crisis period, since this effect would be identified by the coefficient on *SMOOTH*, which the bank fixed effects subsume. In unreported results, we do not find evidence that preemptive provisioners raise more capital in the pre-period. However, these tests should be interpreted cautiously as they exclude bank fixed effects.

5.5.2. Restrained lending in the pre-crisis period

Next, we explore whether preemptive loan loss provisioning acts as a disciplining mechanism by forcing banks to exercise more prudence during regular/boom periods. Banking regulators (e.g., GAO, 2013) contend that having to book preemptive provisions forces banks to restrain risk-taking during "loose money" periods. Table 8 provides preliminary evidence on this mechanism by correlating *SMOOTH* with several pre-period characteristics including risk-taking. In particular, we include bank size (*SIZE*) defined as the log of bank assets, equity capital ratio (*CAP*), the level and change in loans (*LOANS* and Δ*LOANS*, respectively), the amount of deposits (*DEP*), pre-provision profitability (*EBLLP*), non-performing loans as a portion of total loans (*NPL*), and distance-to-default (DTD) which is an inverse measure of risk-taking (measured as capital plus ROA before LLP divided by the standard deviation of pre-provision ROA) – each measured over the pre-crisis period. We present two variants of this association test: (i) based on the panel of bank-quarter observations, and (ii) using one observation for each bank. The former specification uses 119 observations while the latter specification uses 17 observations (i.e., the number of unique affected banks). Given the small sample size for the latter, we use median regressions to alleviate concerns about outliers.[37]

Results in Table 8, Panel A suggest that preemptive loan loss provisioning is associated with less aggressive lending growth (as seen by the negative and significant coefficient on Δ*LOANS*) as well as lower risk-taking (evidenced by a negative and marginally significant coefficient on *NPL*). While these associations are suggestive of preemptive loan loss provisioning restraining risk-taking during regular periods, we caution the reader to interpret these associations with care as the direction of causality is unclear.

[37] Given the small-sample concern, we do not split these banks further based on insider lending.

These pre-period relations do however raise the possibility that it is lower pre-period risk-taking rather than preemptive provisioning *per se* that is driving a weaker capital crunch. To verify that this is not the case, in Panel B of Table 8 we substitute *SMOOTH* with each of these pre-period bank characteristics and re-estimate the capital crunch regression from model (3) of Table 3. We define "Alternative Variables" (*AVAR*) to represent *SIZE*, *CAP*, *LOANS*, Δ*LOANS*, *DEP*, *EBLLP*, *NPL* and *DTD*, respectively, in each of the columns. Results in Panel B show that the majority of these alternative pre-crisis characteristics do not generate similar effects to that of preemptive loan loss provisioning. However, banks with higher pre-crisis profitability (*EBLLP*) and fewer non-performing loans (*NPL*) do experience a weaker capital crunch, as indicated by the negative and significant coefficient on *CAP*EM_CRISIS*EBLLP* and the positive and significant coefficient on *CAP***EM_CRISIS***NPL*, respectively. To ensure that effects for preemptive loan loss provisioning are incremental to these, we include *SMOOTH* and its associated interactions in the same specification with *EBLLP* (and similarly with *NPL*). We find that a weaker capital crunch for preemptive provisioners remains robust (as seen by a negative and significant coefficient on *CAP*EM_CRISIS*SMOOTH* in models [7] and [9]). Overall, we interpret these results as evidence that a weaker capital crunch in preemptive provisioners is not driven by other bank characteristics.

5.6. Endogeneity of preemptive loan loss provisioning and the Senior Loan Officer Opinion Survey

The SEC's 1998 litigation of SunTrust Bank for apparently over-provisioning its reserves was a pivotal point in banks' financial reporting practices. The case sent a clear message regarding the SEC's preference for accounting transparency (i.e., less income smoothing) over bank stability (e.g., Balla and Rose, 2011). To address concerns that our results are confounded by the potential endogeneity of preemptive loan loss provisioning, we use this event as an instrument to extract measures of preemptive provisioning that are orthogonal to underlying bank characteristics.

Similar to Balla and Rose (2011), we expect publicly-listed banks that are under the SEC's jurisdiction to reduce preemptive provisioning in the post-litigation period more than privately-held banks.[38] In addition, we expect cross-sectional variation in public banks' response to the event based on the expected level of SEC enforcement. We predict that the reduction in preemptive loan loss provisioning after the SunTrust litigation will be stronger for banks that are closer to an SEC office. This follows prior work on the resource-constrained SEC view (e.g., Kedia and Rajgopal, 2011) that finds that the SEC is more likely to investigate firms closer to its offices (see also Eisenbach et al., 2016 who document the role of resource constraints on bank supervision). While this design allows us to instrument preemptive loan loss provisioning with a counterpart that is untainted by unobserved bank characteristics, we cannot use this variable around the emerging market crisis as the litigation occurred subsequently. We therefore turn to an alternative setting.

We use changes in aggregate bank lending standards from the Senior Loan Officer Opinion Survey (SLOOS) on Bank Lending to capture bank supply shocks. The purpose of the survey is to provide qualitative and quantitative information on credit availability and demand, as well as on evolving developments and lending practices in U.S. loan markets. Since these surveys capture both supply and demand conditions, they are suitable for examining changes in bank lending due to supply versus demand factors (e.g., Lown and Morgan, 2002, 2006; Leary, 2009; Maddaloni and Peydró, 2011; Axelson et al., 2013; Bassett et al., 2014; Ciccarelli et al.,

[38] Beck and Narayanamoorthy (2013) examine changes in loan loss provisioning timeliness around this event, but restrict their focus to public banks.

2015; Bergbrant et al., 2016). Appendix D provides details on survey administration and the questions underlying measures of lending standards and borrower demand.

Figure 5 plots survey response data over the 1993 to 2014 period, where the solid line denotes lending standards (*Lending*) and the dashed line denotes borrower demand (*Demand*). Since bank lending standards are influenced not only by demand-side factors but also by macroeconomic uncertainty, we follow Bassett et al. (2014) and orthogonalize the lending standards measure with respect to borrower demand (from the survey), the S&P 500 implied volatility index (VIX), and the excess bond premium available from Gilchrist and Zakrajsek (2012).[39] This measure (labeled *Supply*) is denoted by the dotted line.

Panel A of Table 9 presents results of the regression of changes in bank lending on bank supply, borrower demand, and their respective interactions with preemptive loan loss provisioning. Following the monetary transmission literature (e.g., Bernanke and Blinder, 1992; Kashyap and Stein, 2000) we measure changes in bank lending over the subsequent four quarters. We compute preemptive loan loss provisioning (*SMOOTH*) based on a rolling-window of 12 prior quarters, and multiply the borrower demand values from the survey by -1 (and term it *WEAK*) so as to be comparable with supply tightening.

Model (1) of Table 9, Panel A presents results for supply tightening alone while model (2) also includes the demand weakening effect. Consistent with our earlier results, preemptive loan loss provisioning mitigates the contractionary effect of bank supply tightening on lending. In particular, the coefficient on *TIGHT* is negative and significant in both models, while that on

[39] Bassett et al. (2014) use a vector of forward- and backward-looking variables to extract a measure of bank supply. Since the forward-looking variables could be endogenous to bank lending, we exclude them. In addition, we retain VIX and the excess bond premium as some of the other controls could also capture supply effects (such as the Fed Funds rate as shown by Bernanke and Blinder, 1992; Kashyap and Stein, 2000). Since Gilchrist and Zakrajsek (2012) note that the excess bond premium could also capture supply, we verify that our results are robust to excluding it.

*TIGHT*SMOOTH* is positive and significant. Further, while weakening demand also has a similar contractionary effect on bank lending (the coefficient on *WEAK* is negative and significant), preemptive provisioning is uncorrelated with this contraction – as seen by the insignificant coefficient on *WEAK*SMOOTH*. These results are robust to including bank and year-quarter fixed-effects in model (3) (that subsume the coefficients on *TIGHT* and *WEAK*) and also to alternative clustering of standard errors in model (4). Overall, we interpret these results as confirmatory evidence that preemptive loan loss provisioning mitigates bank lending contractions that arise due to adverse bank capital supply shocks. To ensure comparability with the capital crunch results, we split the sample into high and low capital (based on the median value of lagged capital), and estimate model (4) within each subset. Consistent with our earlier capital crunch results, the effect of preemptive provisioning in mitigating supply-based lending contractions comes through in the subset of poorly-capitalized banks in model (5) but not in well-capitalized ones in model (6).[40]

Panel B presents results of the diff-in-diff test of changes in preemptive loan loss provisioning around the SunTrust litigation. We set the *POST_ST* indicator to one for years after the SunTrust case (i.e., 1999 onwards) and to zero for the years before. We define another indicator, *SEC*, that takes one for banks registered with the SEC and zero for those that are not. This indicator captures not only publicly-listed banks but also private banks with public debt. *POST_ST*SEC* identifies the diff-in-diff effect of the litigation on financial reporting changes in banks that report to the SEC compared to those that do not. Consistent with our prediction (and evidence in Balla and Rose, 2011), the coefficient on this interaction term is negative and significant in all specifications indicating that publicly-listed banks engaged in less preemptive

[40] In untabulated tests, we split the set of poorly-capitalized banks into those with and without insider lending. Consistent with our prior results, we find that the beneficial effects of preemptive loan loss provisioning are concentrated in those without insider lending.

provisioning in the aftermath of the SunTrust litigation relative to private banks.[41] The latter in fact experienced no change in their reporting behavior (an insignificant coefficient on *POST_ST*). Model (2) presents the role of enforcement around the event – banks farther from the SEC (captured by *DIST*, the distance between the bank's headquarters and the closest SEC office) have a smaller decrease in preemptive provisioning after the litigation (*POST_ST*SEC*DIST* is positive and significant). Model (3) verifies that these inferences are robust to controlling for loan composition across banks (e.g., Ryan and Keeley, 2013).

