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Loan loss provisions and return predictability: A dynamic perspective

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ABSTRACT

This paper examines the impact of loan loss provisions (LLPs) on return predictability during 1994–2017. We find that on average, LLPs are negatively associated with one year ahead stock returns. This effect is particularly significant during the global financial crisis but much weaker during the Basel II and III periods. Consistent with these findings, a long–short trading strategy based on LLPs generates positive abnormal returns during the Basel II and III periods but negative abnormal returns during the financial crisis. Cross-sectional tests show that this effect is more pronounced among banks with greater information asymmetry. Decomposition of LLPs suggests that these findings are driven mainly by nondiscretionary LLPs. Overall, our results suggest that the relationship between LLPs and future stock returns is not linear but contingent on bank regulations and macroeconomic conditions.

1. Introduction

Banks act primarily as financial intermediaries in the economic system. Loans constitute the largest proportion of assets held by banks (64.7% in our sample), and loan loss provisions (LLPs) represent the largest single accrual by banks (Beatty and Liao, 2014). Consequently, LLPs have long been an important topic of bank accounting research. Although studies suggest that LLPs are associated with contemporaneous stock returns (e.g., Beaver and Engel, 1996; Ahmed et al., 1999), little is known about whether LLPs can predict future stock

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returns. Our study attempts to fill this gap in the literature by examining whether LLPs are associated with future stock returns and, if so, whether this relationship is homogenous across time and banks.

Using data on 1751 unique U.S. banks from 1994 to 2017, we find that on average, LLPs are significantly negatively associated with one year ahead stock returns. This is consistent with banks' use of LLPs for earnings and capital management, which causes opacity in their financial statements (e.g., Ahmed et al., 1999; Kanagaretnam et al., 2009; Perez et al., 2011). As a result, the stock market overreacts to the LLP information that year, leading to a downward correction in future stock returns.

There is considerable variation in the recognition of LLPs over time (Beatty and Liao, 2011), and we expect the relationship between LLPs and future stock returns to vary accordingly. To test this conjecture, we disaggregate our sample period into five subperiods and repeat the main regression. The first subperiod is 1994–2003, before the adoption of Basel II. Basel II enhanced the Basel regulatory framework with three pillars of capital adequacy requirements, supervisory review and market discipline. Although the ordinary least squares (OLS) regression results show a significantly negative relationship between LLPs and future stock returns in this subperiod, this relationship becomes insignificant when using the Fama–Macbeth regression. The second subperiod is 2004–2006, during which Basel II was adopted. Basel II requires banks to disclose the credit risk model used to estimate loan losses, which enhances the transparency of their financial statements. Consistent with our expectation, both the OLS and Fama–Macbeth regressions reveal a positive association between LLPs and future stock returns in this subperiod. The third subperiod covers the 2007–2009 subprime financial crisis, during which banks had stronger incentives to manipulate their reported earnings via LLPs. In this subperiod, our OLS and Fama–Macbeth regressions consistently show a significantly negative relationship between LLPs and future stock returns. The fourth subperiod is the 2010–2015 post-financial crisis period, during which LLPs remain significantly negatively associated with future stock returns. The last subperiod is 2016–2017, during which Basel III was proposed. During this subperiod, LLPs are positively (though not statistically significantly) associated with future stock returns.

To reinforce the above regression results, we examine whether trading strategies based on LLPs generate abnormal stock returns. Specifically, we focus on the value-weighted returns of quarterly rebalanced quintile LLP portfolios. The results show that firms in the lowest quintile portfolio significantly outperform those in the highest quintile, reaffirming the negative association between LLPs and future stock returns. In the subperiod analysis, during the financial crisis period, taking long positions in the quintile with the highest LLPs and short positions in the quintile with the lowest LLPs generates a significantly negative abnormal return of 19.3% per year. In contrast, during the Basel II subperiod, taking long positions in the quintile with the highest LLPs and short positions in the quintile with the lowest LLPs generates a significantly positive abnormal return of 2.5% per year. These findings are consistent with the regression results.

Collectively, our findings suggest that the market does not fully incorporate LLP information. Such mispricing is contingent on bank regulations and macroeconomic conditions. Furthermore, the effects of LLP on stock returns vary between banks according to their characteristics. We hypothesize that the relationship between LLPs and future stock returns exists mainly for banks with an opaque information environment, as such banks tend to have the strongest incentives to use LLPs to manipulate reported earnings. Following the literature (e.g., Kanagaretnam et al., 2004), we measure information transparency using book-to-price ratio, firm size and analyst coverage. Consistent with our prediction, we find that the mispricing of LLPs primarily occurs among banks with greater information asymmetry.

Our study contributes to the literature in several ways. First, we offer insights into the valuation of LLPs. Early studies focus primarily on the relationship between LLPs and contemporaneous stock prices or returns (i.e., the value relevance of LLPs) (e.g., Beaver et al., 1989; Wahlen, 1994; Beaver and Engel, 1996). Beaver et al. (1989) document a positive relationship between loan loss reserves and market value using a 1979–1983 sample period. Consistent with Beaver et al. (1989), Wahlen (1994) finds a positive relationship between the discretionary portion of LLPs and stock returns after controlling for changes in nonperforming loans and loan charge-offs. However, to the best of our knowledge, few studies consider the return predictability of LLPs. One exception is Hwang and Kim (2017). Using a full sample of U.S. banks during 1994 to 2010, they find that LLPs are negatively related to one year ahead future returns. Our study differs from Hwang and Kim (2017) in two important respects. First, whereas Hwang and Kim (2017) consider the mispricing of LLPs to be homogenous across time, we examine how the return predictability of LLPs is conditional on bank regulations and macroeconomic shocks. Second, using more recent data, our study has potential policy implications for the adoption of Basel III, which aims to strengthen banks' transparency. Moreover, our study adds to understanding of how components of LLPs influence valuation. The literature yields mixed findings in this regard. Some research documents a positive relationship between discretionary LLPs (DLLPs) and bank stock returns (e.g., Beaver et al., 1989; Wahlen, 1994; Liu and Ryan, 1995; Kanagaretnam et al., 2004), suggesting that the discretionary component of LLPs conveys favorable information that is incrementally positively priced (Kanagaretnam et al., 2009). However, other studies (e.g., Hwang and Kim, 2017) document that nondiscretionary LLPs (NLLPs) are the main driver of the return predictability of LLPs. In this study, we provide new evidence that NLLPs exhibit a pattern similar to that of LLPs in terms of return predictability.

The remainder of this paper is organized as follows. Section 2 discusses the institutional background of bank regulations. Section 3 provides a literature review and develops our hypotheses. Section 4 presents the empirical models for hypothesis testing. Section 5 describes the empirical results. Section 6 concludes the paper.

2. Institutional background

The bank regulations pertinent to our study are the Basel capital regulations and accounting standards for loan losses. In the U.S., accounting standards are promulgated by the Financial Accounting Standards Board (FASB). The FASB issued Statement of Financial Accounting Standards (SFAS) 114 *Accounting by Creditors for Impairment of a Loan*, which is the accounting standard for credit losses for loans (uncollateralized and collateralized), except for large groups of loans that are collectively evaluated for impairment, loans that are measured at fair value, leases and debt securities as defined in SFAS 115 *Accounting for Certain Investments in Debt and Equity Securities.* SFAS 114 amends SFAS 5 to specify how a creditor should evaluate the collectability of the contractual interest and principal of receivables when assessing the need for a loss accrual. SFAS 114 is effective for fiscal year-ends beginning after 15 December 1994.

The accounting model under SFAS 114 is called the incurred loan loss model. This model requires a loan's loss probability to meet the threshold of "probable" before it can be recognized as an expense on a bank's income statement. The incurred loan loss model is severely criticized for delaying the recognition of loan losses, particularly during the global financial crisis that started in 2008, as incurred loan losses are considered not sufficiently forward-looking (López-Espinosa et al., 2021). The application of the incurred loan loss model varies, as it requires bank managers to use their judgment and discretion to decide whether the "probable" threshold has been met.

In response to criticisms of the incurred loan loss model, the FASB recommended using the expected credit loss model in Accounting Standards Update (ASU) 2016–13 as a replacement for the incurred loan loss model. The expected credit loss model requires banks to estimate future credit losses from the reporting date until loan maturity according to borrowers' probabilities of default. The expected credit loss model is intended to remedy the weaknesses of the incurred loan loss model and make loan loss estimates more forward-looking. ASU 2016–13 is effective for fiscal years ending after 15 December 2019. The banks in our sample follow SFAS 114 and the incurred loan loss model. However, some banks may have changed their loan provisioning practices to align with the new measure of expected credit losses when ASU 2016–13 was issued in 2016.

Banks are highly leveraged entities, and the banks in our sample have an average book-to-market ratio of 0.07%. Given banks' high leverage and pivotal role in the financial stability of economies, central bankers around the world impose capital adequacy requirements based on Bank for International Settlements (BIS) guidelines. The Basel Committee on Banking Supervision (BCBS) of the BIS is the global standard setter for the prudential regulation of banks. Its 45 members are central bankers and bank supervisors from 28 jurisdictions. The first BCBS document to set out agreement between the G-10 central bankers on minimum capital requirements for their banking industries was the Basel Capital Accord (BCBS, 1988), which was to be implemented by year-end 1992. The U.S. government adopted these capital requirements in the Basel Capital Accord. Banks were governed by the Basel Capital Accord until 2003.

