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Discretionary loan loss provisioning and bank stock returns: The Role of economic booms and busts

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Abstract

We provide evidence that discretionary loan loss provisions (DLLP) convey value-relevant information to the market that is highly dependent upon the state of the economy. DLLP is associated with negative abnormal returns during bad economic states characterized by growing default concerns, but it is associated with significantly higher abnormal stock returns in good economic states, as banks relax underwriting standards and look to accelerate loan growth. Exploring the underlying link, we find that banks recording higher provisions during good times realize significantly higher earnings and loan growth in the subsequent year, whereas such banks experience further increases in non-performing loans following periods of distress. These findings are not driven by the 2008 financial crisis when investors responded even more negatively to DLLP. With new accounting standards requiring an even greater degree of subjective judgment, regulators should ensure the informativeness of bank loss reserves is preserved.

Keywords: Loan loss provision, Bank holding company, Business cycle, Lending standards, Valuation, Bank lending

JEL Classification: G21, G28, M40

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1. Introduction

U.S. Generally Accepted Accounting Principles (GAAP) require banks to estimate expected loan defaults and record an expense in the current period to increase reserves for future losses to a sufficient level. Thus, an unusually large loan loss provision expense should inform investors of management's heightened default expectations. Yet, despite this seemingly adverse news prior research generally documents a positive relation between the discretionary component of loan loss provision expenses and bank stock returns (Wahlen, 1994; Beaver and Engel, 1996; Beaver et al., 1997; Liu et al., 1997; Kanagaretnam et al., 2009; Kilic et al., 2013). While several theories for this finding have been proposed in the literature, no comprehensive explanation has been offered. Our study aims to fill this gap in the literature by providing an explanation for prior findings while identifying the value-relevant information provided by discretionary loan loss provisions (DLLP).

The estimation of required loan loss reserves allows for considerable managerial judgment and discretion. Previously, under the incurred loss model loan loss reserves were estimated primarily based on SFAS 5 (ASC 450-20) for unimpaired loans and SFAS 114 (ASC 310-10) for impaired loans. Highlighting the level of subjective judgment involved, SFAS 5 requires losses to be deemed probable and capable of being reasonably estimated, and SFAS 114 states that "measuring impaired loans requires judgment and estimates, and the eventual outcomes may differ from those estimates. Creditors should have latitude to develop measurement methods that are practical in their circumstances." With banks transitioning to the more forward-looking current expected credit losses (CECL) methodology outlined in Accounting Standards Update 2016-13 (ASC 326-20) beginning in 2020, bank managers are expected to possess even greater discretion as the standard "requires consideration of a broader range of reasonable and supportable information to inform credit loss estimates."[1] Thus, it is crucial for bank regulators and financial statement users to understand the primary driving forces behind DLLP and their relation to future bank performance.

We predict that the value-relevant information conveyed by discretionary loan loss provisions

[1]The Coronavirus Aid, Relief, and Economic Security (CARES) Act offers banks the option to delay ASC 326 compliance until the earlier of the end of 2020 or when the President declares the national health emergency over.

depends critically on the state of the economy, because the motivation for recording extra provision expenses varies with overall economic conditions. In particular, prior evidence suggests that lending standards vary over the business cycle with lax credit policies implemented during periods of strong economic growth and tight policies in economic downturns (Asea and Blomberg, 1998; Ruckes, 2004; Dell'Ariccia et al., 2012; Bassett et al., 2014). By recording high DLLP in good economic states, bank managers choosing to implement loan growth strategies are able to boost earnings while also establishing a buffer to protect against future capital losses (Beatty and Liao, 2011). With low default rates expected in good states of the economy, DLLP is associated with higher stock returns driven by expectations of higher future earnings. In contrast, banks tend to tighten underwriting standards and become more averse to granting high-risk loans during economic downturns. With already depressed earnings, bank managers have limited incentive to record discretionary loan loss provisions except as needed to cover rising loan portfolio losses. Thus, based on management's private information of its loan portfolio, high DLLP indicates to the market which banks are facing the most severe default problems, thereby inducing a negative stock market response in bad economic times.

Using a broad panel of publicly traded U.S. bank holding companies (BHCs) over the period from 1997 to 2013, we test the conditional valuation hypothesis and show that consistent with prior findings, DLLP expenses are associated with higher abnormal stock returns and bank valuations but only during good economic times. In contrast, stock returns are significantly lower for banks with higher DLLP when economic prospects are bleak. We attribute this to greater economic distress resulting in increased investor skepticism and a greater likelihood that high DLLP reflects management's inside knowledge of a deteriorating loan portfolio rather than the adoption of loan growth strategies designed to increase future cash flows. We also find non-discretionary loan loss provisions (NDLLP) are associated with lower abnormal returns in bad economic times, but its estimated marginal impact is generally insignificant and close to zero in good times as NDLLP is based on outstanding loan characteristics and does not offer significant new information related to future cash flows.

To evaluate the transmission mechanism underlying the positive link between DLLP and bank stock returns, we explore whether the implementation of more aggressive lending policies by high DLLP banks during good economic times is related to an increase in future accounting earnings and lending activity. Consistent with our predictions, we find DLLP recorded in good economic states is associated with higher earnings driven by an increase in net interest income and stronger loan growth in the following year. Conversely, we find a negative relation between DLLP and future earnings when the economy is weak, and DLLP is instead associated with future increases in non-performing loans. This latter result is consistent with the findings in De Haan and Van Oordt (2018) that banks with growing loan impairment increase loan loss provisions in the current period but not sufficiently to prevent the need for future adjustments to loss reserves. Thus, DLLP is associated with increased earnings potential in good economic states, but it reduces current period earnings and informs market participants of growing loan impairment in bad economic states.