Panel C presents similar tests to Panel A, but now using the instrumented *SMOOTH* measure based on model (3) of Panel B (which we label *SMOOTH_PRED*).[42] Consistent with prior inferences, the instrumented measure of preemptive loan loss provisioning mitigates the effect of supply tightening on bank lending (as seen by the negative and significant coefficient on *TIGHT*SMOOTH_PRED*) but is uncorrelated with lending contractions that accompany weakening of borrower demand (*WEAK*SMOOTH_PRED* is insignificant).[43] These inferences are robust to including year-quarter fixed effects in model (3) and alternative clustering of standard errors in model (4). Finally, we find that the effect of *SMOOTH* in mitigating lending contractions is concentrated in the sub-sample of banks with less capital (models [5] and [6]).[44] Overall, these results suggest that inferences are robust to addressing the endogeneity of preemptive provisioning.

[41] Since these specifications include bank fixed effects, they represent within-bank changes in preemptive loan loss provisioning after the event as compared to before.
[42] To ensure that our instrument is not confounded by bank characteristics, we define *SMOOTH_PRED* based on the coefficients on *POST_ST*, *SEC*, *DIST* and their interactions, but excluding the loan-composition variables.
[43] We do not perform the insider lending split since the instrumented measure is (by construction) orthogonal to agency-related motivations.
[44] We re-compute the instrumental variable (*SMOOTH_PRED*) by estimating the first-stage regression (model [3] of Table 8, Panel B) separately for low capital and high capital banks.

6. Conclusions

Bank regulators and academics have long conjectured the beneficial effects of preemptive loan loss provisioning through income smoothing for bank lending and stability during a crisis, although this has not been established empirically (Bushman and Williams, 2012). We use the emerging market crisis of the late 1990s to identify a supply shock to bank capital and show that the contractionary effects on bank lending are attenuated for banks with greater preemptive loan loss provisioning. These lending differences translate into positive real effects in the valuation and investment behavior of these banks' small borrowers that likely have limited access to alternative funding sources. In addition, we show that the beneficial effects of preemptive loan loss provisioning are absent in banks that presumably smooth earnings for opportunistic reasons – consistent with accounting regulators' concerns that preemptive provisioning engenders opacity.

Our inferences are robust to addressing the endogeneity of preemptive loan loss provisioning and to corroborating the emerging market crisis results with large-sample evidence based on Federal Reserve data on bank supply and borrower demand. It is important to note that we do not directly assess all the potential negative effects of preemptive loan loss provisioning on reporting transparency. Our study provides one piece of evidence for the debate about preemptive loan loss provisioning, and is not intended to be an overall assessment of its net benefits and costs.

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Appendix A: Sample of bank holding companies during the emerging market crises period

Our final sample comprises 57 bank holding companies filing FR Y-9C reports with data available in the Bank Regulatory database available via Wharton Research Database Services (WRDS) with data available for our emerging market crises sample period between 1994 Q3 and 1999 Q2 to estimate the extent of preemptive loan loss provisioning (pre-crisis) and loan growth (pre-crisis and crisis periods). Of these 57 banks, 17 banks are affected by the emerging markets crisis (*TREAT* = 1) as reflected in their charge-offs on loans to foreign banks and governments and the remaining 40 are unaffected (*TREAT* = 0).

Affected Banks	**Unaffected Banks**	
Bank Of New York	Banc One Corp	Keycorp
Bank Boston Corporation	Bank Leumi	Mellon Bank
Bankers Trust	Bankmont Financial	National City
Baybanks	Chase Equity Holdings	New Galveston
Chase Manhattan	Comerica Inc	Northern Trust
Citicorp	Corestates Financial	Norwest
First Union	Crestar Financial	PNC Bancorp
Hamilton Bancorp	Cullen/Frost Bankers	PNC Bank
NB Holdings Corp	First Chicago	Popular, Inc.
Pacific Century	First Fidelity	Sabrina Properties
Rebank Netherlands	First Maryland	State Street
Regions Financial	First Security	Suntrust Banks of Florida
Republic Banking Corp	First Tennessee	Suntrust Banks of Georgia
Republic New York	Granvalor Holdings	Suntrust Banks
Riggs National	Harris Bankcorp	Trans Financial
U.S. Bancorp	Hibernia Corp	Unionbancal Corporation
Union Planters Corp	HSBC USA	Victoria Bankshares
	IBC Subsidiary	Wells Fargo
	Independent Bancorp of Arizona	Whitney Holding
	Intl. Bancshares	Zions Bancorp

Appendix B: Variable definitions

Expressions within parentheses denote corresponding variable names in FR Y-9C reports (BHCK) or for consolidated information of bank branches/subsidiaries available via Call Reports (RCFD). Continuous variables are winsorized at the top and bottom one percent of the variable's distribution.

Variable	Definition
Bank variables:	
CAP	Equity capital ratio measured using total equity capital (BHCK3210) scaled by total assets (BHCK2170).
ΔCAP	Change in contributed equity capital measured as the end of quarter total equity capital (BHCK3210) less beginning of quarter total equity capital (BHCK3210), dividends paid (BHCK4460), and net income for the quarter (BHCK4340) and scaled by beginning of quarter total assets (BHCK2170). This measures the change in equity capital due to net equity issuance during the quarter.
CI_LOANS	Commercial and industrial loans (BHCK1766) scaled by total assets (BHCK2170).
CO_FOR_GB	Charge-offs on loans to foreign banks and governments calculated as the sum of charge-offs on loans to foreign governments and official institutions (BHCK4643) and to foreign banks (BHCK4654) scaled by beginning of quarter total loans and leases net of unearned income (BHCK2122).
CO_FOR_CI	Charge-offs on loans to foreign commercial and industrial borrowers calculated as charge-offs on commercial and industrial loans to non-U.S. addressees (BHCK4646) scaled by beginning of quarter total loans and leases net of unearned income (BHCK2122).
CO_DOM	Charge-offs on loans to domestic (U.S.) borrowers calculated as the difference between total charge-offs for loans and leases (BHCK4635) and the sum of charge-offs to foreign governments (BHCK4643), foreign banks (BHCK4654), and commercial and industrial loans to foreign borrowers (BHCK4646), scaled by beginning of quarter total loans and leases net of unearned income (BHCK2122).
DEP	Deposits measured as the sum of non-interest bearing (BHDM6631+BHFN6631) and interest bearing (BHDM6636+BHFN6636) deposits in foreign and domestic offices scaled by total assets (BHCK2170).
DIST	The distance in miles between the bank holding company headquarters and the closest US Securities and Exchange Commission office.
DTD	Distance-to-default calculated as the mean beginning of quarter capital ratio plus mean return on assets before loan loss provisions divided by the standard deviation of pre-provision return on assets estimated at the bank-holding company level using three years of quarterly observations in the pre-crisis period.
EBLLP	Earnings before loan loss provisions calculated as quarterly pre-tax income (BHCK4340 + BHCK4302) plus the quarterly loan loss provision (BHCK4230) scaled by beginning of quarter total loans and leases net of unearned income (BHCK2122).
EM_CRISIS	An indicator for periods following the devaluation of the Thai currency marking the start of the emerging markets crisis that includes the Russian currency devaluation in August 1998 and the devaluation of the Brazilian real in January 1999. The indicator is set to one for periods following 1997 Q2 and ending with the 1999 Q2, and to zero for periods between 1994 Q3 and 1997 Q1.
ΔGDP	Quarterly growth in real per capita gross domestic product available from the St. Louis FRED database.
ILLIQ	Illiquidity defined for publicly-traded bank holding companies following Amihud (2002) as the natural log of daily unsigned stock returns scaled by dollar trading volume and averaged over the quarter.
INDIV_LOANS	Loans to individuals (BHCK1975) scaled by total assets (BHCK2170).
INSIDE	Loans made to insiders (RCFD6164) scaled by total loans (RCFD1400) available from Call Reports in the Bank Regulatory database. Insider lending and loans aggregated from the Call Reports up to the bank-holding company level using the parent's entity identifier (RSSD9364) and requiring an ownership percentage (RSSD9365) of at least 50%, following the approach in Goetz, Laeven, and Levine (2013).
LLP	Loan loss provision calculated as the quarterly provision (BHCK4230) scaled by beginning of quarter total loans and leases net of unearned income (BHCK2122).
(Δ)LOANS	Ratio of total loans and leases net of unearned income (BHCK2122) to total assets (BHCK2170) measured as of the start of the quarter. Growth in loans (ΔLoans) is measured as the quarterly change in the natural log of total loans and leases net of unearned income (BHCK2122).[45]

[45] The emerging market crisis results are nearly identical when using BHCK2125 (total loans and leases) as an alternative, which is unavailable after 1999Q3.