In June 1999, the BCBS published the first round of proposals for replacing the Basel Capital Accord with Basel II. The BCBS subsequently released additional proposals for consultations in January 2001 and April

2003 and conducted three quantitative impact studies related to the proposals. Basel II has three pillars aimed at enhancing banks' risk management: minimum capital requirements, supervisory review and market discipline. The revised framework includes the Market Risk Amendment, which considers market risks in trading activities, counterparty credit risks and the risk of both borrower and guarantor defaulting on the same obligation. Basel II allows banks with sophisticated risk management systems to use the inputs generated by their internal systems for capital calculations, an internal ratings based approach, as an alternative to the broad standardized approach. The overall objective of the revised framework is to set capital requirements that are more risk sensitive than those in the Basel Capital Accord. The revised framework contains changes to the treatment of expected losses, unexpected losses, securitization exposures, credit risk mitigation and qualifying revolving retail exposures. The BCBS also clarified the incorporation of economic downturns in calculations of loss-given-defaults in the internal ratings based approach (BCBS, 2004). We consider 2004 the year of implementation of Basel II.

In 2006, U.S. housing prices started to falter. In February 2007, Freddie Mac announced that it would no longer purchase risky subprime mortgage loans. Subsequently, fund redemptions were halted by Bear Stearns in June 2007 and by BNP Paribas in August 2007. The following month, Northern Rock, the U.K.'s fifth largest mortgage lender, suffered a bank run after its money market funding was cut. In the first quarter of 2008, the U.S. Federal Reserve slashed the federal funds rate by 75 basis points and announced it would loan US $200 billion in Treasury securities to prop up the mortgage-backed securities market. In September 2008, the U.S. government had to bail out Fannie Mae and Freddie Mac, and then Lehman Brothers filed for bankruptcy. A credit crunch gripped the market. The U.S. government bailed out American International Group. The U.S. banks Washington Mutual and Wachovia went under. The U.S. Treasury secretary announced the Troubled Asset Relief Program to buy bad assets and support the financial sector. The Fed introduced quantitative easing in November 2008. The 2007–2009 period is considered a major pre-crisis/crisis period that saw significant changes to banks' loan provisions and market reactions to them.

The global financial crisis provided the impetus for the BCBS to accelerate the development of the Basel III framework. The Basel III framework was designed to address vulnerabilities in the pre-crisis regulatory framework. Basel III enhanced the risk sensitivity of standardized approaches to credit risk, credit valuation adjustment risk and operational risk. An example of enhanced risk sensitivity is the use of mortgages' loan to value ratios to assign mortgage risk weights, instead of the flat risk weights used under Basel II. Basel III revised the internal ratings based approach in Basel II. The Basel III framework specifies supplementary requirements for risk-weighted capital ratios, one of which is a leverage ratio requirement to constrain excessive risk-taking. A leverage ratio buffer is an additional requirement for systemically important banks. Other requirements are liquidity coverage and net stable funding ratios to mitigate excessive liquidity risk (BCBS, 2010).

Compared with Basel II, Basel III places greater emphasis on loss-absorbing capital in the form of common equity Tier 1 (CET1) capital. Its increased capital requirements are designed to ensure that banks are sufficiently resilient to withstand losses in times of stress. The minimum Tier 1 ratio requirement was raised in phases, from 4.0% in 2012 to 4.5% in 2013, 5.5% in 2014 and 6% in 2015. Basel III incorporated macroprudential elements with the introduction of capital buffers that can be built in good times and drawn down in times of stress to mitigate cyclicality. Capital conservation buffers were phased in, increasing from 0.625% in 2016 to 1.25% in 2017, 1.875% in 2018 and 2.5% in 2019. The minimum total capital remains 8% under Basel III. The sum of minimum total capital and the capital conservation buffer was increased to 8.625% in 2016 (BCBS, 2010). Thus, 2016 is considered the beginning of the post-Basel III period. In the next section, we review the literature pertinent to our study and detail our contributions to it.

3. Literature review and hypothesis development

There is a large body of literature on loan loss accounting. One stream of the literature considers the use of LLPs for earnings management (Ma, 1988; Beatty et al., 1995; Kanagaretnam et al., 2004; Fonseca and Gonzalez, 2008) and regulatory capital management (Moyer, 1990), because LLPs involve considerable managerial estimation of future loan defaults and such estimations inevitably contain errors. Moreover, banks recognize loan losses according to their policies and the state of the economy. As a result, it is difficult for users of financial information to estimate bank loan losses. Ma (1988) provides early evidence that banks use LLPs to smooth income by increasing (decreasing) LLPs when their operating income is high (low). Banks also target certain LLP levels to meet regulatory capital requirements by increasing LLPs when current loan charge-offs are high. Collins et al. (1995) investigate how banks' capital, earnings and tax decisions affect their seven capital raising options: securities gains and losses, LLPs, loan charge-offs, capital notes, common stock, preferred stock and dividends. They estimate bank-specific regressions for each capital raising option on the regulatory capital, earnings and marginal tax rates and provide evidence that banks differ in their responsiveness to capital, earnings and tax incentives. They also provide evidence that U.S. banks use LLPs to manage earnings and capital. Beatty et al. (1995) differ from Collins et al. (1995) by using simultaneous equations to investigate five capital raising options: LLPs, loan loss charge-offs, pension settlements, miscellaneous gains and losses and the issuance of new securities. They document banks' use of LLPs, loan loss charge-offs and new securities issuances to manage regulatory capital.

Moyer (1990) hypothesizes that banks with capital below the regulatory minimum seek to reduce their regulatory costs by adjusting their LLPs to increase capital and finds evidence to support this hypothesis. Ahmed et al. (1999) use the 1990 change in US bank capital regulations to test US banks' use of LLPs to manage capital and earnings. In 1990, the bank capital regulations were changed such that LLPs are no longer Tier 1 capital but still count as total capital, and they are limited to 1.25% of risk-weighted assets. Ahmed et al. (1999) hypothesize that this regulation change reduced (increased) the incentive to use LLPs to manage capital (earnings) and find strong evidence to support their capital management hypothesis but no evidence to support their earnings management hypothesis. Kanagaretnam et al. (2004) examine various situations in which LLPs are used for earnings management. They hypothesize and find that bank managers with pre-managed earnings that deviate more (less) from the median are more (less) likely to use LLPs to smooth earnings. These studies show that LLPs are related to bank opacity. Blau et al. (2017) provide evidence that bank opacity is related to stock price delays and affects stock price efficiency.

Studies of the relationship between LLPS and stock returns include Kanagaretnam et al. (2009) and Liu et al. (1997). Kanagaretnam et al. (2009) find a significant positive association between the discretionary component of LLPs and stock returns for banks audited by Big 5 auditors. Liu et al. (1997) find a statistically significant positive association between bank stock returns and LLPs in the fourth fiscal quarter among banks with low regulatory requirements. Evidence of the return predictability of LLPs is mixed. Marton and Runesson (2017) find that during International Financial Reporting Standards (IFRS) bank years, LLPs are less predictive of future credit losses than local GAAP, although the benefits of local GAAP are limited to high-enforcement regimes. However, Gebhardt and Novotny-Farkas (2018) report that the predictive ability of LLPs improved following IFRS adoption in the European Union. López-Espinosa et al. (2021) report that LLPs under the expected credit loss model, compared with those under the incurred loan loss model, are more predictive of future bank risk. Beatty and Liao (2021) document that analyst provision forecasts incrementally predict future nonperforming loans (NPLs) and market returns, suggesting that incurred LLPs do not incorporate all available future loss information. In contrast with these studies, we examine the relationship between LLPs and one year ahead stock returns over time. We contribute to the literature by providing evidence to support the hypothesis that the relationship between LLPs and future stock returns is not linear but contingent on bank regulations and macroeconomic conditions.

The literature indicates that LLPs may be difficult to decipher, leading to the possibility that equity investors cannot correctly price LLPs and thus overreact to the information they contain (Wahlen, 1994). Accordingly, the overpricing of LLPs in a current period will be corrected downward in future periods. Thus, we propose the following hypothesis:

H1: *On average, LLPs are negatively associated with future stock returns.*

The literature documents that during the financial crisis period, banks tended to overstate the value of their assets and regulatory capital (Huizinga and Laeven, 2012; Cohen et al., 2014). Using a sample of U.S. banks in the 2001–2009 period, El Sood (2012) finds that banks used LLPs more aggressively during the crisis period to smooth income upward. That is, banks experienced more pressure to use LLPs for earnings or capital management during the financial crisis period than during non-crisis periods. Therefore, we hypothesize as follows:

H2: The negative relationship between LLPs and future stock returns is more pronounced during the financial crisis period than during other periods.

As documented in the literature, changes in banking or accounting regulations that affect banks' provisioning practices tend to affect the informativeness of banks' LLPs and their market valuation (Kim and Kross, 1998; Hamadi et al., 2016). For example, under Basel I, reducing LLPs allowed managers to inflate earnings and regulatory capital and thereby obscure the value of their banks (Kim and Kross, 1998). Basel II requires banks to compute a forward-looking measure of expected loss on their loan portfolios and to deduct the difference between this expected measure and the actual (accounting) LLPs from their regulatory capital (BCBS, 2004). Thus, Basel II reduces banks' incentive to smooth income by opportunistically using income-increasing LLPs (Hamadi et al., 2016). As discussed in Section 2, Basel III improves on Basel II by introducing a loan loss provisioning system that requires banks to set aside specific provisions on newly originated loans according to individual borrower characteristics that drive loan performance (Wezel et al., 2012). The Basel III framework prescribes more common equity, creates a capital buffer and introduces leverage, liquidity coverage and net stable funding ratios. These tighter capital and liquidity regulations constrain the use of LLPs for earnings management (Lim et al., 2021). During the Basel III period, the use of LLPs to signal positive private information (Wahlen, 1994) is likely to dominate earnings management incentives. However, if banks increase capital by reducing LLPs (i.e., manage capital) because of the stringent Basel III capital requirements (Lim et al., 2021), future stock returns will react negatively to the decrease in current-period LLPs. Based on these arguments, we hypothesize the following

H3: The negative relationship between LLPs and future stock returns is weaker during the Basel II and III periods than during non-Basel II and III periods.