We choose to focus on loan loss provisions for two primary reasons. First, loan loss provisions are by far the most economically significant accrual for banking institutions. The median loan loss provision (LLP) expense in our sample is 12.51% as a percentage of earnings prior to taxes and provision expenses, and the ratio exceeds one hundred percent in 5.66% of bank-years illustrating its substantial impact on earnings. Second, loan loss provisions are based on estimates that require a high degree of subjective judgment, which is expected to increase further under new accounting standards. During the incurred loss model regime banks relied primarily on current conditions and historical loss experience to form the basis of loan loss estimates, but following the 2008 financial crisis many critics expressed concern that this contributed to loan loss provisions that were "too little, too late" resulting in depleted bank capital and a greater procyclicality of bank lending (Dugan, 2009; Financial Stability Forum, 2009; Dahl, 2013). As a result, Accounting Standards Update (ASU) 2016-13 requires banks to incorporate forward-looking information into credit loss estimates while noting some banks may already be more closely aligned with the new standards depending on their use of discretion during the incurred loss model regime. We investigate the information content of such discretion while exploring the market's conditional response to DLLP.

Our goal is not to identify all possible discretionary factors that contribute to bank loan loss provisions but rather to assess DLLP's overall relation with future bank performance and how the incentives for biasing loss estimates vary over time.

Our study makes three main contributions to the literature. First, we show the positive link between DLLP and bank stock returns documented in prior literature is strongly conditional on the state of the economy – it is positive only during good economic times but negative in economic downturns. Second, we provide evidence that high DLLP banks exhibit significant differences in future performance. Consistent with DLLP being used to support increased lending activity when the economy is strong, we find high DLLP banks experience higher earnings in the following period fueled by significantly higher loan growth and net interest income. These results are consistent with our hypotheses and highlight that the information conveyed by DLLP depends strongly on economic conditions. Third, we use multiple methods to address potential endogeneity concerns often ignored by prior studies. Specifically, we consider an array of models for estimating DLLP to limit omitted variable concerns, and we evaluate our conditional valuation hypothesis for each resulting DLLP estimate. We also examine the return performance of high versus low DLLP banks around major events during the 2008 financial crisis, and we conduct a matched sample analysis comparing banks that are otherwise similar but differ in their use of reporting discretion. Overall, the results add strong support for the conditional valuation hypothesis.

Prior studies frequently rely on a single DLLP estimate, yet the estimation procedures used differ across studies without a consensus for which model is most appropriate (Beatty and Liao, 2014). This represents a significant limitation, as the inferences drawn may depend upon the particular model used. To enhance the reliability of our results, we explore a variety of specifications which incorporate a robust set of controls, and we utilize different DLLP estimation procedures that include estimating a series of cross-sectional regressions that allow the coefficients on each predictor to vary over time, static models that utilize fixed effects to control for unobservable time-specific or bank-specific factors, and dynamic panel models that explicitly account for the potential dependence of current period loan loss provisioning on its lagged values. We also propose a new adjusted-LLP measure for estimating expected loss provisions that overcomes common estimation pitfalls. Specifically, we adjust reported LLP by the net difference of gross charge-offs and recoveries which helps isolate the discretionary component of LLP while avoiding any mechanical relation since both charge-offs and recoveries directly impact bank loss reserves.[2] Using the resulting DLLP estimates, we find consistent support for the conditional valuation hypothesis across all specifications.

We subsequently explore several different treatments of loan charge-offs in robustness tests given their impact on bank loan loss reserves and inconsistent handling in prior studies. In particular, we first re-estimate DLLP by modelling loan loss provisions adjusted for recoveries with gross charge-offs included as a regressor. This is similar to the approach used in prior studies that explicitly model the relation between loan loss provisions and net charge-offs (Kanagaretnam et al., 2010; Beck and Narayanamoorthy, 2013; Basu et al., 2020), except the regression equation is adjusted by the amount of recoveries given their mechanical relation with loan loss reserves. Next, given that several prominent studies suggest that controlling for charge-offs may subsume too much variation in LLP and understate the full extent of discretionary reporting, we re-estimate expected LLP while excluding charge-offs from the set of predictors (Bushman and Williams, 2012; Beatty and Liao, 2014, 2020). In both instances, our second-stage regressions indicate that DLLP exhibits a negative association with bank stock returns in bad economic states, and the interaction of DLLP with our measure of economic conditions is positive and significant, consistent with the negative information related to default expectations being counteracted by good news related to future loan growth and cash flow expectations. Additionally, the estimated marginal impact of DLLP on returns during good economic states is positive and significant for our first set of alternate DLLP estimates when including our baseline set of controls, and the impact becomes positive and significant for both sets of alternate estimates when controlling for any direct impact of charge-offs on returns in the second-stage regression. Altogether, the results reinforce our finding of a significant

[2]For instance, both recoveries and loan loss provisions add to the bank's loan loss reserves, so an increase in recoveries directly reduces required LLP.

conditional valuation effect.