(Δ)NPL	Non-performing loans are calculated using data available in FR Y-9C reports for bank-holding companies provided by the Chicago Federal Reserve as the sum of total loans and leases in non-accrual status (BHCK5526) and total loans that are 90 days or more past due and still accruing (BHCK5525). Changes in non-performing loans (ΔNPL) are calculated by taking the difference in non-performing loans relative to the prior quarter. Levels and changes in non-performing loans are scaled by beginning of quarter total loans and leases net of unearned income (BHCK2122).
(Δ)NPL_FOR	Non-performing loans for foreign borrowers calculated using data available in FR Y-9C reports as the sum of loans and leases for non-U.S. addressees in non-accrual status (BHCK1913) and loans that are 90 days or more past due and still accruing (BHCK1912) less the sum of these values in the prior quarter scaled by beginning of quarter total loans and leases net of unearned income (BHCK2122).
OTH_LOANS	Remaining loans measured as the difference between gross loans (BHCK2122+BHCK2123) and the sum of real estate loans (BHCK1410), commercial and industrial loans (BHCK1766), and loans to individuals (BHCK1975) and scaled by total assets (BHCK2170).
POST_ST	An indicator set to one for the years after the SunTrust Banks SEC inquiry and settlement in 1999, and to zero for the years before 1999.
RE_LOANS	Real estate loans (BHCK1410) scaled by total assets (BHCK2170).
SEC	An indicator set to one for bank holding companies registered with the US Securities and Exchange Commission (RSSD9056 = 1), and to zero for those that are not registered.
SIZE	Natural logarithm of the book value of total assets (BHCK2170).
SMOOTH	Preemptive loan loss provisioning is calculated as the coefficient on earnings before loan loss provisions in the following regression run at the bank-holding company level using three years of pre-crisis quarterly observations: $LLP_{it} = \alpha + \beta_1 EBLLP_{iq} + \beta_2 CAP_{iq-1} + \beta_3 SIZE_{iq-1} + \beta_4 \Delta GDP_q + \beta_5 \Delta NPL_{iq-1} + \beta_6 \Delta NPL_{iq} + \beta_7 \Delta NPL_{iq+1} + \varepsilon_{iq}$ where i denotes the bank-holding company and t denotes the fiscal quarter. Each regression requires a minimum of 10 quarterly observations with data available over the 3-year pre-crisis window. Capital and Size variables are measured as of the start of quarter t. Observations with growth in non-loan assets exceeding 10% are eliminated as likely merger and acquisition observations following the approach in Beatty and Liao (2011).
TIGHT	Bank lending supply tightening is computed using data available from the Senior Loan Officer Opinion Survey (SLOOS) conducted by the Federal Reserve each quarter. The supply measure is the aggregated net percent tightening, defined as 100 × [(# reporting tightening standards - # reporting easing)/total # reporting] where bank lending standards are measured based on responses to the following question: Over the past three months, how have your bank's credit standards for approving applications for C&I (commercial and industrial) loans or credit lines—other than those to be used to finance mergers and acquisitions—to large and middle-market firms changed? 1) Tightened considerably 2) tightened somewhat 3) remained basically unchanged 4) eased somewhat 5) eased considerably. We orthogonalize bank lending supply with respect to borrower demand (from the SLOO survey), the S&P 500 implied volatility index (VIX), and the excess bond premium measured by Gilchrist and Zakrajsek (2012) to arrive at our measure of supply tightening.
TIMELY	Loan loss provision timeliness is measured following the approach in Beatty and Liao (2011) as the difference in the adjusted R2 ([b] – [a]) from the following two regressions run at the bank-holding company level using three years of pre-crisis quarterly observations: $LLP_{it} = \alpha + \beta_1 EBLLP_{iq} + \beta_2 CAP_{iq-1} + \beta_3 SIZE_{iq-1} + \beta_4 \Delta GDP_q + \beta_5 \Delta NPL_{iq-1} + \varepsilon_{iq} \quad (a)$ $LLP_{it} = \alpha + \beta_1 EBLLP_{iq} + \beta_2 CAP_{iq-1} + \beta_3 SIZE_{iq-1} + \beta_4 \Delta GDP_q + \beta_5 \Delta NPL_{iq-1} + \beta_6 \Delta NPL_{iq} + \beta_7 \Delta NPL_{iq+1} + \varepsilon_{iq} \quad (b)$ where *i* denotes bank-holding company and *q* denotes fiscal quarter. Each regression requires a minimum of 10 quarterly observations with data available over the prior 3-year window. Capital is measured as of the start of quarter. Observations with growth in non-loan assets exceeding 10% are eliminated as likely mergers and acquisitions following the approach in Beatty and Liao (2011).
TREAT	An indicator set to one for bank holding companies with charge-offs on loans to foreign governments and official institutions (BHCK4643) or to foreign banks (BHCK4654) following the third-quarter of 1997. We set the indicator to zero for a control sample of bank holding companies with non-zero values for loans to foreign governments (BHCK2081) and/or foreign banks (BHCK1296) during the emerging markets sample period beginning with 1994 Q3 and ending with 1999 Q2. Bank holding companies with

	no foreign lending to these groups are excluded from this analysis.
WEAK	Borrower demand is computed using data available from the Senior Loan Officer Opinion Survey (SLOOS) conducted by the Federal Reserve each quarter. The demand measure is the aggregated net percent stronger demand, defined as 100 × [(# reporting stronger demand - # reporting weaker demand)/total # reporting] where demand is measured using the following survey question: Apart from normal seasonal variation, how has demand for C&I loans changed over the past three months? (Please consider only funds actually disbursed as opposed to requests for new or increased lines of credit.) 1) Substantially stronger 2) Moderately stronger 3) About the same 4) Moderately weaker 5) Substantially weaker. We multiply the resulting borrower demand measure by negative one to result in a measure that increases as demand weakens.
<u>Borrower Variables:</u>	
INV	Investment measured as capital expenditure during the year (CAPX) scaled by beginning of fiscal year total assets from COMPUSTAT.
LEV	Leverage calculated as the book value of long-term debt plus debt in current liabilities scaled by total assets from COMPUSTAT.
MVE	Market value of common equity as of fiscal year-end measured using data available in COMPUSTAT.
Q	Tobin's Q measured as fiscal year-end market value of common equity plus the book value of total liabilities scaled by the book value of total assets using data available in COMPUSTAT.
ROA	Return on assets calculated as income before extraordinary items scaled by beginning of fiscal year total assets from COMPUSTAT.

Appendix C: Estimating preemptive loan loss provisioning (*SMOOTH*)

This panel comprises 679 bank-quarter observations over the period 1993 to 1996. The dependent variable is quarterly loan loss provisions (*LLP*) scaled by lagged total loans. *EBLLP* denotes earnings before the loan loss provision. *CAP* denotes bank equity as a proportion of total assets and measured as of the beginning of the quarter. *SIZE* is measured as the natural log of beginning of quarter total assets for the bank holding company. ΔGDP denotes quarterly growth in real per capita gross domestic product. ΔNPL_{q-1}, ΔNPL_q and ΔNPL_{q+1} indicate total non-performing loans in the prior, current, and next quarters, respectively, each scaled by lagged total loans and scaled by 10^{-2} (for ease of interpretation). Detailed variable definitions are provided in Appendix B. All models include bank and year fixed effects. Robust standard errors clustered by bank and by year are presented under the coefficients in parentheses.

Dep. variable	***LLP***	
	(1)	**(2)**
EBLLP (SMOOTH)	0.189	0.166
	[0.070]***	[0.053]***
CAP	0.011	0.005
	[0.019]	[0.016]
SIZE	0.000	0.001
	[0.000]	[0.000]
ΔGDP	0.007	0.009
	[0.003]**	[0.002]***
ΔNPL_{q-1}	0.045	0.061
	[0.023]*	[0.025]**
ΔNPL_q		0.075
		[0.043]*
ΔNPL_{q+1}		0.007
		[0.022]
Clustering	Bank, year	Bank, year
Fixed effects	Bank, year	Bank, year
Adj. R^2	0.44	0.47
Obs.	679	679

Appendix D: Senior Loan Officer Opinion Survey (SLOOS)

The Federal Reserve circulates a survey typically four times a year to senior loan officers of up to 60 large domestically chartered commercial banks and up to 24 large U.S. branches and agencies of foreign banks (Federal Reserve Board, 2013). See https://www.federalreserve.gov/boarddocs/SnLoanSurvey/about.htm for additional details on the SLOO Survey.

Bank lending standards are measured based on the responses to the following question:

> "Over the past three months, how have your bank's credit standards for approving applications for C&I (commercial and industrial) loans or credit lines—other than those to be used to finance mergers and acquisitions—to large and middle-market firms changed? 1) Tightened considerably 2) tightened somewhat 3) remained basically unchanged 4) eased somewhat 5) eased considerably"

The lending standards measure is the aggregated *net* percent tightening, defined as 100 × [(# reporting tightening standards - # reporting easing)/total # reporting].

Borrower demand measures are similarly estimated based on the following question:

> "Apart from normal seasonal variation, how has demand for C&I loans changed over the past three months? (Please consider only funds actually disbursed as opposed to requests for new or increased lines of credit.)
> 1) Substantially stronger 2) Moderately stronger 3) About the same 4) Moderately weaker
> 5) Substantially weaker"

The demand measure is the aggregated *net* percent stronger demand, defined as 100 × [(# reporting stronger demand - # reporting weaker demand)/total # reporting].