4. Data and methodology

4.1. Data sources

We collect banks' fundamental data from Compustat, which provides information on banks' quarterly LLPs, nonperforming loans, net charge-offs, total loans, Tier 1 risk-adjusted capital ratio, earnings, total assets, and total equity. Similar to Beatty and Liao (2011), we scale LLPs, nonperforming loans and net charge-offs by lagged total loans. The equity returns, share price and shares outstanding data are downloaded from the Center for Research in Security Prices (CRSP) database. We construct risk-adjusted return (*ARET*) as quarterly returns adjusted for the value-weighted returns of all the banks in the same quarter. *ARET1* is risk-adjusted quarterly returns from the following month of the reporting quarter. The analyst coverage data are from the Institutional Brokers Estimate System (IBES) database. After merging the data from Compustat, CRSP and IBES, our sample contains 51,743 bank-year observations, covering 1751 unique banks from January 1994 to December 2017.

4.2. Methodology

To link LLPs to bank opacity, we first conduct a mediation analysis following Blau et al. (2017). We use the turnover ratio to measure bank opacity and run an OLS regression on the following models:

$$ARET_{i,t} = \alpha + \beta_1 LLP_{i,t-1} + Controls_{i,t-1} + \epsilon \tag{1}$$

$$TURN_{i,t-1} = \alpha + \beta_1 LLP_{i,t-1} + Controls_{i,t-1} + \varepsilon \tag{2}$$

$$ARET_{i,t} = \alpha + \beta_1 LLP_{i,t-1} + TURN_{i,t-1} + Controls_{i,t-1} + \varepsilon \tag{3}$$

For bank i in quarter t, $LLP_{i,t-1}$ is lagged LLPs divided by lagged total loans. *Controls* includes the following: $Lag(dNPL_{i,t-1})$ is $NPL_{i,t-2}$minus$NPL_{i,t-3}$; $dNPL_{i,t-1}$ equals $NPL_{i,t-1}$minus$NPL_{i,t-2}$; $NPL_{i,t-1}$ is lagged nonperforming loans divided by lagged total loans; $NCO_{i,t-1}$ is net charge-offs divided by lagged total loans;

$TLTA_{i,t-1}$ is lagged total loans divided by total assets; $SIZE_{i,t-1}$is the log of banks' market capitalization. $CAPR1Q_{i,t-1}$ is the Tier 1 risk-adjusted capital ratio; $EBP_{i,t-1}$ is earnings before LLPs; $MB_{i,t-1}$is market capitalization divided by total equity; $ARET_{i,t-1}$ is risk-adjusted returns and $TURN_{i,t-1}$ is the turnover ratio calculated as trading volume divided by shares outstanding. By observing a statistically significant natural indirect effect, we can link LLPs to bank opacity.

In our main analysis, we test the ability of LLPs to predict returns with the OLS regression as model [1]. Equation (1) is run for the entire sample and each subsample period. To study investors' perceptions of the return predictability of LLPs over time, we divide the sample into Basel II and Basel III subsamples. The first subsample covers 1994 to 2003, which is the pre-Basel II period. The second subsample is from 2004 to 2006 and covers the Basel II policy implementation period. The third subsample is from 2007 to 2009, which is before the financial crisis. The fourth subsample is from 2010 to 2015, which is the pre-Basel III period. The fifth subsample is from 2016 to 2017,[1] during which Basel III was proposed.[2]

As a robustness check, we report the panel regression results using year fixed effects in the following model:

$$ARET_{i,t} = \alpha + \beta_1 LLP_{i,t-1} + Controls_{i,t-1} + YearFE + \varepsilon \tag{4}$$

As a second robustness check, we report the estimates from a multivariate Fama and MacBeth (1973) regression of the following model:[3]

$$ARET_{i,t} = \alpha + \beta_1 LLP_{i,t-1} + Controls_{i,t-1} + \varepsilon \tag{5}$$

We calculate the standard errors of the slope coefficients in equation (5) using the Newey–West (1987) adjustment for serial correlations.

As a third robustness check, we report the estimates from a generalized method of moments (Hansen, 1982) regression of the following model:

$$ARET_{i,t} = \alpha + \beta_1 LLP_{i,t-1} + Controls_{i,t-1} + \varepsilon \tag{6}$$

Our generalized method of moments (Hansen, 1982) uses heteroskedasticity-robust weight matrix in the estimation of the regression coefficients. We also run equations (4), (5) and (6) for the entire sample and each subsample period. We report the estimated coefficients with their standard errors clustered by GICS industry for all of the regression models, except the Fama–Macbeth regression, in which we compute Newey–West standard errors. This follows the finding of Hrazdil and Scott (2013) that GICS results in more reliable industry groupings for industry analysis and research, compared with the three alternatives: the Standard Industrial Classification codes, North American Industry Classification System and Fama–French classification. In our sample, the GICS industries include banks, thrifts, and mortgage finance, diversified financial services, capital markets and consumer finance. As our sample comprises U.S. listed banks, using GICS helps us further classify their business models to be controlled by fixed effects. The fixed effects include banks, thrifts and mortgage finance, diversified financial services, capital markets and consumer finance. By controlling the sub-industry fixed effects, our estimated coefficients of regression are less likely to be biased due to omitted factors that vary across the business models of our sample.

As a fourth robustness check, we report the estimates from an OLS regression of the following equation using an alternate measure of risk-adjusted return:

[1] A study on the effect of Basel II on the market valuation of discretionary LLPs also uses a short 3-year period (Hamadi et al., 2016). The use of short 2-year and 3-year subsample periods is a potential shortcoming.

[2] The literature and regulatory documents provide the timelines that mark the key events. The initial Basel II policy implementation period is defined as the period after the Basel II policy document were released but before Basel II was effective and before the financial crisis, i.e., 2004–2006 (BCBS, 2004). The financial crisis period (2007–2009) follows Cohen et al. (2014). Lim and Ow Yong (2016) document an initially negative market reaction to the Basel II regulatory announcements, with the reaction weakening over time. We define the post-Basel II and post-financial crisis period as 2010–2015. The Basel III period is defined as 2016–2017, when the capital conservation buffers were added.

[3] Fama and MacBeth's (1973) estimation approach is commonly used in the return prediction literature. Following this stream of the literature, our estimation involves the following steps. We (1) regress each stock return against the control variables to determine that bank's beta for that risk factor; (2) regress all stock returns for a fixed period against the estimated betas to determine the risk premium; and (3) report the model estimates and t-statistics with standard errors adjusted for serial correlations, with up to four lags (Newey and West, 1987).

$$ARET_{i,t} = \alpha + \beta_1 LLP_{i,t-1} + Controls_{i,t-1} + \varepsilon \tag{7}$$

We calculate risk-adjusted returns following Fama and French (2015), including market premium, size (SMB), growth (HML), profitability (RMW) and investment (CMA) factors.

To decompose the return predictability of LLPs, we perform OLS regression analysis for each year and report the coefficient estimates on LLP, discretionary LLPs ($DLLP$) and non-dictionary LLPs ($NDLLP$). We decompose LLP into $DLLP$ and $NDLLP$ using the following equation:

$$LLP_{i,t} = \alpha + \beta_1 NPL_{i,t-1} + \beta_2 dNPL_{i,t-1} + \beta_3 Lag(dNPL_{i,t-1}) + \beta_4 Future(dNPL_{i,t+1}) + \beta_5 NCO_{i,t-1} + \beta_6 TLTA_{i,t-1} + \varepsilon \tag{8}$$

where $DLLP$ is discretionary LLPs, calculated as the residuals of equation (8). $NDLLP$ is nondiscretionary LLPs, calculated as the fitted value of equation (8). $NDLLP$ behaves similarly to LLP in predicting future returns because of the design of the decomposition. One concern regarding the decomposition is that it incorporates future changes in NPL, which can only be observed in the next quarter, t. Therefore, the significant coefficient estimates in the OLS regression do not translate into a meaningful trading strategy.

5. Empirical results

5.1. Summary statistics and correlations

Table 1 presents the descriptive statistics for the variables in our analyses. The mean LLP for the firms in our sample is 0.001, and the mean $DLLP$ ($NDLLP$) is 0.000 (0.001). Nonperforming loans account for 1.9% of total loans on average, and net charge-offs account for 0.1%.

Table 2 presents the correlation matrix. LLP is significantly negatively associated with one-quarter ahead stock returns, lending initial support to H1, which predicts that LLPs are overvalued in the current period. Decomposing LLP suggests that both $DLLP$ and $NDLLP$ have negative relationships with future stock returns. Furthermore, the correlation between $DLLP$ and $NDLLP$ is negative.