Our study is related to the literature on lending cycles which play a key role in driving fluctuations in loan loss provisions over time. Asea and Blomberg (1998) show that credit policies fluctuate systematically over the business cycle with lax lending policies implemented during expansions and tighter policies in recessions. Consistent with this, Bassett et al. (2014) note that the most commonly cited reasons for banks to alter lending standards are changes in the economic outlook and shifts in risk tolerance. We add to this line of research by focusing on the difference in the market's assessment of DLLP during good and bad economic states, as provision expenses should reflect underlying lending activity and loan performance.

Our work is also closely related to the literature on the market recognition of bank accounting discretion. Huizinga and Laeven (2012) offer evidence that accounting discretion was widespread in 2008, and investors placed significant discounts on bank assets whose value was likely to be overstated. Prior evidence also indicates that banks only partially adjust loss reserves in response to newly impaired loans (De Haan and Van Oordt, 2018) with delays in loss recognition creating loss overhangs that result in significant downside tail risk (Bushman and Williams, 2015). Consistent with this, our results show that investors interpret discretionary provisions as negative cash flow news during market downturns when fundamentals and underlying asset quality are expected to be weak. To our knowledge, we are the first to explore the market's assessment of bank loan loss provisions conditional on the business cycle, which appears to be of first order importance in explaining the effect of DLLP on bank stock prices.

Despite increased debate over optimal loss provisioning practices in the aftermath of the 2008 financial crisis, Beatty and Liao (2014) highlight that few studies have recently examined the impact of DLLP on bank stocks across a broad sample of institutions. Instead, researchers have generally focused on the effects within specific subsamples such as banks audited by industry specialists (Kanagaretnam et al., 2009) and the banks most impacted by SFAS 133 which limited reporting discretion related to derivatives hedging (Kilic et al., 2013). One possible explanation for the lack of research across the broader industry is that when failing to condition on the economic environment, we find DLLP's impact on returns is negative and insignificant. Our study helps to fill this gap in the literature while providing an explanation for the strong conditional valuation effect. With new accounting standards potentially affording bank management even greater leeway to set loss reserves based on estimates and judgmental factors, understanding the use of bank reporting discretion will be of critical importance to both regulators and financial statement users.

The rest of this paper is organized as follows. Section 2 reviews the existing literature on the stock market assessment of DLLP and credit cycles and subsequently outlines our main hypotheses. Section 3 describes the data and provides summary statistics. Section 4 outlines our methodology. Section 5 presents our main empirical results and discusses our findings. Section 6 offers a series of robustness tests, and Section 7 concludes.

2. Hypothesis Development

2.1. Background

Bank loan loss provisions carry significant valuation implications due to the large degree of information asymmetry between bank management and market participants as well as their direct impact on bank financial statements. The *traditional view* predicts DLLP will be negatively related to bank stock returns and valuations, because investors do not directly observe the performance of bank loan portfolios. Positive DLLP informs market participants that expected loan defaults are higher than anticipated based on portfolio characteristics and should thus be associated with a negative stock price response and lower valuations, all else equal. Beaver et al. (1989) provide initial empirical evidence on this topic, however, and document a surprising positive relation between a bank's allowance for loan losses, which reflects total accumulated loss reserves, and its market-to-book ratio. They argue that an increase in the allowance for loan losses may be seen as positive news, because it conveys the bank is able to absorb the "hit to earnings" associated with recording additional provision expenses (see also, e.g., Elliott et al., 1991; Wahlen, 1994). Liu et al. (1997) suggest these positive valuation implications only hold for low regulatory capital banks in the fourth fiscal quarter. Loan loss provisions may reflect management's commitment to resolving problem loans in these instances, yet it is also possible the positive effect is driven by provisions alleviating capital constraints in the pre-BASEL period when loan loss reserves were included as part of regulatory capital (Ahmed et al., 1999; Beatty and Liao, 2014).[3]

Subsequent studies have exploited differences across subsamples of banks to gain further insights into DLLP's valuation effect. For instance, Kanagaretnam et al. (2009) find discretionary loan loss provisions are associated with significantly higher stock returns among banks using an industry specialist auditor with their provisions expected to be more informative. Likewise, both Kilic et al. (2013) and Hamadi et al. (2016) find the market valuation of DLLP is greater for banks with less incentive to use DLLP for earnings smoothing which impairs its informativeness regarding future loan performance. Our study builds on this line of work by providing insight into the information content underlying the positive DLLP-return relation while exploiting a longer sample period that allows us to highlight how this information depends on economic conditions.

2.2. *Impact of Credit Cycles*

A related body of work within the finance literature explores credit cycles – the notion that banks and other institutions ease lending standards in boom periods when expected defaults are low while tightening underwriting in downturns when expected defaults are high. Using a large sample of commercial and industrial loans, Asea and Blomberg (1998) find that banks provide credit to borrowers on more lenient terms during expansions, whereas they charge higher risk premia and increase collateral requirements during recessions. In related work, Dell'Ariccia et al. (2012) provide evidence that mortgage denial rates were lower in high credit growth areas, and lenders placed less weight on applicants' loan-to-income ratios. Applying a unique credit supply indicator derived from the Federal Reserve's Loan Officer Opinion Survey, Bassett et al. (2014) find macroeconomic factors and shifts in risk tolerance are among the most commonly cited reasons for tightened lending standards. Further, Ruckes (2004) and Thakor (2016) present theoretical models

[3] Prior to 1989 regulatory changes, the allowance for loan losses account was included in a bank's primary capital; however, afterwards it is excluded from bank Tier 1 capital and only included as part of Tier 2 capital up to 1.25% of risk-weighted assets.

adding support to the notion that risk assessment in the banking industry contributes to lax lending policies in expansions and tight policies in recessions. Our study focuses on the related impact of bank loan loss provisioning and its valuation effects, as the information content of DLLP should vary with underwriting standards and default expectations.