Table 1: Descriptive statistics

The sample comprises 805 bank-quarter observations for 57 banks (17 affected and 40 unaffected banks) over the period 1996Q1 to 1999Q3. Panel A presents descriptive statistics for the full sample. Panels B and C present univariate differences between affected (*TREAT*=1) versus unaffected (*TREAT*=0) banks in the pre-period and pre-versus-post periods respectively. *SMOOTH* denotes income smoothing, defined over the 1993-1996 period. We estimate *SMOOTH* by regressing loan loss provisions (*LLP*) on pre-provisioning income (*EBLLP*) and other controls, where the coefficient on *EBLLP* represents *SMOOTH*. The period from 1996Q1 to 1997Q3 is defined as the pre-crisis period (*EM_CRISIS*=0), while the period from 1997Q4 to 1999Q3 is the crisis period (*EM_CRISIS*=1). Δ*LOANS* denotes quarterly loan growth. *CAP* denotes bank equity as a proportion of total assets. *SIZE* indicates bank size and is measured as the natural log of total assets (in millions). *LOANS* (*DEP*) denotes the proportion of loans (deposits) to total assets. *CO_FOR_GB* and *CO_FOR_CI* denote foreign loan charge-offs on government/bank and commercial/industrial loans, respectively each scaled by lagged total loans (and multiplied by 10^4). Δ*NPL_FOR* denotes foreign non-performing-loans scaled by lagged total loans (and multiplied by 10^4). Appendix B presents detailed variable definitions

Panel A: Full sample

Variable	Obs.	Mean	Median	S.D.	Min	Max
TREAT	805	0.308	0.000	0.462	0.000	1.000
SMOOTH	805	0.104	0.076	0.242	-0.841	0.763
Δ*LOANS*	805	0.039	0.023	0.092	-0.103	0.620
CAP	805	0.080	0.079	0.021	0.027	0.150
SIZE	805	9.945	10.168	1.547	5.314	12.797
LOANS	805	0.580	0.617	0.145	0.146	0.782
DEP	802	0.693	0.687	0.116	0.257	0.882
CO_FOR_GB	805	0.087	0.000	0.561	0.000	4.876
CO_FOR_CI	805	0.484	0.000	1.680	0.000	10.732
Δ*NPL_FOR*	805	0.474	0.000	5.154	-16.726	33.592

Table 1, continued

Panel B: Pre-crisis differences between affected and unaffected banks

Variables	Affected (N=119)				Unaffected (N=280)			
	Mean	S.D.	Min	Max	Mean	S.D.	Min	Max
SMOOTH	0.099	0.244	-0.179	0.763	0.090	0.255	-0.841	0.609
ΔLOANS	0.046	0.106	-0.103	0.620	0.038	0.087	-0.103	0.620
CAP	0.076***	0.016	0.041	0.150	0.082	0.022	0.027	0.150
SIZE	10.083***	1.835	6.423	12.771	9.566	1.489	5.314	11.712
LOANS	0.580	0.157	0.146	0.765	0.578	0.132	0.146	0.774
DEP	0.690**	0.153	0.257	0.878	0.718	0.094	0.496	0.882
CO_FOR_GB	0.027**	0.116	0.000	0.753	0.007	0.066	0.000	0.986
CO_FOR_CI	0.484***	1.292	0.000	9.134	0.060	0.629	0.000	9.946
ΔNPL_FOR	0.273	5.940	-15.594	33.592	-0.127	3.017	-16.726	33.592

Panel C: Foreign and domestic loan charge-offs

Variables	Affected		Unaffected	
	Pre-crisis	Crisis	Pre-crisis	Crisis
CO_FOR_GB	0.027	0.503	0.007	0.000
Diff. (Post-Pre)	0.476***		-0.007	
Diff.-in-Diff.	0.483***			

	Pre-crisis	Crisis	Pre-crisis	Crisis
CO_FOR_CI	0.484	1.977	0.060	0.217
Diff. (Post-Pre)	1.493***		0.157**	
Diff.-in-Diff.	1.336***			

	Pre-crisis	Crisis	Pre-crisis	Crisis
CO_DOM	17.713	17.517	18.167	16.430
Diff. (Post-Pre)	-0.196		-1.737	
Diff.-in-Diff.	1.543			

Table 2: Effect of the emerging markets crisis on bank lending

This table presents regressions predicting quarterly loan growth (Δ*LOANS*) defined as the change in the log of total loans and leases net of unearned income between quarter *q* and quarter *q-1*. *CAP* denotes the bank equity ratio as a percent of total bank assets defined as of the end quarter *q-1*. *TREAT* is an indicator variable that takes the value one for banks with exposure to the emerging market crises, and zero for unaffected banks with foreign lending. *EM_CRISIS* is an indicator that takes the value of one during the emerging market crisis period (1997Q4 to 1999Q3) and 0 for the pre-crisis period (1996Q1 to 1997Q3). Appendix B presents detailed variable definitions. Robust standard errors clustered by bank in models (1) and (2) and by bank and year in model (3) are tabulated under the coefficients in parentheses. In addition, models (2) and (3) include bank fixed effects. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. variable	**Δ*LOANS***		
	(1)	**(2)**	**(3)**
CAP	0.244	-0.337	-0.337
	[0.190]	[1.007]	[1.579]
EM_CRISIS	0.049	0.042	0.042
	[0.022]**	[0.035]	[0.028]
*CAP*EM_CRISIS*	-0.593	-0.534	-0.534
	[0.259]**	[0.409]	[0.301]*
TREAT	0.071		
	[0.040]*		
*CAP*TREAT*	-0.818	0.939	0.939
	[0.499]	[1.623]	[1.950]
*EM_CRISIS*TREAT*	-0.254	-0.248	-0.248
	[0.061]***	[0.068]***	[0.035]***
CAP*EM_CRISIS*TREAT	**3.172**	**3.121**	**3.121**
	[0.867]*	**[0.948]***	**[0.575]***
Clustering	Bank	Bank	Bank, year
Fixed effects	None	Bank	Bank
Adj. R^2	0.03	0.04	0.04
Obs.	805	805	805

Table 3: Role of preemptive loan loss provisioning in the crisis-induced capital crunch

The dependent variable is quarterly loan growth (Δ*LOANS*). *CAP* denotes lagged bank equity as a percent of total bank assets. *EM_CRISIS* is an indicator set to one during the emerging market crisis period and to 0 for the pre-crisis period. *PRE_CRISIS* is an indicator that is set to 1 for the quarter preceding the start of the crisis. *SMOOTH* denotes the estimate of preemptive loan loss provisioning estimated as of the pre-crisis period. Appendix B presents detailed variable definitions. All regressions contain bank fixed effects. Robust standard errors clustered by bank in models (1) and (2), and by bank and year in models (3) and (4) are tabulated under coefficients in parentheses. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. variable	**Δ*LOANS***			
	Affected banks			**Unaffected banks**
	(1)	**(2)**	**(3)**	**(4)**
CAP	1.211	0.991	0.991	0.302
	[0.427]**	[1.001]	[0.702]	[1.761]
PRE_CRISIS		0.046	0.046	
		[0.082]	[0.065]	
EM_CRISIS	-0.233	-0.236	-0.236	0.035
	[0.065]***	[0.070]***	[0.084]***	[0.022]
*CAP*PRE_CRISIS*		-0.259	-0.259	
		[1.302]	[0.860]	
CAP*EM_CRISIS	**2.936**	**3.029**	**3.029**	**-0.334**
	[0.971]***	**[1.015]*****	**[1.132]*****	**[0.272]**
*CAP*SMOOTH*	-5.559	-3.754	-3.754	-5.983
	[2.166]**	[2.030]*	[1.724]**	[2.931]**
*PRE_CRISIS*SMOOTH*		0.287	0.287	
		[0.392]	[0.296]	
*EM_CRISIS*SMOOTH*	0.695	0.828	0.828	-0.092
	[0.273]**	[0.291]**	[0.361]**	[0.064]
*CAP*PRE_CRISIS*SMOOTH*		-4.820	-4.820	
		[4.127]	[3.080]	
CAP*EM_CRISIS*SMOOTH	**-8.488**	**-10.267**	**-10.267**	**0.331**
	[3.670]**	**[3.479]*****	**[4.348]****	**[0.656]**
Clustering	Bank	Bank	Bank, year	Bank, year
Fixed effects	Bank	Bank	Bank	Bank
Adj. R^2	0.12	0.12	0.12	0.09
Obs.	248	248	248	557

Table 4: Robustness tests

The dependent variable is quarterly loan growth (Δ*LOANS*). All regressions contain the full set of control variables as in model (3) of Table 3. However, only the relevant variables are tabulated for parsimony. *SMOOTH* denotes the estimate of preemptive loan loss provisioning estimated as of the pre-crisis period. *CAP* denotes lagged bank equity as a percent of total bank assets. *EM_CRISIS* is an indicator set to one during the emerging market crisis period and to zero for the pre-crisis period. Δ*NPL_FOR* denotes foreign non-performing-loans scaled by lagged total loans. Appendix B presents detailed variable definitions. All regressions contain bank fixed effects. Robust standard errors clustered by bank and year are tabulated under coefficients in parentheses. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. variable	**Δ*LOANS***		
	Affected banks		
	Using ranks between [0,1]	**Controlling for differential crisis severity**	**Controlling for reporting timeliness**
	(1)	**(2)**	**(3)**
*CAP*EM_CRISIS*SMOOTH*	**-4.706**	**-8.263**	**-9.512**
	[0.359]***	**[3.710]****	**[1.442]*****
Δ*NPL_FOR*		0.002	
		[0.001]**	
*CAP*EM_CRISIS*TIMELY*			-1.250
			[3.790]
Other controls	Yes	Yes	Yes
Clustering	Bank, year	Bank, year	Bank, year
Fixed effects	Bank	Bank	Bank
Adj. R^2	0.13	0.14	0.13
Obs.	248	248	248