Table 1

Summary statistics. This table reports the descriptive statistics of the main variables in the regression analysis. We obtain quarterly U.S. bank data from CRSP and Compustat for the 1 January 1994 to 30 June 2017 sample period. There are 1751 unique banks in the sample. LLP is loan loss provisions, calculated as loan loss provisions (Compustat "pllq") divided by lagged total loans (Compustat "lntalq"). NPL is nonperforming loans, calculated as nonperforming loans (Compustat "npatq") divided by lagged total loans (Compustat "lntalq"). NCO is net charge-offs, calculated as net charge-offs divided by lagged total loans (Compustat "lntalq"). $TLTA$ is total loans calculated as lagged total loans (Compustat "lntalq") divided by total asset. $SIZE$ is the log of market capitalization. $CAPR1Q$ is the Tier 1 risk-adjusted capital ratio (Compustat "capr1q") at the beginning of the quarter. EBP is earnings before loan loss provisions, calculated as (Compustat "piq" plus Compustat "pllq" scaled by lagged Compustat "lntalq"). MB is market-to-book ratio. $DLLP$ is discretionary loan loss provision, calculated as the residuals of the regression of LLP on NPL, changes in NPL from the last quarter, lagged changes in NPL and future changes in NPL, NCO and $TLTA$. $NDLLP$ is nondiscretionary loan loss provision, calculated as the fitted value of the regression of LLP on NPL, changes in NPL from the last quarter, one quarter lagged changes in NPL, changes in NPL in the coming quarter, NCO and $TLTA$. $ARET$ is risk-adjusted quarterly returns calculated as quarterly returns minus the value-weighted returns of all of the banks in the same quarter.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
LLP	57,115	0.001	0.003	−0.008	0.043
DLLP	51,776	0.000	0.003	−0.126	0.131
NDLLP	51,776	0.001	0.016	−0.853	0.123
NPL	56,740	0.019	0.031	0.000	0.949
NCO	56,954	−0.001	0.003	−0.046	0.007
TLTA	58,241	0.648	0.134	0.012	0.927
SIZE	59,822	11.918	1.764	7.432	19.471
CAPR1Q	57,348	11.746	4.021	−0.700	70.370
EBP	57,112	0.006	0.009	−0.062	0.489
MB	57,870	1.432	0.705	−0.211	6.398
ARET	59,520	−0.003	0.093	−0.574	0.968

Table 2

Correlation matrix. This table reports the cross-sectional correlations for the entire sample period. *LLP* is loan loss provisions scaled by lagged total loans. *NPL* is nonperforming loans scaled by lagged total loans. *NCO* is net charge-offs scaled by lagged total loans. *TLTA* is lagged total loans scaled by total assets. *SIZE* is the log of market capitalization. *CAPR1Q* is the Tier 1 risk-adjusted capital ratio. *EBP* is earnings before loan loss provisions scaled by lagged total loans. *MB* is market-to-book ratio. *DLLP* is discretionary loan loss provision, calculated as the residuals of the regression of *LLP* on *NPL*, changes in *NPL* from the last quarter, lagged changes in *NPL* and future changes in *NPL*, *NCO* and *TLTA*. *NDLLP* is nondiscretionary loan loss provision, calculated as the fitted value of the regression of *LLP* on *NPL*, changes in *NPL* from the last quarter, one quarter lagged changes in *NPL*, changes in *NPL* in the coming quarter, *NCO* and *TLTA*. *ARET* is risk-adjusted quarterly returns calculated as quarterly returns minus the value-weighted returns of all of the banks in the same quarter. *ARET1* is risk-adjusted quarterly returns from the last month of the reporting quarter. All of the variables are winsorized at 0.5% and 99.5% by year.

Variable	*ARET1*	*LLP*	*DLLP*	*NDLLP*	*NPL*	*NCO*	*TLTA*	*SIZE*	*CAPR1Q*	*EBP*	*MB*	*ARET*
ARET1	1.000											
LLP	−0.075	1.000										
DLLP	−0.015	0.545	1.000									
NDLLP	−0.016	0.120	−0.005	1.000								
NPL	−0.032	0.383	−0.006	−0.084	1.000							
NCO	0.039	−0.629	−0.286	0.058	−0.484	1.000						
TLTA	−0.020	0.027	0.020	0.087	−0.088	0.063	1.000					
SIZE	−0.020	−0.031	−0.023	−0.018	−0.159	0.044	−0.180	1.000				
CAPR1Q	−0.001	−0.073	−0.041	−0.018	0.019	0.049	−0.216	0.002	1.000			
EBP	0.032	−0.095	−0.036	−0.085	0.067	−0.013	−0.305	0.271	0.121	1.000		
MB	−0.056	−0.183	−0.018	−0.021	−0.320	0.174	−0.091	0.449	−0.036	0.314	1.000	
ARET	0.011	−0.133	−0.062	−0.022	−0.054	0.069	−0.017	−0.015	0.004	0.065	−0.048	1.000

5.2. Baseline regression results

We conduct a mediation analysis to link LLPs to bank opacity, which is a price efficiency channel. Following Blau et al. (2017), we measure bank opacity using the stock turnover ratio (*TURN*), calculated as trading volume divided by total shares outstanding, and find that the mediation effect is significant.

Panel A of Table 3 presents the OLS regression estimates. In column (1), we predict risk-adjusted stock return using *LLP* and *Lag(dNPL)*, *dNPL*, *NPL*, *NCO*, *TLTA*, *SIZE*, *CAPR1Q*, *EBP*, *MB* and *ARET*. In column (2), we predict the quarterly turnover ratio, which represents bank opacity, using *LLP* and *Lag (dNPL)*, *dNPL*, *NPL*, *NCO*, *TLTA*, *SIZE*, *CAPR1Q*, *EBP*, *MB* and *ARET*. In column (3), we predict quarterly returns using *LLP* and *Lag(dNPL)*, *dNPL*, *NPL*, *NCO*, *TLTA*, *SIZE*, *CAPR1Q*, *EBP*, *MB*, *ARET* and the mediating factor *TURN*. In columns (1) and (2), we find that *LLP* is significant in explaining both future stock returns and concurrent period turnover ratios, but the significance level drops in column (3) when we include turnover ratio. To further check the mediation effect, we report the natural direct effect, natural indirect effect and total effect in Panel B. We find that although the magnitude of the drop is small, the *t*-statistic is −5.14, which is statistically significant at the 1% level.

Panel A of Table 4 presents the OLS results for the multivariate regression analysis. In column (1) the entire sample is tested, and the coefficient on *LLP* is significantly negative at the 1% level. This is consistent with H1 that *LLP* has a negative effect on future stock returns. We then divide the sample into five subperiods pertinent to bank regulations and economic conditions. The results are reported in columns (2)–(7). Column (2) covers 1994 through 2003. The coefficient on *LLP* is negative but insignificant. Column (4) covers 2004 to 2006, during which Basel II was adopted. The coefficient on *LLP* is positive and statistically significant at the 5% level. Column (5) covers the subprime financial crisis from 2007 to 2009. *LLP* appears to have a significantly negative impact on future stock returns. Column (6) covers 2010–2015 (the post-crisis period), during which *LLP* remains significantly negatively associated with future stock returns. Column (7) is estimated based on the 2016–2017 period, when Basel III and the expected credit loss model were proposed. During this period, *LLP* is positively associated with future stock returns. Overall, the results reported in Panel A of Table 4 suggest that LLPs are negatively associated with future stock returns, on average. Consistent with our H2 and H3, this effect mainly occurs in the financial crisis period but is moderated during the initial stages of the Basel II and III periods.

Table 3
Mediation analysis. This table presents the regression results for the mediation analysis. Panel A reports the ordinary least squares regression estimates. The first model explains risk-adjusted return using *LLP* and other control variables, including *Lag(dNPL)*, *dNPL*, *NPL*, *NCO*, *TLTA*, *SIZE*, *CAPR1Q*, *EBP*, *MB* and *ARET*. The second model explains the mediation factor, turnover ratio (*TURN*), using the same control variables as model [1]. The third model includes *TURN* and all of the control variables in model [1]. Panel B reports the mediation analysis based on the natural indirect effect, which is the difference between the natural direct effect and the total effect. The *t*-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Ordinary least squares regression

	[1] ARET1	[2] TURN	[3] ARET1
LLP	−3.801***	36.688***	−3.579***
	[−18.55]	[17.35]	[−12.07]
Lag(dNPL)	−0.968***	2.486**	−0.953***
	[−5.54]	[3.71]	[−5.82]
dNPL	−0.762	−0.465	−0.765
	[−1.78]	[−1.14]	[−1.80]
NPL	−0.125	0.429	−0.123
	[−1.63]	[0.90]	[−1.63]
NCO	0.200	−4.011**	0.177
	[1.23]	[−4.48]	[1.05]
TLTA	−0.007	−0.143*	−0.008
	[−1.67]	[−2.71]	[−2.01]
SIZE	−0.000	0.208***	0.001
	[−0.72]	[55.29]	[0.86]
CAPR1Q	−0.001*	−0.010**	−0.001*
	[−2.22]	[−3.51]	[−2.45]
EBP	2.072***	−5.003*	2.036***
	[7.20]	[−2.30]	[7.36]
MB	−0.025***	−0.228***	−0.027***
	[−7.39]	[−20.68]	[−8.87]
ARET	−0.020	0.068	−0.019
	[−1.47]	[0.99]	[−1.45]
TURN			−0.006
			[−1.63]
Intercept	0.037*	−1.461***	0.027
	[2.14]	[−16.11]	[1.19]
Obs.	49,443	50,993	49,443
Adj. R^2	0.021	0.239	0.022

Panel B: Mediation analysis

	Estimate	t-value	95% Conf. Interval	
Natural Direct Effect	−3.444***	[−8.96]	−4.198	−2.691
Natural Indirect Effect	−0.217***	[−5.14]	−0.299	−0.134
Total Effect	−3.661***	[−9.58]	−4.410	−2.912

We also analyze the full sample in three broad subperiods in columns (2), (3) and (7). Column (3) covers the entire Basel II period from 2004 to 2015. *LLP* is significantly negatively associated with one-quarter-ahead returns during this period. The results for the Basel II period remain negative but are more significant than those for the Basel I period. This indicates that the market initially reacted to the regulation change from Basel I to Basel II as having a significant effect on the use of LLPs. Similarly, the relationship between *LLP* and one-quarter-ahead returns becomes positive during the initial stage of the Basel III period. This is consistent with our theory that during the Basel III period, when banks are required to meet new capital conservation buffers, their ability to manage earnings is constrained (Lim et al., 2021). The use of LLPs to signal positive private information (Wahlen, 1994) dominates earnings management incentives during the Basel III period. As a result, LLPs are positively associated with future stock returns.