A primary criticism of the incurred loss model is banks were only required to establish reserves for probable losses that could be reasonably estimated, thereby often resulting in insufficient reserves following long periods of economic stability. Despite no requirement to incorporate forward-looking information, however, banks were still encouraged by regulators to build reserves that reflect changes in risk-taking through the use of reporting discretion. Former Comptroller of the Currency, John Dugan stated on March 2, 2009 to the Institute of International Bankers that "bankers could use their judgment that takes into account other, forward-leaning factors, such as changes in underwriting standards and changes in the economic environment." Although some banks felt limited by the degree of discretion permitted, most sophisticated institutions found ways to justify loss provisions higher than suggested by their historical experiences (Dugan, 2009).

Several studies highlight benefits to recording timely provisions during expansions rather than waiting until substantial losses begin to materialize during downturns. In particular, banks that build reserves to protect against increased credit risk benefit from less lending procyclicality (Beatty and Liao, 2011; Bhat et al., 2019) and reduced crash risk (Cohen et al., 2014; Bushman and Williams, 2015; Andreou et al., 2017). Consistent with this, Laeven and Majnoni (2003) state that "a prudent bank should show a positive association between the amount of loan loss provisions and the growth rate of its loan portfolio." Bushman and Williams (2012) further highlight that forward-looking provisioning is associated with enhanced risk-taking discipline, and establishing sufficient reserves during good times prevents banks from facing capital constraints in bad economic states when raising capital is particularly costly.

Given the cyclical variation in risk assessment and lending standards, we expect to find a strong conditional stock market response to discretionary loan loss provisions. In particular, banks that relax underwriting standards during good economic states to facilitate loan growth tend to record higher DLLP to protect against potential defaults. In turn, investors expect higher profits on average due to increased loan interest income, and the banks are better protected against future capital adequacy concerns than similar banks with low reserves (Beatty and Liao, 2011; Bushman and Williams, 2015). This leads to a positive association between DLLP and bank stock returns. In contrast, banks reduce overall lending during recessions and only provide credit to the lowest credit risk borrowers. Consequently, higher DLLP in bad economic states predominantly reflects the impaired credit quality of existing loans and higher expected default rates. This leads to a negative expected DLLP-return relation, as higher provision expenses indicate to market participants which banks have been most adversely impacted by the downturn. Our main hypothesis is summarized as follows:

Hypothesis 1: Conditional Valuation Hypothesis (CVH). Banks with higher discretionary loan loss provisions (DLLP) will experience lower abnormal returns during economic downturns, but the relation between DLLP and abnormal returns will be more positive in good economic states.

Our view that DLLP's information is conditional on economic conditions due to the cyclical variation in lending standards is consistent with bank executives' statements in 2016 that while the economy remained strong overall, banks were bolstering loan loss reserves while ”lowering credit-score requirements and taking on riskier customers.”[4] As a result, increases in loan loss reserves informed market participants of bank efforts to increase loan volume. In general, high DLLP banks benefit from increased loan interest income and overall earnings while ensuring they are equipped to deal with a future economic downturn. This leads us to our second hypothesis:

Hypothesis 2: Conditional Predictive Power of DLLP. Banks with higher discretionary loan loss provisions during good economic times will experience higher loan growth and future earnings.

[4] http://www.wsj.com/articles/banks-bet-on-consumers-is-getting-riskier-1469221959

Wahlen (1994) suggests that, "because accounting for loan loss provisions requires management judgment, investors are likely to interpret unexpected provisions as the sum of management's expectations of future loan losses plus a discretionary component." Our hypotheses reflect a similar view and predict that the discretionary (unexpected) portion of loan loss provisions conveys to the market bank managements' efforts to accelerate loan growth, enhance profits, and build prudential loan loss reserves during economic booms, whereas discretionary loan loss provisions reflect a deterioration in loan quality when the economy is weak.[5] Consequently, investors view DLLP as negative cash flow news during bad economic states but positive cash flow news when the economy is strong, with higher expected future loan growth and earnings underlying the positive link between DLLP and stock returns in good economic times.

3. Data and Summary Statistics

3.1. Data Description

We obtain bank holding company data from the Bank Regulatory database, which maintains data collected from the FR Y-9C consolidated financial statements of bank holding companies. Our sample includes all bank holding companies that have non-missing annual data on LLP expenses, the control variables necessary to predict the expected level of LLP, and available stock return data. The CRSP-FRB Link provided by the Federal Reserve Bank of New York website is used to match the bank identifier, rssdid, from the Bank Regulatory database with the corresponding permco in CRSP.[6] Our sample period spans from 1997 to 2013 which captures both the expansionary period leading up to the dot-com bubble when economic concerns were limited as well as the 2001 and 2007–2009 recessions. The data in the Bank Regulatory database is incomplete before the year 2000, so we merge in non-performing loan data from the Federal Reserve Bank of Chicago for

[5] A potential concern is the conditional valuation implications could incentivize all banks to record higher DLLP in good times and lower DLLP in bad times. This is unlikely, however, because recording higher DLLP reduces both current earnings and Tier 1 capital and can potentially contribute to higher external financing costs, insurance premiums, and supervisory risk ratings. In contrast, under-reporting loan loss provisions overstates bank health and increases valuation during bad times resulting in the need for heightened regulatory scrutiny during financial downturns.