Table 5: Real effects of preemptive loan loss provisioning on the industrial sector

The sample comprises firms borrowing in the syndicated loan market from the sample banks. We first match bank holding companies in our sample to lenders in the syndicated loan market with information on loans available in the Thomson Reuters DealScan database via a match on bank name. We then use the link file provided by Chava and Roberts (2008) to obtain financial information from COMPUSTAT. Panel A presents descriptive statistics for this firm-quarter panel. Panels B and C tabulate the value and investment implications respectively for the borrowers and whether these vary with preemptive loan loss provisioning by affected lenders. We split borrowing firms at the median value of beginning of year total assets into subsamples of "Small firms" and "Large firms." The dependent variable for tests in Panel B is borrowers' Tobin's Q (*Q*) measured using fiscal quarter-end market value of common equity plus the book value of total liabilities scaled by the book value of total assets. Panel C examines both borrowers' *Q* and investment (*INV*) measured as capital expenditure during the quarter scaled by beginning of fiscal quarter total assets. Appendix B presents detailed variable definitions. Robust standard errors clustered by bank are tabulated under the coefficients in parentheses. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Panel A: Descriptive statistics

Variable	Obs.	Mean	Median	S.D.	Min	Max
Q	7,865	1.727	1.455	0.854	0.819	5.816
MVE	7,865	6.558	6.595	1.866	2.410	11.153
ROA	7,865	0.010	0.012	0.025	-0.128	0.072
LEV	7,865	0.312	0.303	0.193	0.000	0.876
INV	7,315	0.024	0.016	0.029	-0.001	0.188

Panel B: Value implications for bank borrowers

Dep. variable	***Q***				
	Entire sample			**Small firms**	**Large firms**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
TREAT	0.046	0.027	0.027	0.096	-0.004
	[0.049]	[0.060]	[0.050]	[0.079]	[0.016]
EM_CRISIS	0.132	0.127	0.127	0.050	0.198
	[0.033]***	[0.032]***	[0.054]**	[0.063]	[0.038]***
*TREAT*EM_CRISIS*	**-0.082**	**-0.056**	**-0.056**	**-0.190**	**0.014**
	[0.067]	**[0.059]**	**[0.037]**	**[0.044]*****	**[0.024]**
MVE		0.084	0.084	0.251	0.209
		[0.007]***	[0.018]***	[0.032]***	[0.034]***
ROA		6.105	6.105	1.089	12.066
		[1.306]***	[1.244]***	[1.213]	[3.274]***
LEV		-0.678	-0.678	-0.731	-0.218
		[0.130]***	[0.155]***	[0.169]***	[0.069]***
Clustering	Bank	Bank	Bank, year	Bank, year	Bank, year
Fixed effects	None	None	None	None	None
Adj. R^2	0.01	0.12	0.12	0.16	0.28
Obs.	7,865	7,865	7,865	3,936	3,929

Table 5, continued

Panel C: Role of preemptive provisioning by the lender

Dep. variable	***Q***				***INV***	
	Small firms		**Large firms**		**Small firms**	**Large firms**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
SMOOTH	-0.036	-0.002	-0.042	0.032	-0.212	0.065
	[0.118]	[0.009]	[0.046]	[0.002]***	[0.062]***	[0.043]
EM_CRISIS	-0.177	-0.035	0.200	0.039	-0.127	0.000
	[0.102]*	[0.014]**	[0.056]***	[0.034]	[0.049]**	[0.160]
*SMOOTH*EM_CRISIS*	**0.219**	**0.049**	**0.041**	**-0.011**	**0.423**	**0.007**
	[0.111]*	**[0.020]****	**[0.056]**	**[0.024]**	**[0.093]*****	**[0.107]**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Bank, year	Bank, year	Bank, year	Bank, year	Bank, year	Bank, year
Fixed effects	None	Firm	None	Firm	Firm	Firm
Adj. R^2	0.14	0.01	0.26	0.03	0.01	0.02
Obs.	1,375	1,375	1,833	1,833	1,327	1,638

Table 6: Opportunistic smoothing

The dependent variable is quarterly loan growth (Δ*LOANS*). The first column (model [1]) re-tabulates results presented in model (1) of Table 3. The next two specifications split the sample into banks without any insider lending (model [2] labeled "Low insider-lending") versus those with insider-lending (model [3] labeled "High insider-lending") measured by firms with insider lending reported in the Call Reports of underlying branches/subsidiaries (*INSIDE*). *CAP* denotes lagged bank equity as a percent of total bank assets. *EM_CRISIS* is an indicator set to one during the emerging market crisis period and to 0 for the pre-crisis period. *SMOOTH* denotes the estimate of preemptive loan loss provisioning estimated as of the pre-crisis period. Appendix B presents detailed variable definitions. All regressions contain bank fixed effects. Robust standard errors clustered by bank are tabulated under coefficients in parentheses. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. variable	**Δ*LOANS***		
	All affected banks	**Low insider-lending**	**High insider-lending**
	(1)	**(2)**	**(3)**
CAP	1.211	-0.042	1.382
	[0.427]**	[0.114]	[0.987]
EM_CRISIS	-0.233	-0.358	-0.125
	[0.065]***	[0.063]***	[0.033]***
*CAP*EM_CRISIS*	**2.936**	**4.730**	**1.261**
	[0.971]***	**[0.517]*****	**[0.534]****
*CAP*SMOOTH*	-5.559	-7.239	-0.990
	[2.166]**	[2.869]**	[0.868]
*EM_CRISIS*SMOOTH*	0.695	1.615	0.265
	[0.273]**	[0.523]**	[0.197]
*CAP*EM_CRISIS*SMOOTH*	**-8.488**	**-17.341**	**-2.530**
	[3.670]**	**[3.816]*****	**[2.141]**
p. value of diff.: *CAP*EM_CRISIS*SMOOTH*		0.001	
Clustering	Bank	Bank	Bank
Fixed effects	Bank	Bank	Bank
Adj. R^2	0.12	0.30	0.02
Obs.	248	63	185

Table 7: Underlying mechanisms: Crisis-period illiquidity and equity financing

This panel presents results for affected banks. The dependent variable in models (1) and (2) is stock illiquidity (*ILLIQ*) measured following Amihud (2002) as the log ratio of unsigned stock returns scaled by dollar trading volume and averaged over the quarter. The dependent variable in models (3) and (4) is quarterly change in net contributed equity capital (Δ*CAP*) defined as change in total equity capital less net income and dividends paid, scaled by beginning of quarter total assets. Appendix B presents detailed variable definitions for all remaining variables. All regressions contain bank fixed effects. Robust standard errors clustered by bank and year are tabulated under coefficients in parentheses. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. variable	***ILLIQ***		**Δ*CAP***	
	Affected banks			
	(1)	**(2)**	**(3)**	**(4)**
EM_CRISIS	0.002	0.002	0.003	0.003
	[0.002]	[0.003]	[0.001]**	[0.002]*
*EM_CRISIS*SMOOTH*	**0.012**	**0.011**	**-0.005**	**-0.005**
	[0.005]**	**[0.003]*****	**[0.001]*****	**[0.001]*****
*EM_CRISIS*TIMELY*		-0.001		0.001
		[0.005]		[0.001]*
CAP	1.091	1.089	-0.151	-0.153
	[0.783]	[0.777]	[0.144]	[0.145]
SIZE	0.003	0.003	-0.012	-0.012
	[0.004]	[0.004]	[0.004]***	[0.004]***
Clustering	Bank, year	Bank, year	Bank, year	Bank, year
Fixed effects	Bank	Bank	Bank	Bank
Adj. R^2	0.78	0.78	0.11	0.11
Obs.	196	196	248	248

Table 8: Underlying mechanisms: Restrained risk-taking during boom/regular periods

This panel presents results for banks affected by the emerging market crisis and is restricted to the pre-crisis period. Model (1) presents a regular OLS specification using the entire pre-period panel, while model (2) employs a median regression using one observation per bank. The dependent variable is preemptive loan loss provisioning (*SMOOTH*). *SIZE* denotes the log of bank assets while *CAP* indicates bank equity. *LOANS* and Δ*LOANS* denote the level and quarterly change in total loans scaled by total assets, respectively. *DEP* represents deposits as a proportion of total assets. *EBLLP* represents earnings before loan loss provision scaled by lagged total loans. *NPL* denotes non-performing loans scaled by lagged total loans. *DTD* refers to the distance-to-default ratio and is the inverse measure of bank risk. It is defined as the ratio of earnings before LLP and capital scaled by the volatility of pre-provision earnings. Appendix B presents detailed variable definitions. Robust standard errors are tabulated under the coefficients. These are clustered by bank in model (1). (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Panel A: Pre-period associations

Dep. Variable	***SMOOTH***	
	Affected Banks	
	(1) (OLS)	**(2) (Median)**
SIZE	-0.009	-0.080
	[0.063]	[0.076]
CAP	7.917	6.971
	[6.223]	[7.232]
LOANS	0.520	**1.808**
	[0.630]	**[0.706]****
Δ*LOANS*	**-7.781**	**-15.435**
	[4.043]*	**[6.108]****
DEP	-0.543	**-2.716**
	[1.187]	**[1.052]****
EBLLP	7.043	-0.784
	[30.186]	[33.423]
DTD	-0.048	-0.090
	[0.067]	[0.075]
NPL	-0.067	**-0.226**
	[0.093]	**[0.100]***
Sample	Pre-period	Collapsed pre-period
Clustering	Bank	None
Adj./Pseudo R^2	0.40	0.25
Obs.	119	17

Table 8, continued

Panel B: Are the pre-period characteristics driving the results?