Panel B of Table 4 presents the panel regression with year fixed effects. The result is largely consistent with the results in Panel A for the entire sample period and during 1994–2003 (i.e., the pre-Basel II period),

Table 4

Multivariate regression analysis. This table presents the results of the multivariate regression analysis. Panel A reports the ordinary least squares regression estimates. Panel B reports the panel regression with year fixed effects. Panel C reports the Fama–Macbeth regressions estimates. Standard errors are calculated with the Newey–West adjustment. Panel D reports the generalized method of moments regression estimates. Panel E reports the ordinary least squares regression estimates using an alternative risk-adjusted returns based on the Fama and French (2015) five factors. Standard errors are clustered by GICS industry in Panels A, B, D and E. The first model tests the entire sample from January 1994 to June 2017. The second model tests from 1994 to 2003, which is the pre-Basel II period. The third model tests 2004 to 2015, the entire Basel II period. We separate the Basel II period into three stages: the initial stage in model [4] (2004–2006), the financial crisis in model [5] (2007–2009) and the last stage in model [6] (2010–2015). The seventh model covers the initial stage of Basel III from January 2016 to June 2017. The *t*-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Ordinary least squares regression

	[1] All	[2] 1994–2003	[3] 2004–2015	[4] 2004–2006	[5] 2007–2009	[6] 2010–2015	[7] 2016–2017
LLP	−3.792***	−0.926	−3.979***	3.880**	−1.530**	−6.906***	2.586
	[−19.05]	[−1.51]	[−42.06]	[3.30]	[−3.43]	[−34.21]	[0.49]
Lag(dNPL)	−0.976***	0.446**	−1.698***	−1.355***	−1.666*	−1.243**	0.345
	[−5.59]	[3.03]	[−5.46]	[−5.75]	[−3.18]	[−5.29]	[1.59]
dNPL	−0.750	−0.256***	−0.939	−0.588***	−2.512**	−0.093	−0.444
	[−1.77]	[−11.64]	[−1.48]	[−5.96]	[−5.65]	[−0.14]	[−1.83]
NPL	−0.121	−0.309***	0.201**	−0.483	0.207*	0.102	0.264
	[−1.59]	[−49.06]	[3.10]	[−2.13]	[3.12]	[1.03]	[1.82]
NCO	0.223	0.377	−0.330	1.489	−1.870	0.060	7.472
	[1.32]	[1.49]	[−1.11]	[0.74]	[−1.51]	[0.09]	[0.69]
TLTA	−0.007	0.022*	−0.027*	0.017	−0.125***	0.012	−0.001
	[−1.74]	[2.22]	[−2.22]	[1.51]	[−6.02]	[1.31]	[−0.12]
SIZE	−0.000	0.002	−0.001	−0.004**	0.002	−0.001	−0.003
	[−1.00]	[1.33]	[−2.10]	[−3.73]	[0.69]	[−1.76]	[−2.02]
CAPR1Q	−0.001*	−0.002**	0.001	−0.001	0.005***	−0.000**	−0.003**
	[−2.23]	[−4.56]	[1.73]	[−0.93]	[8.36]	[−4.89]	[−5.30]
EBP	2.058***	1.770***	1.895**	1.851**	1.532**	1.759**	4.889*
	[7.20]	[8.31]	[3.79]	[2.89]	[4.26]	[3.35]	[2.42]
MB	−0.025***	−0.037***	−0.013***	0.002	−0.014	−0.038***	−0.056**
	[−7.40]	[−8.84]	[−4.75]	[1.28]	[−2.35]	[−14.58]	[−3.52]
ARET	−0.020	0.050**	−0.100***	−0.031*	−0.122***	−0.127***	−0.169***
	[−1.46]	[2.86]	[−13.26]	[−2.50]	[−9.46]	[−30.13]	[−12.10]
Intercept	0.037*	0.028	−0.002	0.004	−0.039	0.036*	0.149**
	[2.22]	[1.41]	[−0.14]	[0.15]	[−1.13]	[2.39]	[4.10]
Obs.	49,312	23,593	22,788	6511	6137	10,140	2932
Adj. R^2	0.021	0.025	0.038	0.015	0.045	0.041	0.053

Panel B: Panel regression with year fixed effects

	[1] All	[2] 1994–2003	[3] 2004–2015	[4] 2004–2006	[5] 2007–2009	[6] 2010–2015	[7] 2016–2017
LLP	−4.735***	−3.498***	−4.124***	2.115**	−2.132	−3.867***	−5.407
	[−30.10]	[−9.18]	[−76.29]	[3.32]	[−2.12]	[−6.22]	[−1.80]
Lag(dNPL)	−0.802***	0.408	−1.316**	−0.498**	−1.195*	−1.018**	2.149***
	[−5.83]	[1.80]	[−4.31]	[−3.65]	[−3.04]	[−4.07]	[21.04]
dNPL	−0.745	−0.378***	−0.807	−0.247**	−2.093**	0.065	−0.360**
	[−2.05]	[−18.22]	[−1.33]	[−3.56]	[−5.60]	[0.11]	[−4.43]
NPL	−0.228	−0.348	−0.066	−1.372***	−0.291	0.101	−1.432***
	[−1.80]	[−1.46]	[−0.32]	[−4.97]	[−1.38]	[0.55]	[−7.73]
NCO	−0.110	−0.239**	−0.393	1.154	−1.517	1.275**	−1.682
	[−0.42]	[−2.89]	[−0.94]	[0.65]	[−1.21]	[4.25]	[−0.25]
TLTA	0.008	0.051**	−0.035*	−0.081	−0.237	−0.098	0.360**
	[0.76]	[4.42]	[−2.53]	[−1.50]	[−2.13]	[−1.56]	[5.68]
SIZE	−0.046***	−0.081***	−0.054***	−0.155***	−0.136***	−0.072***	−0.169***
	[−36.37]	[−13.84]	[−7.66]	[−47.31]	[−6.14]	[−14.24]	[−31.00]

(*continued on next page*)

Table 4 (*continued*)

Panel B: Panel regression with year fixed effects

	[1] All	[2] 1994–2003	[3] 2004–2015	[4] 2004–2006	[5] 2007–2009	[6] 2010–2015	[7] 2016–2017
CAPR1Q	−0.000	−0.000	0.001***	0.000	0.010**	0.000	−0.006***
	[−0.55]	[−0.38]	[8.11]	[0.22]	[4.33]	[0.79]	[−17.67]
EBP	1.855***	0.559**	2.299***	2.673***	2.398***	1.185**	1.879
	[5.26]	[3.92]	[7.62]	[25.83]	[9.23]	[3.79]	[0.49]
MB	−0.024***	−0.040***	−0.003*	−0.033**	0.033	−0.077***	−0.221***
	[−6.62]	[−5.10]	[−2.64]	[−3.62]	[2.18]	[−7.59]	[−42.42]
ARET	−0.161***	−0.186***	−0.162***	−0.242***	−0.251***	−0.227***	−0.496***
	[−26.59]	[−40.26]	[−34.18]	[−33.96]	[−102.58]	[−31.54]	[−75.25]
YEAR FE	Yes	YES	YES	YES	YES	YES	YES
Intercept	0.463***	0.862***	0.659***	2.005***	1.565**	0.910***	2.369***
	[22.88]	[10.60]	[7.36]	[34.14]	[5.25]	[9.22]	[255.78]
Obs.	49,312	23,593	22,788	6511	6137	10,140	2932
Adj. R^2	0.133	0.221	0.067	0.142	0.076	0.113	0.342

Panel C: Fama−Macbeth regression

	[1] All	[2] 1994–2003	[3] 2004–2015	[4] 2004–2006	[5] 2007–2009	[6] 2010–2015	[7] 2016–2017
LLP	−2.861***	−2.456**	−4.017***	1.129	−6.083**	−5.557***	2.057
	[−3.65]	[−2.42]	[−3.46]	[0.51]	[−2.73]	[−4.08]	[0.69]
Lag(dNPL)	−0.475**	−0.184	−0.689***	−0.549	−1.343**	−0.432*	−0.643
	[−2.60]	[−0.56]	[−3.06]	[−1.17]	[−2.39]	[−1.76]	[−1.32]
dNPL	−0.302	−0.574	−0.302	0.257	−1.244	−0.110	1.052
	[−1.29]	[−1.60]	[−0.91]	[0.43]	[−1.43]	[−0.31]	[1.68]
NPL	−0.299***	−0.223**	−0.434***	−0.758***	−0.814**	−0.081	0.135
	[−3.53]	[−2.28]	[−3.19]	[−4.85]	[−2.64]	[−0.49]	[0.48]
NCO	−0.367	0.992	−1.502	−0.169	−3.313	−1.263	−0.359
	[−0.52]	[1.11]	[−1.49]	[−0.10]	[−1.25]	[−1.01]	[−0.10]
TLTA	−0.002	0.007	−0.006	0.047*	−0.101	0.016	−0.021
	[−0.16]	[0.64]	[−0.27]	[1.97]	[−1.57]	[1.22]	[−0.85]
SIZE	−0.001	−0.001	−0.001	−0.002	0.002	−0.002	−0.003
	[−0.49]	[−0.29]	[−0.25]	[−1.29]	[0.19]	[−0.71]	[−0.92]
CAPR1Q	−0.000	−0.001***	0.001	−0.000**	0.006**	−0.001*	−0.002**
	[−0.80]	[−3.87]	[0.98]	[−2.43]	[2.89]	[−2.07]	[−2.44]
EBP	1.509***	2.043***	1.075***	1.719***	0.063	1.259**	1.441
	[5.99]	[6.64]	[2.73]	[4.86]	[0.06]	[2.27]	[1.51]
MB	−0.018***	−0.017***	−0.021**	−0.004	0.001	−0.040**	−0.011*
	[−3.65]	[−4.52]	[−2.16]	[−1.28]	[0.07]	[−2.79]	[−2.28]
ARET	−0.096***	−0.099***	−0.091***	−0.067***	−0.085	−0.106***	−0.112*
	[−7.45]	[−5.40]	[−4.75]	[−3.21]	[−1.24]	[−6.89]	[−2.09]
Intercept	0.021	0.027	0.004	−0.029	−0.070	0.057	0.098***
	[0.74]	[0.73]	[0.08]	[−1.12]	[−0.39]	[1.54]	[3.53]
Obs.	50,109	23,874	23,208	6607	6244	10,357	3027