[6] Linking table available at: https://www.newyorkfed.org/research/banking_research/datasets.html.

financial statements filed between 1996 (to account for lagged predictors) and 1999 by matching year and rssdid.[7] Last, we drop all observations with missing return data as well as observations where the listed institution type is not a BHC. This results in our final sample of 734 unique BHCs and 5,675 bank-year observations.

To construct the explanatory variables used to estimate discretionary and non-discretionary LLP, we scale all accounting variables by prior year-end total loans which limits skewness and accounts for differences in bank loan portfolio size. We also lag accounting data from bank regulatory filings by four months to ensure all information is publicly available. Risk-adjusted stock returns are then computed over the corresponding twelve months. To compute risk-adjusted returns we first regress each bank's excess stock returns from the 24 months prior to the year that DLLP is measured on the contemporaneous risk factors from the Fama-French (1993) 3-factor model.[8] Similar to Borgers et al. (2015), we require each bank to have at least 20 monthly returns to estimate the factor loadings; otherwise, the risk-adjusted return is set to missing. Next, using the estimated factor loadings (betas), we compute each bank's expected holding period return for the subsequent 12-month period in which DLLP is measured. The risk-adjusted return is then computed as the difference between the actual bank stock return and the estimated expected return over the same 12-month period. The use of risk-adjusted returns ensures that differences in measured performance are not driven by differences in systematic risk. In further tests, we examine whether the cash flow news conveyed by DLLP has an effect on bank valuation using a common scaled price measure, Tobin's Q, as the dependent variable. Tobin's Q measures the relation between the market value and replacement value of assets which we compute as the sum of the market value of equity and book value of liabilities scaled by the book value of assets.

We examine the market's conditional assessment of DLLP by generating several indicator variables that reflect the strength of the overall economy. We define our primary measure, *HighGDP*,

[7] We merge in data for line items bhck5525 and bhck5526 used to compute non-performing loans which are obtained from Schedule HC-N. Data is available at the following website: https://www.chicagofed.org/applications/bhc/bhc-home.

[8] We obtain monthly data on the risk-free rate and asset pricing factors from Ken French's website.

as an indicator equal to one if the real GDP growth rate was above its time series median and zero otherwise. The growth rate of real GDP provides an indication of overall economic activity and is a primary variable used in Bassett et al. (2014) to capture the state of the economy. Following Wang et al. (2010), we define our second proxy using the industry median Tobin's Q. Investors assign higher valuations when they expect strong economic growth; thus, we set the variable *HighQ* equal to one when the median bank Tobin's Q is above its time series median and zero otherwise. Our third proxy is a business cycle indicator variable, *BOOM*, which we set equal to one if the economy was determined to be in expansion at the end of the holding period according to the National Bureau of Economic Research (NBER) and zero for recessions. Our final proxy of economic conditions, *SENT*, is based on the University of Michigan's Index of Consumer Sentiment which is derived from economic survey responses from a representative sample of U.S. households regarding current and future economic conditions.[9] We record the index value at the end of each holding period and set the variable *SENT* equal to one in years when the index is above its time series median and zero otherwise. Figure 1 displays the time series of the index since its inception in 1978 as well as the official recession periods. The index experiences a distinct decline during each of the recessions, thereby providing assurance that the proxy is closely related to the business cycle while containing unique information.

3.2. Summary Statistics

Table 1 presents summary statistics for the main variables used in our regression analyses with accounting variables reported in Panel A and market variables reported in Panel B. We compute loan loss provisions, *LLP*, as the ratio of provision expenses in year *t* to total loans from year-end *t–1*. The mean (median) bank-year loan loss provision expense in our sample is approximately 0.69% (0.38%) of total loans, and *LLP* has a standard deviation of 1.00% highlighting the presence of substantial variation in loan loss provisions across bank-years. We also report statistics for two adjusted loan loss provision measures used to estimate DLLP. To avoid estimating a mechanical

[9] Data available at https://data.sca.isr.umich.edu/data-archive/mine.php.

relation given the direct impact of charge-offs on bank loan loss reserves, we define our primary measure, *ALLP*, as bank loan loss provisions less net charge-offs scaled by total loans. Additionally, our alternate measure used in robustness tests, *ALLP**, is computed as loan loss provisions plus recoveries scaled by total loans. We multiply all loan loss provision measures by 100 to enhance the readability of coefficients in our regression analyses. While annual provision expenses typically represent a small percentage of the overall loan portfolio, their economic significance is apparent when compared to the ratio of bank earnings before taxes and loan loss provision expenses to total loans, *EBTP*, which has a median value of 2.75%.

The mean (median) bank-year allowance for loan losses (*ALL*) is 1.53% (1.36%) of total loans suggesting the typical bank has sufficient reserves set aside to absorb multiple years of average sized loan losses. Additionally, real estate loans tend to represent the largest component of bank loan portfolios with commercial and industrial loans and consumer loans comprising smaller portions. The mean values for the percentage of real estate (*RE*), commercial and industrial (*CI*), and consumer loans (*CONS*) are 69.93%, 16.84%, and 8.52%, respectively. Consumer loans include loans for automobiles, credit cards, education, and other personal uses, and these are pooled together as they represent a small portion of the typical balance sheet.[10] Panel B reveals that the mean (median) annual risk-adjusted return is 1.53% (0.35%), and Appendix A provides a list of all variable definitions.