This panel presents results for affected banks only. The dependent variable is quarterly loan growth (Δ*LOANS*). *AVAR* stands for "Alternative variables" and represents individual bank-characteristics depicted at the top of each column. *SMOOTH* denotes preemptive provisioning during the pre-crisis period. *CAP* denotes lagged bank equity as a percent of total assets. *TREAT* is an indicator variable set to one for affected banks, and to zero for unaffected banks. *EM_CRISIS* is an indicator set to one during the emerging market crisis period and to zero for the pre-crisis period. Appendix B presents detailed variable definitions. All regressions contain bank and year fixed effects. Robust standard errors clustered by bank and year are tabulated under coefficients in parentheses. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. variable	**Δ*LOANS***									
	Affected banks									
Alternative (pre-crisis) variables (*AVAR*):	***SIZE***	***CAP***	***LOANS***	**Δ*LOANS***	***DEP***	***EBLLP***		***NPL***		***DTD***
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
*EM_CRISIS*AVAR*	-0.044	-1.541	0.265	1.905	0.380	0.350	0.537	0.010	-0.001	-0.017
	[0.039]	[4.852]	[0.257]	[3.463]	[0.436]	[0.128]***	[0.191]***	[0.001]***	[0.000]***	[0.074]
*CAP*EM_CRISIS*AVAR*	0.737	37.238	-4.152	-39.742	-4.083	**-5.115**	**-7.327**	**0.121**	**0.014**	0.328
	[0.558]	[47.409]	[4.121]	[48.444]	[7.682]	**[2.526]****	**[3.182]****	**[0.050]****	**[0.002]*****	[0.865]
*EM_CRISIS*SMOOTH*							0.600		0.420	
							[0.031]***		[0.173]*	
*CAP*EM_CRISIS*SMOOTH*							**-6.638**		**-4.759**	
							[0.896]***		**[1.673]***	
Other controls and interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Bank, year	Bank, year	Bank, year	Bank, year	Bank, year	Bank, year	Bank, year	Bank, year	Bank, year	Bank, year
Fixed effects	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Adj. R^2	0.22	0.20	0.19	0.19	0.22	0.20	0.23	0.20	0.23	0.20
Obs.	248	248	248	248	248	248	248	248	248	248

Table 9: Disentangling supply and demand shocks using SLOO Survey data

Panel A: Preemptive loan loss provisioning and the supply of (demand for) bank lending

The dependent variable is loan growth over the next four quarters (Δ*LOANS*). Preemptive provisioning (*SMOOTH*) is defined based on a rolling window of 12 prior quarters. *TIGHT* denotes bank supply tightening computed by orthogonalizing bank lending standards available from the Senior Loan Officer Opinion Survey (SLOOS) conducted by the Federal Reserve each quarter with respect to macroeconomic variables measuring borrower demand (from the SLOO survey), the S&P 500 implied volatility index (VIX), and the excess bond premium measured by Gilchrist and Zakrajsek (2012). *WEAK* denotes borrower demand weakening defined as the number of SLOO survey respondents reporting substantially weaker or moderately weaker demand for business loans minus those reporting substantially stronger or moderately stronger demand. Appendix B presents detailed variable definitions. Robust standard errors clustered by bank in models (1), (2) and (3) and by year-quarter in models (4), (5) and (6) are tabulated under the coefficients in parentheses. In addition, models (3) to (6) contains bank and year-quarter fixed effects. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. variable	**Δ*LOANS***					
	All banks				**Low capital banks**	**High capital banks**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
SMOOTH	0.022	0.022	0.008	0.008	0.011	0.001
	[0.002]***	[0.002]***	[0.002]***	[0.001]***	[0.001]***	[0.002]
TIGHT	-0.115	-0.055				
	[0.004]***	[0.005]***				
*TIGHT*SMOOTH*	**0.024**	**0.028**	**0.019**	**0.019**	**0.026**	**0.011**
	[0.007]***	**[0.010]*****	**[0.008]****	**[0.006]*****	**[0.007]*****	**[0.007]**
WEAK		-0.065				
		[0.004]***				
*WEAK*SMOOTH*		**-0.001**	**0.002**	**0.002**	**-0.004**	**0.004**
		[0.009]	**[0.007]**	**[0.006]**	**[0.006]**	**[0.006]**
Clustering	Bank	Bank	Bank	Year-qtr	Year-qtr	Year-qtr
Fixed effects	None	None	Bank, year-qtr	Bank, year-qtr	Bank, year-qtr	Bank, year-qtr
Adj. R^2	0.05	0.05	0.32	0.32	0.39	0.32
Obs.	64,318	64,318	64,318	64,318	33,878	30,440

Table 9, continued

Panel B: Using the Sun Trust case as an exogenous shock to preemptive provisioning

The dependent variable is preemptive loan loss provisioning (*SMOOTH*) defined based on a rolling window of 12 prior quarters. *POST_ST* is an indicator that takes 1 for the years after 1999 and 0 for the years before. *SEC* is an indicator that takes 1 for banks that report to the U.S. Securities and Exchange Commission and 0 for those that do not. This captures not only publicly-listed banks but also private banks with public debt. *DIST* captures the distance between the bank's headquarters and the closest SEC office. Remaining variables capture loan composition differences across banks, where *CI_LOANS*, *RE_LOANS*, *INDIV_LOANS* and *OTH_LOANS* represent the proportion of commercial and industrial loans, real estate loans, individual loans and all remaining loans, respectively, expressed as a proportion of total assets. Appendix B presents detailed variable definitions. All regressions contain bank fixed effects. Robust standard errors clustered by year-quarter are tabulated under the coefficients in parentheses. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. Variable		***SMOOTH***	
	(1)	**(2)**	**(3)**
POST_ST	0.005	0.010	0.012
	[0.005]	[0.007]	[0.007]
SEC	0.023	0.042	0.041
	[0.011]**	[0.014]***	[0.014]***
*POST_ST*SEC*	**-0.020**	**-0.042**	**-0.040**
	[0.009]**	**[0.014]*****	**[0.014]*****
DIST		0.014	-0.002
		[0.095]	[0.099]
*POST_ST*DIST*		-0.023	-0.019
		[0.033]	[0.035]
*SEC*DIST*		-0.093	-0.091
		[0.060]	[0.061]
*POST_ST*SEC*DIST*		**0.111**	**0.106**
		[0.049]**	**[0.051]****
CI_LOANS			-0.037
			[0.142]
RE_LOANS			0.025
			[0.132]
INDIV_LOANS			0.122
			[0.153]
OTH_LOANS			0.012
			[0.124]
Clustering	Year-qtr	Year-qtr	Year-qtr
Fixed effects	Bank	Bank	Bank
Adj. R^2	0.27	0.27	0.27
Obs.	51,931	51,931	51,931

Table 9, continued

Panel C: Using instrumented *SMOOTH*

The dependent variable is loan growth over the next four quarters (Δ*LOANS*). *SMOOTH_PRED* denotes the instrumented measure of *SMOOTH* derived from model (3) of Panel B above. *TIGHT* denotes bank supply tightening computed by orthogonalizing bank lending standards with respect to macroeconomic variables such as changes in the VIX index and the excess bond premium. *WEAK* denotes borrower demand weakening defined as the number of respondents reporting substantially weaker or moderately weaker demand for business loans minus those reporting substantially stronger or moderately stronger demand. *CI_LOANS*, *RE_LOANS*, *INDIV_LOANS* and *OTH_LOANS* represent the proportion of commercial and industrial loans, real estate loans, individual loans and other loans, respectively, expressed as a proportion of total assets. Appendix B presents detailed variable definitions. All regressions contain bank fixed effects. In addition, models (3) to (6) include year-quarter fixed effects. Robust standard errors clustered by bank in models (1), (2) and (3) and by year-quarter in models (4), (5) and (6) are tabulated under the coefficients in parentheses. (***), (**), (*) denote statistical significance at the two-tailed 1%, 5% and 10% levels, respectively.