Panel D: Generalized method of moments regression

	[1] All	[2] 1994–2003	[3] 2004–2015	[4] 2004–2006	[5] 2007–2009	[6] 2010–2015	[7] 2016–2017
LLP	−3.430***	−0.005	−3.547***	5.236**	−0.697	−7.435***	7.306
	[−3.16]	[−0.00]	[−2.76]	[2.06]	[−0.36]	[−5.00]	[1.21]
Lag(dNPL)	−1.196***	1.036**	−1.711***	−1.416**	−1.763**	−1.197***	−1.343
	[−4.56]	[2.47]	[−5.22]	[−2.30]	[−2.40]	[−2.93]	[−1.52]
dNPL	−0.167	0.070	−0.301	−0.441	−1.563	0.665	0.947
	[−0.42]	[0.12]	[−0.62]	[−0.49]	[−1.39]	[1.19]	[0.63]
NPL	−0.356***	−1.014***	−0.064	−0.928**	−0.004	−0.239*	−0.211
	[−4.56]	[−5.36]	[−0.57]	[−2.26]	[−0.02]	[−1.88]	[−0.36]

Table 4 (*continued*)

Panel D: Generalized method of moments regression

	[1] All	[2] 1994–2003	[3] 2004–2015	[4] 2004–2006	[5] 2007–2009	[6] 2010–2015	[7] 2016–2017
NCO	−1.280	0.323	−1.441	1.296	−2.593	−2.497	8.762
	[−1.03]	[0.20]	[−0.98]	[0.48]	[−0.97]	[−1.42]	[1.55]
TLTA	−0.020*	−0.000	−0.008	0.024	−0.089**	0.033	−0.031
	[−1.77]	[−0.01]	[−0.52]	[1.39]	[−2.46]	[1.36]	[−0.62]
SIZE	−0.000	0.002	0.002	−0.006***	0.007	0.000	−0.007**
	[−0.17]	[0.90]	[1.21]	[−3.01]	[1.42]	[0.26]	[−2.03]
CAPR1Q	−0.000	−0.002***	0.002***	0.000	0.004***	0.001	−0.003*
	[−0.82]	[−4.38]	[4.03]	[0.02]	[3.09]	[1.64]	[−1.94]
EBP	1.413***	1.600***	0.985***	2.574***	1.116	0.923***	3.540
	[5.07]	[2.76]	[3.68]	[3.34]	[1.02]	[4.75]	[1.22]
MB	−0.024***	−0.035***	−0.017***	−0.004	−0.023	−0.032***	−0.041***
	[−7.46]	[−5.51]	[−4.36]	[−1.00]	[−1.51]	[−4.26]	[−4.44]
ARET	−0.005	0.062***	−0.068***	−0.003	−0.103***	−0.086***	−0.160***
	[−0.36]	[4.62]	[−3.65]	[−0.10]	[−3.79]	[−3.50]	[−5.27]
Intercept	0.041***	0.063**	−0.044**	0.014	−0.095	−0.009	0.199***
	[2.61]	[2.26]	[−2.04]	[0.63]	[−1.43]	[−0.30]	[3.68]
Obs.	16,812	6054	9448	2482	2541	4425	1310

(continued on next page)

Table 4 (continued)

Panel E: OLS regression on risk-adjusted return by Fama and French (2015)

	[1] All	[2] 1994–2003	[3] 2004–2015	[4] 2004–2006	[5] 2007–2009	[6] 2010–2015	[7] 2016–2017
LLP	−0.617***	−0.787**	−0.583	−0.053	0.131	−1.131**	−1.598
	[−8.29]	[−3.15]	[−1.28]	[−0.09]	[0.16]	[−4.18]	[−1.45]
Lag(dNPL)	−0.021	−0.018	−0.020	0.039	0.242	−0.053	−0.049
	[−0.26]	[−0.40]	[−0.19]	[0.19]	[1.52]	[−0.35]	[−0.57]
dNPL	−0.146*	−0.338***	−0.059	−0.116	−0.423	0.097	0.142
	[−2.18]	[−26.23]	[−0.52]	[−1.82]	[−1.28]	[0.33]	[2.15]
NPL	−0.071**	−0.111***	−0.058*	−0.066	−0.168	−0.016	0.020
	[−3.46]	[−6.64]	[−2.76]	[−0.91]	[−1.34]	[−0.65]	[0.83]
NCO	−0.046	0.007	−0.234	−1.142*	−0.242	−0.282	−1.284
	[−0.20]	[0.04]	[−0.27]	[−2.76]	[−0.11]	[−1.95]	[−1.21]
TLTA	−0.003	−0.009**	0.005	0.012**	−0.013	0.005	−0.004
	[−0.97]	[−3.47]	[0.52]	[3.62]	[−0.65]	[0.87]	[−0.82]
SIZE	0.001**	−0.000	0.002***	−0.001*	0.004**	0.003***	−0.005***
	[4.12]	[−0.04]	[5.54]	[−2.14]	[4.14]	[6.25]	[−9.74]
CAPR1Q	0.000	−0.000***	0.001**	0.000	0.003**	−0.000	−0.000
	[1.89]	[−6.16]	[3.21]	[0.89]	[3.22]	[−0.05]	[−0.01]
EBP	0.522**	0.353***	0.692**	0.586*	1.133***	0.161	0.437
	[3.70]	[6.38]	[2.94]	[2.23]	[7.55]	[0.70]	[1.06]
MB	−0.002***	−0.002	−0.001	−0.002*	0.001	−0.002	0.005
	[−5.73]	[−1.72]	[−1.54]	[−2.15]	[1.02]	[−0.87]	[1.34]
ARET	−0.011***	0.008	−0.030***	−0.005	−0.049***	−0.013*	0.013**
	[−4.74]	[2.01]	[−14.81]	[−0.49]	[−9.71]	[−2.81]	[5.64]
Intercept	−0.007***	0.012	−0.036**	−0.001	−0.076	−0.034*	0.052*
	[−7.17]	[1.66]	[−3.51]	[−0.09]	[−2.25]	[−2.75]	[3.06]
Obs.	48,622	23,185	22,532	6423	6061	10,048	2906
Adj. R^2	0.003	0.002	0.007	0.002	0.016	0.006	0.016

2004–2015 (i.e., the Basel II period) and 2007–2009 (i.e., the financial crisis period). Nevertheless, these results should be interpreted with caution because of the short event windows.

Panel C of Table 4 presents the Fama–Macbeth regression results. For the full sample, *LLP* is significantly negatively associated with future stock returns. The negative relationship remains during 1994–2003 (i.e., the pre-Basel II period), 2004–2015 (i.e., the Basel II period), 2007–2009 (i.e., the financial crisis period) and

Table 5
Time-series analysis.

Panel A

Year	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
LLP	**−5.688**	**−6.614**	**−2.095**	−2.93	2.631	**−4.043**	**−3.708**	−1.091	−0.536	**4.374**	**4.655**	**4.419**
DLLP	**−3.385**	**−2.903**	**−5.631**	**−2.613**	−0.08	**−1.614**	−2.575	4.936	**−3.304**	1.208	−0.952	**1.747**
NDLLP	**−3.087**	**−2.401**	**3.347**	**−2.358**	**3.34**	**−7.273**	**−5.308**	**−9.658**	4.177	2.379	**7.044**	**4.444**

Panel B

Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
LLP	**−5.582**	**−19.15**	**−4.902**	0.000	**−4.601**	**−4.581**	−2.949	−5.400	−4.063	**−10.522**	**6.964**	−1.35
DLLP	**−4.092**	−0.403	0.06	**2.853**	−0.941	−0.175	−1.136	0.787	−0.914	**−0.495**	1.856	−5.352
NDLLP	−3.951	**−14.187**	−2.266	**−5.978**	−2.672	−0.507	−2.004	0.483	**0.674**	**0.434**	−1.369	**7.521**

This table presents the ordinary least squares regression estimates of quarterly return predictions by year. The first regression model is $ARET_{i,t} = \alpha + \beta_1 LLP_{i,t-1} + Controls_{i,t-1} + \varepsilon$ where β_1 is reported in the first row.
The second regression model is
$ARET_{i,t} = \alpha + \beta_2 DLLP_{i,t-1} + Controls_{i,t-1} + \varepsilon$ where β_2 is reported in the second row.
The third regression model is
$ARET_{i,t} = \alpha + \beta_3 NDLLP_{i,t-1} + Controls_{i,t-1} + \varepsilon$ where β_3 is reported in the third row.
Controls includes *NPL*, change and the lagged changes in *NPL*, *NCO*, *TLTA*, *SIZE*, *CAPR1Q*, *EBP*, *MB* and *ARET*. Panel A reports the regression estimates of *LLP*, *DLLP* and *NDLLP* for each year from 1994 to 2005. Panel B reports the regression estimates of *LLP*, *DLLP* and *NDLLP* for each year from 2006 to 2017. Standard errors are clustered by GICS industry. Estimates that are significant at at least the 10% level are in bold.

2010–2015 (i.e., the post-crisis period). However, this negative relationship is less significant during the period when Basel III and the expected credit loss model were proposed. These results lend further support to our hypotheses.

Panel D of Table 4 presents the results using the generalized method of moments approach. The estimated coefficients are consistent with those in Panel A, with slightly lower *t*-statistics for the full sample and each subperiod. The statistically significant results reported in Panel A remain for the entire sample period and 1994–2003 (i.e., the pre-Basel II period), 2004–2015 (i.e., the Basel II period), 2010–2015 (i.e., the post-crisis period) and 2016–2017 (when Basel III and the expected credit loss model were proposed). These results further bolster our main findings.