4. Methodology

4.1. Estimating Discretionary Loan Loss Provisions (DLLP)

Bank financial reporting guidelines allow for considerable latitude in determining the loan loss provision expense, yet there are many factors that necessitate additional loss reserves per regulation. For instance, a BHC with a large increase in non-performing loans would require a higher provision expense to cover the increased expected losses. We partition loan loss provisions into a

[10] Loans to other banks and depository institutions represent an even smaller percentage of the average portfolio and carry negligible default risk and are therefore not explicitly modeled.

discretionary and non-discretionary component by regressing *ALLP* on a set of predictors generated from bank financial statements that capture differences in expected loan losses. This generates an expected value of *ALLP* based on bank loan portfolio characteristics. Substantial deviations from the expected value may indicate management's inside information regarding expected loan portfolio performance but can also reveal forward-looking information related to management initiatives to increase lending activity.

We make two important modifications to the traditional approach used to estimate expected loan loss provisions. First, we allow the coefficients on each predictor to vary over time in our primary specification by estimating a series of cross-sectional regressions. This ensures our estimates account for time variation in the loss expectations associated with each predictor, such as greater losses on real estate loans during and immediately after the 2008 financial crisis (Laeven and Majnoni, 2003). Second, we use a charge-off-adjusted loan loss provision measure, *ALLP*, as the dependent variable rather than controlling for net charge-offs to avoid estimating a mechanical relation.[11] Our primary equation that we estimate each year is shown below in Equation 1.

$$\begin{aligned} ALLP_{i,t} = {} & \beta_0 + \beta_1 ALL_{i,t-1} + \beta_2 NPL_{i,t-1} + \beta_3 \Delta NPL_{i,t} + \beta_4 RE_{i,t-1} + \beta_5 \Delta RE_{i,t} + \beta_6 CI_{i,t-1} \\ & + \beta_7 \Delta CI_{i,t} + \beta_8 CONS_{i,t-1} + \beta_9 \Delta CONS_{i,t} + \epsilon_{i,t} \end{aligned} \tag{1}$$

We control for the lagged value of the allowance for loan losses (*ALL*) account and expect its coefficient to be negative, because a larger *ALL* implies the bank has more loss reserves set aside to begin the year resulting in less need to increase reserves further. To capture the greater expected losses associated with delinquent loans, we include both the lagged value of non-performing loans (*NPL*) as well as the change in non-performing loans (ΔNPL). The expected sign on each is positive, but we expect the ΔNPL coefficient to be larger because previously identified non-performing loans may not require additional reserves beyond what was recorded in prior periods. We also control for the lagged values of real estate loans (*RE*), commercial and industrial loans (*CI*), and

[11] We thank an anonymous referee for providing valuable suggestions to address the issue of estimating a mechanical relation. Both components of net charge-offs, gross charge-offs and recoveries, affect the allowance for loan losses, so our adjustment effectively undoes their direct impact by subtracting net charge-offs from both sides of the equation.

consumer loans (*CONS*) as well as the growth within each loan segment to capture differences in average default risk and changes in portfolio composition. All other unmodeled factors affecting loan loss provisions including changes in underwriting standards and managers' private information of expected losses are captured in the regression residual. Our model decomposes *ALLP* into two components as shown below in Equations 2 and 3 where the non-discretionary component of loan loss provisions (*NDLLP*) is the predicted value from equation 1, and the discretionary component (*DLLP*) is the difference between actual and predicted loan loss provisions.

$$NDLLP = \widehat{ALLP} \tag{2}$$

$$DLLP = ALLP - \widehat{ALLP} \tag{3}$$

While many variables are directly related to loan portfolio risk and thus used throughout the majority of studies to estimate expected loan loss provisions, Beatty and Liao (2014) highlight that no consensus exists in the banking literature on how to best model discretionary provisions. Consequently, we enhance the reliability of our results by considering a variety of specifications while offering a discussion of any sensitivity to alternate assumptions. Our second specification includes the same set of controls as displayed in Equation 1, but we use a panel regression approach with year fixed effects to control for the aggregate impact of economic conditions, changes in the regulatory environment, and unobservable time-specific factors.[12] This is similar to the approach used in many prior studies within the literature (e.g., Kanagaretnam et al., 2009, 2010; DeBoskey and Jiang, 2012; Kilic et al., 2013; Hamadi et al., 2016). Our third specification adds controls for Tier 1 capital, earnings (*EBTP*), market beta, and squared loan growth terms for each loan type. We estimate *Beta* using a rolling 2-year window to test for differences in provisioning behavior related to systematic risk while squared loan growth terms test for non-linear effects associated with extreme growth rates. In our fourth specification, we include interactions of non-performing loans and the change in non-performing loans with the real GDP growth rate (*GDPR*) to examine

[12]The inclusion of year fixed effects precludes the simultaneous inclusion of our proxies for economic conditions as control variables, as this would result in multicollinearity issues.

whether their effects differ in good versus bad economic states. We also include bank fixed effects to control for any time-invariant unobservable differences in bank-specific loan portfolio risk. As a result, our fourth *DLLP* estimate only reflects within-bank variation in discretion across years while removing any difference in average discretion across banks. Our fifth specification controls for economic conditions by directly including GDP growth (*GDPR*) instead of year fixed effects, and last, we consider a dynamic panel model that accounts for the potential dependence of *ALLP* on its prior values.