Dep. variable	**Δ*LOANS***					
	All banks				**Low capital banks**	**High capital banks**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
SMOOTH_PRED	0.300	0.321	0.202	0.202	-0.094	0.071
	[0.240]	[0.259]	[0.258]	[0.269]	[0.149]	[0.089]
TIGHT	-0.107	-0.056				
	[0.008]***	[0.009]***				
*TIGHT*SMOOTH_PRED*	**2.879**	**2.587**	**2.824**	**2.824**	**1.274**	**-0.307**
	[0.708]***	**[0.652]*****	**[0.664]*****	**[1.644]***	**[0.544]****	**[0.279]**
WEAK		-0.049				
		[0.007]***				
*WEAK*SMOOTH_PRED*		**0.399**	**0.114**	**0.114**	**-0.709**	**0.070**
		[0.503]	**[0.497]**	**[0.943]**	**[0.382]***	**[0.236]**
CI_LOANS	0.109	0.097	0.053	0.053	0.127	-0.040
	[0.113]	[0.113]	[0.111]	[0.087]	[0.089]	[0.154]
RE_LOANS	-0.056	-0.059	-0.044	-0.044	0.052	-0.132
	[0.120]	[0.120]	[0.117]	[0.081]	[0.081]	[0.154]
INDIV_LOANS	0.235	0.206	0.061	0.061	0.195	-0.089
	[0.128]*	[0.128]	[0.128]	[0.086]	[0.097]*	[0.153]
OTH_LOANS	0.162	0.150	0.058	0.058	0.156	-0.035
	[0.127]	[0.126]	[0.123]	[0.078]	[0.109]	[0.147]
Clustering	Bank	Bank	Bank	Year-qtr	Year-qtr	Year-qtr
Fixed effects	Bank	Bank	Bank, year-qtr	Bank, year-qtr	Bank, year-qtr	Bank, year-qtr
Adj. R^2	0.27	0.27	0.29	0.29	0.34	0.32
Obs.	51,931	51,931	51,931	51,931	27,192	24,739

Figure 1: Charge-offs on loans to foreign governments and banks around the emerging market crisis

This figure presents charge-offs on loans to foreign governments and banks. Affected banks (in the solid line) are defined as those with positive values of these charge-offs during the emerging markets crisis starting in 1997Q4. Unaffected banks (in the dotted line) are those with foreign lending but zero charge-offs during the crisis.

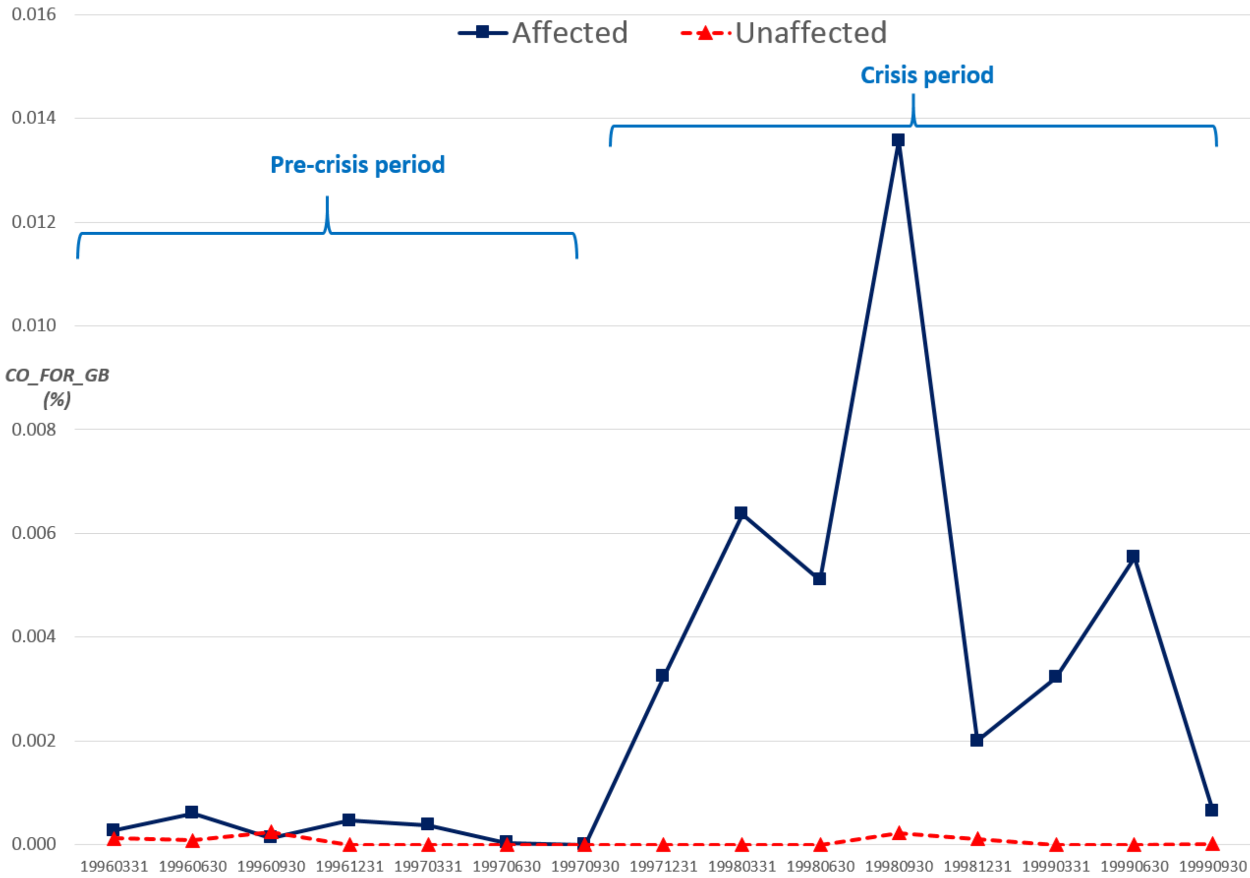


Figure 2: Economic significance of the emerging market crisis sample

This figure presents the ratio of total loans made by the sample banks scaled by total loans made by all banks filing FR Y-9C reports with data available in the Bank Regulatory database. The solid line plots this ratio for both affected and unaffected banks, while the large (small) dotted line denotes affected (unaffected) banks

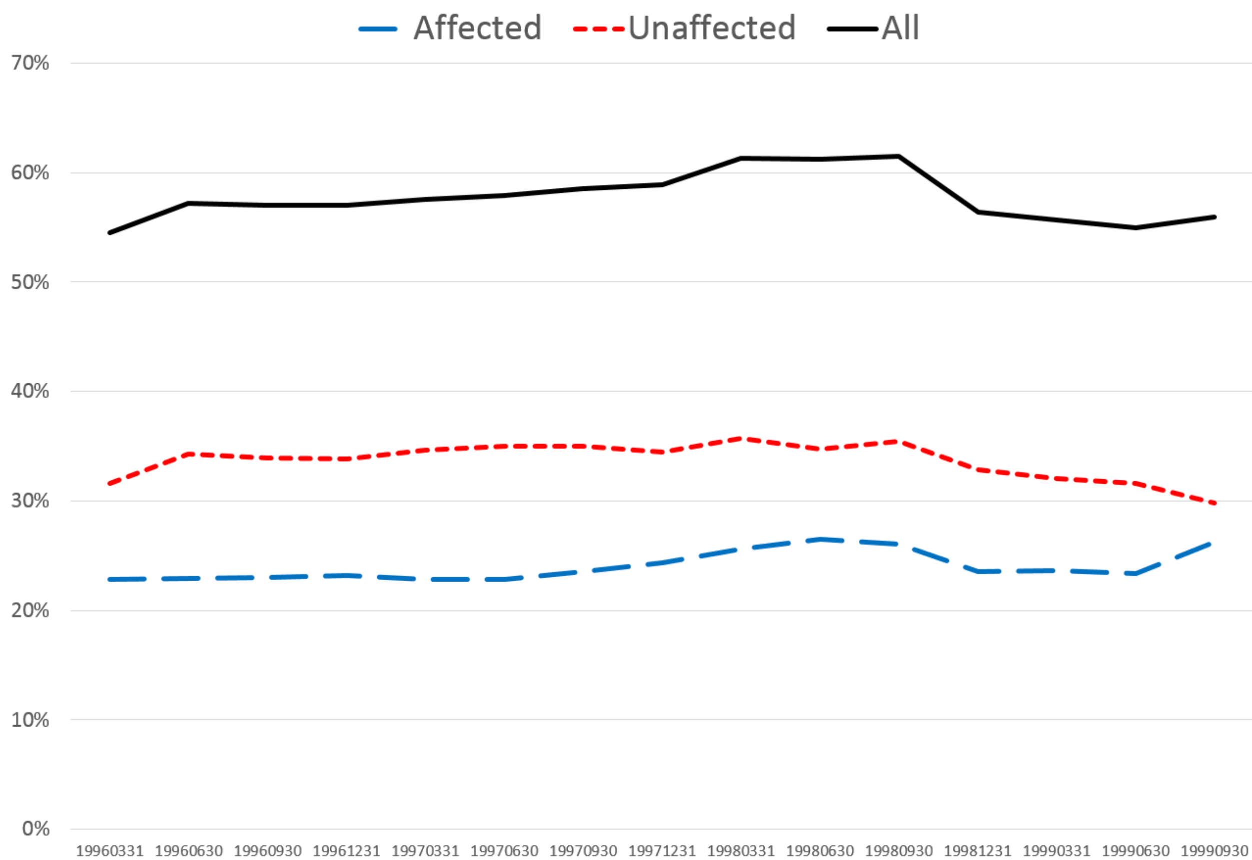
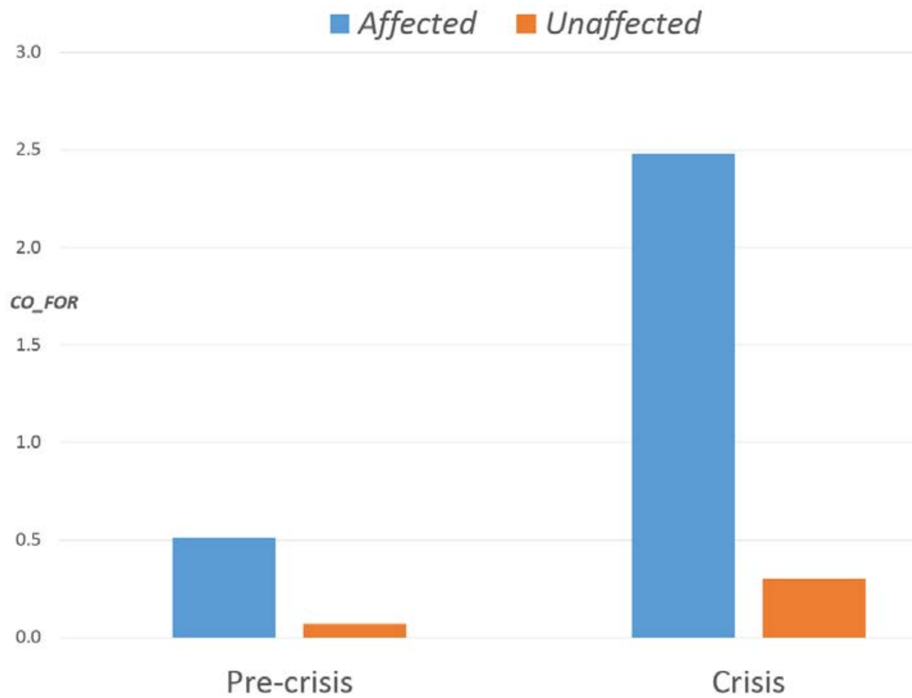