Panel E of Table 4 presents the OLS regression results using an alternative risk-adjusted return based on Fama and French (2015), adjusting for market premium, size (*SMB*), growth (*HML*), profitability (*RMW*) and investment (*CMA*) factors. The estimated coefficients are consistent with those in Panel A, with slightly lower *t*-statistics for the full sample and each subperiod. The statistically significant results reported in Panel A remain largely unchanged for the entire sample period and during 1994–2003 (i.e., the pre-Basel II period), 2004–2015 (i.e., the Basel II period) and 2007–2009 (i.e., the financial crisis period).[4]

5.3. Year-by-year regression results

To further explore the return predictability of LLPs on a time-series basis, Table 5 presents the OLS regression estimates of quarterly return predictions by year. In most of the sample years (11 of 24 years), the coefficient on *LLP* is statistically negative. In particular, the coefficient is the most negative in the financial crisis period (2007: −19.150) versus the average coefficient of −3.801 during the full sample period. However, the coefficient on *LLP* turns positive for the initial years of Basel II (2004: 4.655) and Basel III (2016: 6.964).

[4] We perform subsample analysis rather than DiD for the following reasons: First, a major objective of our study is to test the time-series variation in the relationship between LLPs and future stock returns. This differentiates our study from those that look at the entire sample period. Second, because the time gap between events is short, there is overlap in the event windows. For example, the post-Basel II period is also the pre-crisis period. In the presence of such confounding effects, it is challenging to draw meaningful conclusions based on the DiD design.

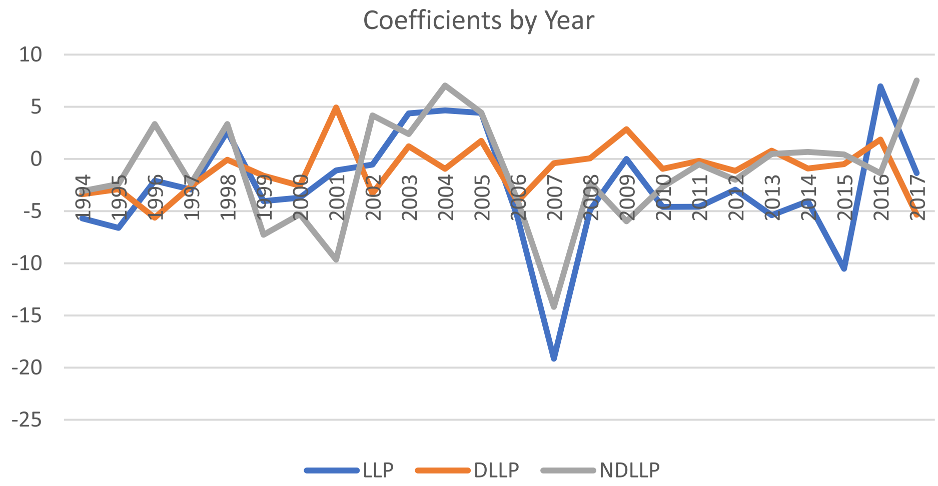

Fig. 1. OLS regression estimates of *LLP*, *DLLP* and *NDLLP* by year.

In addition, we decompose *LLP* into *DLLP* and *NDLLP*. Although both *DLLP* and *NDLLP* show patterns similar to that of *LLP*, the effect of *LLP* on future stock returns is mainly driven by *NDLLP*. For example, during the 2007–2009 financial crisis period, the coefficients on *DLLP* are −0.403, 0.06 and 2.853 in 2007, 2008 and 2009, respectively, whereas the coefficients on *NDLLP* are −14.187, −2.266 and −5.978 in 2007, 2008 and 2009 respectively. Moreover, the average coefficient on *DLLP* during the Basel II (III) period is 0.038 (−1.349), compared with 0.751 for *NDLLP* (−0.833). The coefficients by year are graphically represented in Fig. 1.

5.4. Hedge portfolio analysis

Table 6 reports the mean annual returns to various LLP quintile portfolios and their hedge returns. The results in column (1), based on the full sample, show that the higher the LLPs, the lower the future returns. The hedge portfolio strategy based on the level of *LLP* yields a positive annual return of 6.1% that is statistically significant at the 1% level. The results in column (3), based on the Basel II period, suggest that the higher the LLPs, the higher the future returns. Thus, taking long positions on stocks in the highest quintile and short positions on stocks in the lowest quintile generates a significantly positive annual return of 4.7%. In contrast, the results in column (4) are for the financial crisis period and show that the higher the LLPs, the lower the future returns. During this period, taking long positions on stocks in the lowest quintile and short positions on stocks in the highest quintile generates a significantly positive annual return of 34.4%, which is statistically and economically sizable. These results are also consistent with the regression results in Table 4.

5.5. Cross-sectional variation tests

In this subsection, we test whether the relationship between LLPs and future stock returns is conditional on banks' information environment. We measure information transparency using book-to-price (B/P) ratio, bank size and analyst coverage. The literature suggests that when a bank's B/P ratio is high, the bank is relatively undervalued, and therefore its managers have stronger incentives to use LLPs to signal private good news (Kanagaretnam et al., 2004). Bank size is measured by market capitalization, and analyst coverage is measured by the number of analysts following the bank. Both size and analyst coverage are positively related to banks' information environment.

Table 7 presents the subsample results based on B/P ratio. In Panel A, the coefficient estimate on *LLP* is −2.729 with a t-statistic of −5.20 for the entire sample period for the banks with a low B/P ratio. The next two rows consist of high B/P ratio banks, where the coefficient on *LLP* is −4.908 with a t-statistic of −32.64 for the entire sample period. The difference between the two subsamples is −2.179, with a t-statistic of −3.99. The difference in the coefficients on *LLP* between the banks with high versus low B/P ratios are positive and sig-

Table 6

Univariate portfolio analysis. This table reports the value-weighted returns of quarterly rebalanced quintile *LLP* portfolios; the return differentials between the top and bottom *LLP* quintiles are at the quarterly and annual levels. The first model tests the entire sample. The second model tests the 1994–2003 period. The third model tests the 2004–2006 Basel II period. The fourth model tests the 2007–August 2009 financial crisis period. The fifth model tests the September 2010–2015 period. The sixth model tests the 2016–2017 period, when Basel III was proposed. We do not have sufficient data to calculate the one year ahead return of the portfolio in this model. Standard errors are clustered by GICS industry. The *t*-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	[1]	[2]	[3]	[4]	[5]	[6]
Low	−0.035	−0.021	−0.076	−0.091	−0.054	0.055
2	−0.045	−0.025	−0.063	−0.229	−0.067	0.064
3	−0.060	−0.036	−0.047	−0.272	−0.090	0.062
4	−0.070	−0.041	−0.050	−0.260	−0.091	0.054
High	−0.083	−0.050	−0.029	−0.306	−0.122	0.097
High-Low	−0.061***	−0.031	0.047**	−0.344***	−0.069	0.042
	[−2.72]	[−1.61]	[2.06]	[−3.02]	[−1.47]	[1.43]
ARET1Y	−0.022*	−0.005	0.025***	−0.193***	−0.008	
	[−1.95]	[−0.54]	[2.96]	[−4.69]	[−0.36]	

nificant during 1994–2003, which is the Basel I period. Panel B reports the results based on bank size. Similarly, for the small banks, the coefficient on *LLP* is −5.903, with a *t*-statistic of −7.41 for the entire sample period. However, for the large banks, the coefficient on *LLP* is −0.457, with a *t*-statistic of −2.27 for the entire sample. The difference between the two groups is 5.446, with a *t*-statistic of 6.63. The coefficients on *LLP* are economically and statistically more significant for smaller banks during the Basel I and Basel II periods. In Panel C, the differences between high and low analyst coverage are also positive, but they are only statistically significant during the Basel III period.

The results reported in Table 7 suggest that the baseline regression results are mainly driven by banks with a high level of information asymmetry, which have the strongest incentives to use LLPs to manage their earnings or regulatory capital.

5.6. Discretionary and nondiscretionary loan loss provisions

The literature uses signaling as a key explanation for market reactions to LLPs (Elliott et al., 1991; Wahlen, 1994; Beaver and Engel, 1996, Liu et al., 1997). Wahlen (1994) seeks to determine what investors learn from unexpected changes in nonperforming loans, LLPs and loan charge-offs. LLPs incorporate managerial expectations regarding loan losses and a discretionary element. Wahlen (1994) argues that unexpected changes in nonperforming loans and unexpected loan charge-offs are correlated with nondiscretionary unexpected future loan losses and unexpected loan losses in the current period, respectively, and that investors can estimate the discretionary component of unexpected LLPs. He demonstrates that unexpected changes in nonperforming loans and unexpected loan charge-offs are negatively related to stock returns and future cash flows. Wahlen (1994) finds that after conditioning for the unexpected increase in nonperforming loans and loan charge-offs, there is a positive relationship between unexpected loan losses and returns and between unexpected loan losses and future cash flows. He interprets this result as evidence that the stock market interprets higher discretionary LLPs from managers as a signal of private good news.

Following this stream of the literature, we decompose *LLP* into *DLLP* and *NDLLP*. Panel A of Table 8 presents the results based on *DLLP*. The coefficients on *DLLP* are largely insignificant, except those for the financial crisis period (2007–2009). Panel B presents the results based on *NDLLP*. Similar to the pattern of *LLP*, *NDLLP* is negatively associated with future returns, significant at the 1% level, especially during the financial crisis period. Comparing the significance levels of the relations of *DLLP* and *NDLLP* with future returns, we find that the relationship between *LLP* and future stock returns is primarily driven by the nondiscretionary component of *LLP*.