4.2. Testing the Conditional Market Response to DLLP

Our conditional valuation hypothesis predicts that the previously documented positive association between *DLLP* and bank stock returns will only hold in good economic states when managers implement policies designed to increase loan volume. In contrast, *DLLP* recorded in bad economic states is expected to primarily reflect management's private information regarding existing loan impairment. To test our hypothesis, we estimate the following regression:

$$\begin{aligned} EXRET_{i,t} = {} & \beta_0 + \beta_1 DLLP_{i,t} + \beta_2 DLLP_{i,t} * HighGDP_t + \beta_3 NDLLP_{i,t} \\ & + \beta_4 NDLLP_{i,t} * HighGDP_t + \beta_5 LoanGr_{i,t} + \beta_6 LoanGr_{i,t} * HighGDP_t \\ & + \beta_7 EBTP_{i,t} + \beta_8 Tier1_{i,t-1} + \beta_9 Log(Size)_{i,t-1} + \beta_{10} Log(BTM)_{i,t-1} + Time_t + \epsilon_{i,t}. \end{aligned} \tag{4}$$

where *EXRET* is the risk-adjusted return of bank i in year t, and the regressors include *DLLP*, *NDLLP*, interactions of each loan loss provision component with *HighGDP*, and controls for known determinants of stock returns. Our primary coefficients of interest are β_1 and β_2. A negative value for β_1 supports our hypothesis that discretionary loan loss provisions are associated with negative abnormal returns when economic growth is weak and default concerns are elevated, and a positive value for β_2 is consistent with a conditional valuation effect in which negative information concerning expected loan defaults is counteracted by positive information related to expected future loan growth and cash flows during good economic states. We also examine the sum of β_1 and β_2 which indicates the marginal effect of *DLLP* on *EXRET* during good states. We repeat this analysis for each of our four proxies of economic conditions and expect to find consistent results.[13]

The non-discretionary component of loan loss provisions, *NDLLP*, is expected to have a negative association with bank stock returns, as it represents higher expected losses directly related to observable loan portfolio characteristics. It is unclear whether the magnitude of the *NDLLP* coefficient should differ in periods of strong versus weak economic growth, but we empirically test this possibility by including its interaction with *HighGDP*. Foos et al. (2010) and Fahlenbrach et al. (2018) document strong relations between loan growth, loan loss provisioning, and bank performance, so we also include each bank's loan growth rate (*LoanGr*) and its interaction with *HighGDP* to ensure the measured return effect of *DLLP* is independent from the direct impact of recent loan growth.[14] Lastly, we include year fixed effects in all specifications to account for time-specific factors that influence the market performance of the banking sector.[15]

In further analyses, we examine whether the information provided by *DLLP* is conditionally associated with bank valuations using each bank's Tobin's Q measured at the start of the following holding period as the dependent variable. This tests whether the cash flow news effect reflected in bank stock returns has a discernible effect on bank valuations. Higher values of Tobin's Q indicate that a bank is priced more aggressively with values above one indicating that the bank's current market value exceeds the historical cost recorded in its financial statements. As before, the coefficients of interest are those for *DLLP* and the *DLLP-HighGDP* interaction term, and we expect high DLLP banks to take higher values of Tobin's Q when the economy is strong.

4.3. Estimating the Conditional Relation Between DLLP and Future Performance

We estimate the relation between *DLLP* and future bank performance to evaluate Hypothesis 2. The performance measures we consider include earnings (*EBTP*), net interest income (*NII*), loan

[13]Consistent with the existing literature, our setup utilizes contemporaneous regressions to explore how the market interprets and responds to the value-relevant information provided by *DLLP*. While it is possible to explore predictive regressions to test whether *DLLP* forecasts future returns, our approach addresses the more interesting and counterintuitive result in the literature that higher current period *DLLP* is associated with higher stock returns.

[14]We thank an anonymous referee for making this suggestion.

[15]Once again, we do not include the *HighGDP* variable in the same specification, as it cannot be estimated due to perfect collinearity with year controls.

growth (*LoanGr*), and changes in non-performing loans (ΔNPL). The high persistence of such performance measures renders fixed effects models inappropriate, as their inability to capture the dynamic nature of performance creates omitted-variable concerns; however, the simultaneous inclusion of both lagged dependent variables and fixed effects leads to biased ordinary least squares (OLS) estimates (Nickell, 1981). As a result, we utilize dynamic panel techniques that overcome the shortcomings of OLS estimation while allowing performance outcomes to be directly related to their prior realizations (see Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). Difference GMM utilizes first-differences to remove the effects of time-invariant unobservable heterogeneity and instruments to remove the remaining correlation between the differenced lagged dependent variable and the disturbance process.[16] The procedure uses lagged values of the explanatory variables as instruments, because deeper lags of performance are correlated with the recent performance lags included as explanatory variables as well as their differences but uncorrelated with the current value of performance and the composite error process. Arellano and Bover (1995) and Blundell and Bond (1998) suggest this GMM estimator can be further improved by including the equations in both levels and first-differences, so we estimate the following system of equations,