Figure 3: Supply versus demand shocks

CO_FOR denotes foreign loan charge-offs on government/bank and commercial/industrial loans. *CO_DOM* denotes domestic loan charge-offs. Both variables are scaled by lagged loans and multiplied by 10^4.

Panel A: Supply shock (foreign loan charge-offs)



Panel B: Demand shock (domestic loan charge-offs)

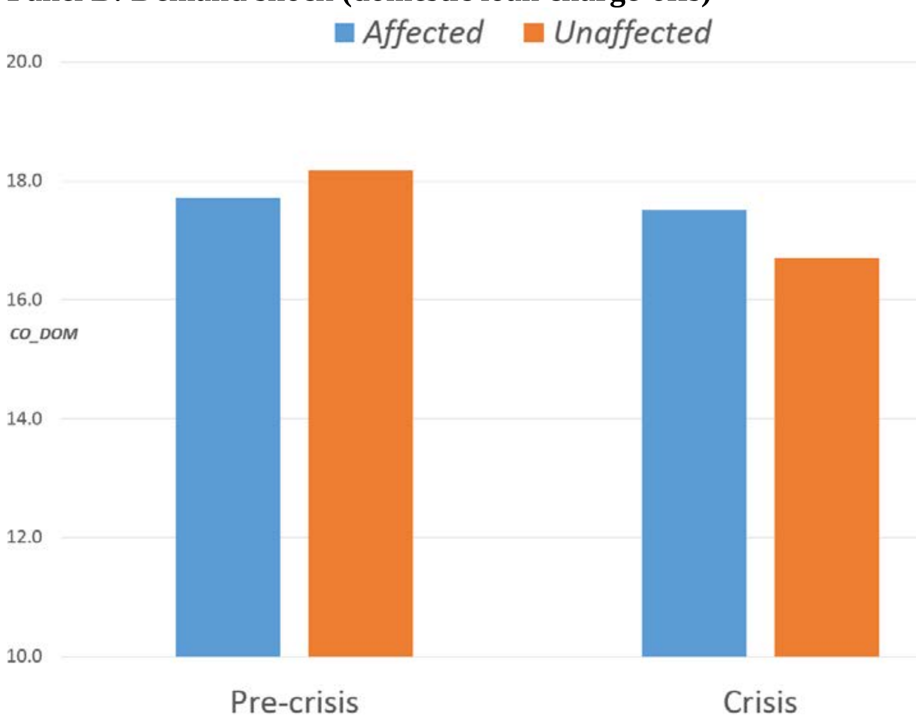
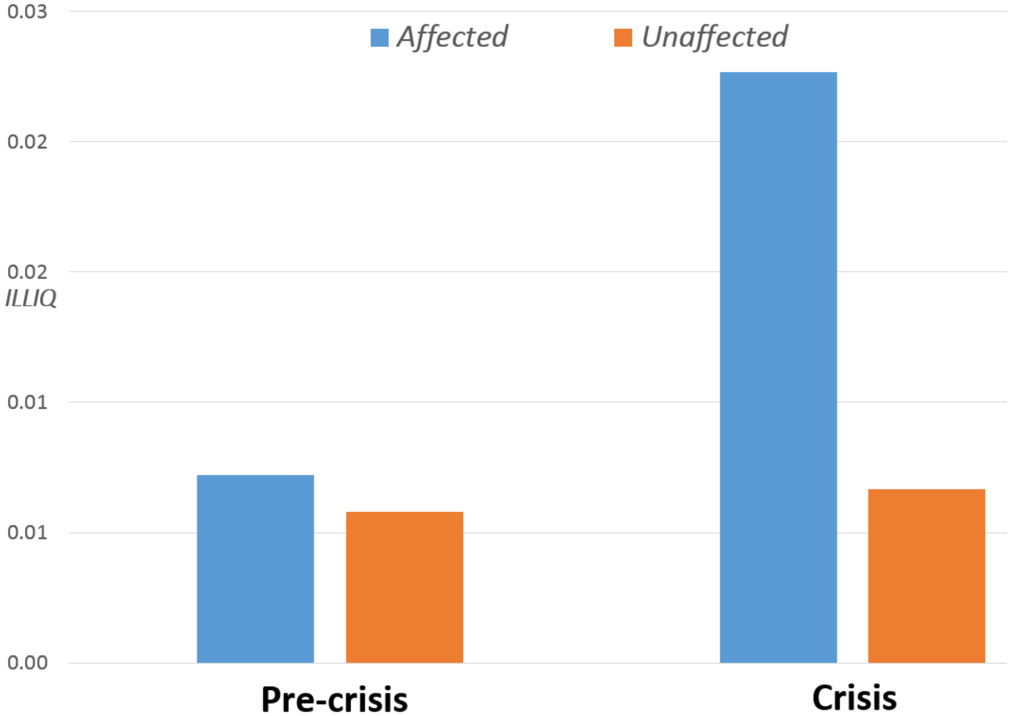


Figure 4: Illiquidity before and during the crisis

Panel A presents results for affected and unaffected banks. Panel B splits the former into smoothers (*SMOOTH*>0) and non-smoothers (*SMOOTH*<=0). The horizontal axis depicts the pre-crisis and crisis periods while the vertical axis plots average illiquidity (*ILLIQ*) defined as the natural log of unsigned stock returns scaled by dollar trading volume.

Panel A: Affected versus unaffected banks



Panel B: Affected banks: Smoothers versus non-smoothers

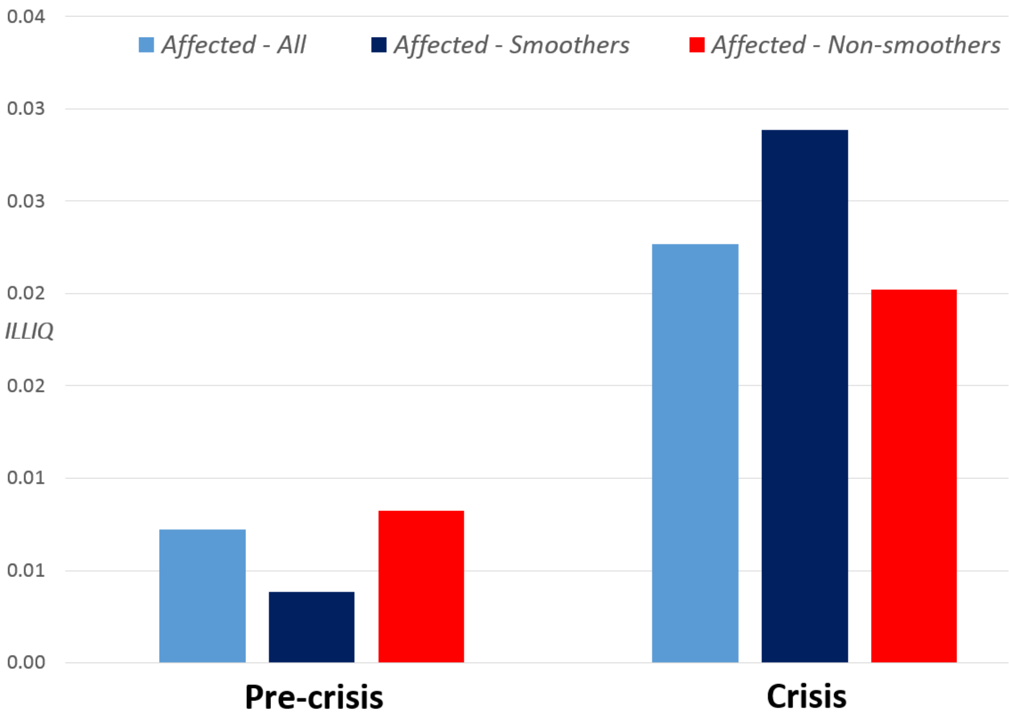


Figure 5: Lending standards, capital supply and borrower demand

The horizontal axis denotes the sample period, while the vertical axis plots the value of lending standards (Lending), bank supply tightening (Tighten), and borrower demand (Demand) that correspond to each quarter. These data are obtained from the Senior Loan Officer Opinion Survey (SLOOS) conducted by the Federal Reserve each quarter.