Table 7

Subsample analysis In the panels, the full sample is divided into two groups according to proxies for managers' incentives to signal and information asymmetry: low (<50 percentile) and high (>50 percentile). *B/P* ratio is the book-to-price ratio. We follow Ohlson's (1995) framework to compute the intrinsic value of a bank. If the *B/P* ratio is high, the bank is relatively undervalued, and its managers therefore have more incentive to use LLPs as a signal of performance. We use bank size and analyst coverage as proxies for information asymmetry in Panels B and C, respectively. The slope coefficients and *t*-statistics (in parentheses) are reported from the ordinary least squares estimations. Standard errors are clustered by GICS industry. The associated *t*-statistics are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Panel A: B/P				Panel B: Size				Panel C: Analyst coverage			
	All	1994–2003	2004–2015	2016–2017	All	1994–2003	2004–2015	2016–2017	All	1994–2003	2004–2015	2016–2017
	low	low	low	low	small	small	small	small	low	low	low	low
LLP	−2.729***	−1.854**	−3.055**	−0.503	−5.903**	−3.091***	−5.588***	−0.221	−4.911***	−1.45	−5.026***	−11.9***
	[−5.20]	[−4.18]	[−3.45]	[−0.06]	[−7.41]	[−2.56]	[−10.46]	[−0.06]	[−4.31]	[−1.37]	[−5.33]	[−5.26]
	high	high	high	high	large	large	large	large	high	high	high	high
LLP	−4.908***	−0.629	−4.498***	3.409*	−0.457*	1.297**	−0.459**	6.091	−2.116**	0.023	−2.554***	8.675
	[−32.64]	[−1.21]	[−14.49]	[2.47]	[−2.27]	[2.09]	[−4.59]	[1.04]	[−2.14]	[0.04]	[−2.59]	[1.34]
	high-low				large-small				high-low			
LLP	−2.179***	1.225*	−1.443	3.912	5.446***	4.388***	5.129***	6.312	2.795*	1.473	2.472*	20.575***
	[−3.99]	[1.79]	[−1.54]	[0.46]	[6.63]	[3.23]	[9.44]	[0.91]	[1.85]	[1.22]	[1.81]	[3.00]

Table 8

Discretionary and nondiscretionary loan loss provision analysis. This table presents the ordinary least squares regression estimates of discretionary loan loss provision (DLLP) and nondiscretionary loan loss provision (NDLLP). Panel A reports the regression estimates of *DLLP*. Panel B reports the regressions estimates of *NDLLP*. The first model tests the entire sample. The second model tests the 1994–2003 period. The third model tests the 2004–2015 Basel II period. The fourth model tests the 2004–2006 pre-financial crisis period. The fifth model tests the 2007–2009 financial crisis period. The sixth model tests the 2010–2015 post-crisis period. The seventh model tests the 2016–2017 period during which Basel III was proposed. Standard errors are clustered by GICS industry. The *t*-statistics are reported in parentheses ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

	Panel A: DLLP						
	[1] All	[2] 1994–2003	[3] 2004–2015	[4] 2004–2006	[5] 2007–2009	[6] 2010–2015	[7] 2016–2017
DLLP	−0.253	−0.894	0.038	−0.569	1.722***	−0.424	0.751
	[−0.32]	[−1.35]	[0.05]	[−0.43]	[15.25]	[−0.30]	[0.39]
Lag(dNPL)	−1.105***	0.424*	−1.810***	−1.234**	−1.706**	−1.344**	0.447***
	[−6.87]	[2.51]	[−5.45]	[−4.55]	[−3.33]	[−5.18]	[13.20]
dNPL	−0.834	−0.255***	−1.092	−0.274	−2.613**	−0.265	−0.435**
	[−1.78]	[−13.30]	[−1.56]	[−1.53]	[−4.34]	[−0.37]	[−4.95]
NPL	−0.160	−0.336***	0.210*	−0.362*	0.251*	0.102	0.381**
	[−1.68]	[−19.48]	[2.52]	[−2.49]	[2.39]	[0.75]	[5.09]
NCO	2.207**	0.458	2.757**	0.014	0.353	4.778***	6.242
	[4.17]	[1.83]	[3.65]	[0.01]	[0.18]	[6.98]	[0.86]
TLTA	−0.010**	0.022*	−0.032**	0.017*	−0.127***	0.004	0.001
	[−3.04]	[2.18]	[−2.86]	[2.18]	[−5.85]	[0.50]	[0.08]
SIZE	−0.001	0.002	−0.001*	−0.004**	0.002	−0.001	−0.003
	[−1.66]	[1.21]	[−2.35]	[−3.14]	[0.66]	[−1.14]	[−1.93]
CAPR1Q	−0.001*	−0.002***	0.001	−0.001	0.005***	−0.000**	−0.003***
	[−2.24]	[−4.70]	[1.82]	[−0.98]	[8.28]	[−5.65]	[−10.15]
EBP	2.010***	1.739***	1.906**	1.819*	1.597**	1.581*	4.970*
	[6.40]	[8.54]	[3.44]	[2.54]	[3.73]	[2.88]	[2.50]
MB	−0.025***	−0.037***	−0.012**	0.003	−0.015*	−0.036***	−0.057**
	[−7.36]	[−8.81]	[−4.15]	[1.26]	[−2.55]	[−15.08]	[−3.49]
ARET	−0.016	0.051**	−0.095***	−0.040*	−0.119***	−0.114***	−0.174***
	[−1.17]	[2.90]	[−10.72]	[−2.16]	[−8.32]	[−26.28]	[−10.96]
Intercept	0.041*	0.029	0.001	0.004	−0.035	0.035*	0.149**
	[2.54]	[1.43]	[0.11]	[0.13]	[−1.07]	[2.37]	[3.84]
Obs.	49,274	23,577	22,767	6507	6126	10,134	2931
adj. R^2	0.019	0.025	0.035	0.012	0.045	0.032	0.056

Panel B: NDLLP

	[1] All	[2] 1994–2003	[3] 2004–2015	[4] 2004–2006	[5] 2007–2009	[6] 2010–2015	[7] 2016–2017
NDLLP	−1.949*	−1.205**	−1.349	2.372*	−5.412**	−0.741	−0.833
	[−2.32]	[−3.98]	[−1.37]	[2.35]	[−4.01]	[−1.00]	[−0.69]
Lag(dNPL)	−1.033***	0.479**	−1.768***	−1.300**	−1.522**	−1.327**	0.479***
	[−6.33]	[3.26]	[−5.47]	[−4.38]	[−3.66]	[−5.24]	[8.65]
dNPL	−0.754	−0.253***	−1.010	−0.368	−2.292**	−0.223	−0.392**
	[−1.65]	[−10.13]	[−1.49]	[−2.01]	[−5.15]	[−0.31]	[−4.32]
NPL	−0.121*	−0.282***	0.218***	−0.429*	0.372*	0.108	0.379***
	[−2.59]	[−38.83]	[5.01]	[−2.62]	[2.87]	[1.08]	[6.93]
NCO	1.590**	0.333	2.144**	0.604	−2.439	4.601***	5.483
	[3.17]	[1.89]	[3.00]	[0.36]	[−2.00]	[12.55]	[0.70]
TLTA	−0.008	0.022*	−0.030*	0.016	−0.122***	0.005	0.002
	[−2.12]	[2.28]	[−2.60]	[1.79]	[−5.84]	[0.59]	[0.33]
SIZE	−0.000	0.002	−0.001	−0.004**	0.004	−0.001	−0.003
	[−1.15]	[1.31]	[−2.12]	[−3.24]	[1.04]	[−1.75]	[−2.07]
CAPR1Q	−0.001*	−0.002***	0.001	−0.001	0.005***	−0.000**	−0.003***
	[−2.16]	[−4.66]	[1.60]	[−1.03]	[9.53]	[−4.33]	[−11.03]
EBP	2.031***	1.785***	1.884**	1.810*	1.516**	1.532**	5.063*
	[6.73]	[8.77]	[3.61]	[2.62]	[3.87]	[3.45]	[2.64]

Table 8 (*continued*)

Panel B: NDLLP

	[1] All	[2] 1994–2003	[3] 2004–2015	[4] 2004–2006	[5] 2007–2009	[6] 2010–2015	[7] 2016–2017
MB	−0.025***	−0.037***	−0.012**	0.002	−0.018*	−0.036***	−0.057**
	[−7.20]	[−8.81]	[−4.00]	[1.29]	[−2.56]	[−10.99]	[−3.52]
ARET	−0.017	0.051**	−0.096***	−0.040	−0.122***	−0.114***	−0.174***
	[−1.25]	[2.91]	[−11.12]	[−2.04]	[−8.82]	[−35.41]	[−11.00]
Intercept	0.039*	0.028	0.000	0.005	−0.048	0.035	0.148**
	[2.36]	[1.38]	[0.01]	[0.17]	[−1.45]	[2.18]	[3.77]
Obs.	49,274	23,577	22,767	6507	6126	10,134	2931
adj. R^2	0.020	0.025	0.036	0.013	0.047	0.033	0.056

6. Conclusion

This study examines the effect of LLPs on future stock returns on a time-series basis. We find that on average, LLPs are negatively associated with future returns. After separating the full sample into five subperiods, our results show that the negative relationship between LLPs and future returns mainly occurs during the 2007–2009 financial crisis period. However, the relationship between LLPs and future returns is positive during the Basel II period. These results are primarily driven by the nondiscretionary component of LLPs and are more pronounced among banks with high information asymmetry.

These results have implications for various market participants, such as investors, regulators and standard-setters. First, as primary information users, investors should be aware of the information contained in LLPs, because it has valuation consequences. Second, regulators should enhance market participants' understanding of LLPs by improving the disclosure system pertinent to loan losses. Finally, standard-setters such as the FASB and IASB should develop a more credible loan loss provisioning model, aimed at providing more informative measures of expected loan losses.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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