$$\begin{bmatrix} Perf_{it} \\ \Delta Perf_{it} \end{bmatrix} = \alpha + \lambda \begin{bmatrix} Perf_{it-p} \\ \Delta Perf_{it-p} \end{bmatrix} + \beta \begin{bmatrix} DLLP_{it-1} \\ \Delta DLLP_{it-1} \end{bmatrix} + \gamma \begin{bmatrix} Z_{it-1} \\ \Delta Z_{it-1} \end{bmatrix} + \epsilon_{it} \tag{5}$$

where the dependent variable, *Perf*, is one of our four performance measures, and its first p lags are included as explanatory variables to capture performance dynamics. Our key test variable is *DLLP*, and we include its interaction with *HighGDP* to test for a conditional relation between discretionary loan loss provisions and future bank performance. We also control for bank characteristics, denoted by Z, which include non-discretionary loan loss provisions (*NDLLP*), the interaction of *NDLLP* with *HighGDP*, loan growth, the interaction of loan growth with *HighGDP*,

[16]Specifically, the remaining correlation occurs because the differenced lagged dependent variable for performance, $\Delta y_{i,t-1}$, contains $y_{i,t-1}$, and the differenced error term, $\Delta\epsilon_{i,t}$, contains $\epsilon_{i,t-1}$.

non-performing loans, the change in non-performing loans, the ratio of total loans to assets, log bank size, and bank Tier 1 capital. The procedure uses lagged levels as instruments for the first differenced equations and lagged differences as instruments for the levels equations. Our instrument sets include the first lag of all predictor variables (i.e. *t-2* values) plus an additional lag of the performance variable, non-performing loans, the ratio of loans to assets, and bank size to allow for over-identification tests. All specifications also include year indicator variables, which are the only predictors treated as exogenous.

4.4. Effect of the Financial Crisis on DLLP Valuation

Lending standards tightened significantly and bank loan portfolios were highly distressed during the 2008 financial crisis. Consequently, our hypotheses predict that the relation between *DLLP* and bank stock returns should be stronger during the crisis than in less severe downturns. We evaluate this using a dummy variable, *CRISIS*, equal to one during the holding period ending in the year 2008 and zero otherwise, and we add an additional interaction term between the crisis indicator and *DLLP* with the regression equation displayed below.

$$\begin{aligned} EXRET_{i,t} = {} & \beta_0 + \beta_1 DLLP_{i,t} + \beta_2 DLLP_t * HighGDP_{i,t} + \beta_3 DLLP_t * CRISIS_{i,t} \\ & + \beta_4 NDLLP_{i,t} + \beta_5 NDLLP_t * HighGDP_{i,t} + \beta_6 NDLLP_t * CRISIS_{i,t} \\ & + \beta_7 LoanGr_{i,t} + \beta_8 LoanGr_t * HighGDP_{i,t} + \beta_9 EBTP_{i,t} + \beta_{10} Tier1_{i,t-1} \\ & + \beta_{11} Log(Size)_{i,t-1} + \beta_{12} Log(BTM)_{i,t-1} + Time_t + \epsilon_{i,t} \end{aligned} \tag{6}$$

We expect to find a negative value for β_1 and positive value for β_2 as before; however, this specification tests whether there is a differential impact on the *DLLP*-return relation when the economy is experiencing a severe recession compared to periods of relative weakness. We expect a negative value for β_3, which indicates a more extreme negative investor reaction to *DLLP* during the financial crisis when loan performance issues and default concerns are expected to be the primary driving force behind managers' decisions to record extra loan loss provisions.

5. Results

5.1. Discretionary Loan Loss Provisions (DLLP) Estimation

Table 2 presents the estimation results from our expected loan loss provision models. The reported coefficients from our primary model in specification 1 reflect the averages of the cross-sectional estimates, and the *t*-statistics are based on Fama and MacBeth (1973) standard errors computed from the time series standard deviations of the cross-sectional estimates. All coefficients enter with the expected signs with only the allowance for loan losses (*ALL*) exhibiting a significant negative relation with loan loss provisions. Additionally, only lagged non-performing loans and the loan growth variables are not statistically significant.

Our second specification which uses the same set of predictors with time fixed effects yields similar signs and significance levels for most variables although lagged non-performing loans (*NPL*), the change in real estate loans (ΔRE), and the change in commercial and industrial loans (ΔCI) become significant at the five percent level. Additionally, the change in consumer loans ($\Delta CONS$) enters with a negative coefficient but is not statistically significant. Specifications 3 through 5 aim to further ensure the reliability of our results by examining the influence of additional predictors. We find the bank Tier 1 capital ratio, squared change in non-performing loans, squared change in consumer loans, and interaction of GDP growth with the change in non-performing loans are significant at the five percent level or better in one or more specifications.[17] Our final specification addresses potential dynamic relations in loan loss provisioning, as we add the first two lags of *ALLP* as regressors, use system GMM, and find the coefficient on the first lag of *ALLP* is positive and statistically significant. Although several control variables in our alternate specifications are significant, their inclusion generally has limited impact on the predicted values of *DLLP*, and in unreported results we find the correlation between our primary *DLLP* measure and the five alternate measures ranges from 0.76 to 0.90. This suggests the performance and valuation

[17] Our R^2 values are not directly comparable to those reported in prior studies, since our dependent variable (*ALLP*) is adjusted by net charge-offs. Differences in net loan charge-offs contribute to the overall variation in loan loss provisions; however, the relation occurs partly by construction.

results are unlikely to vary substantially across specifications; however, our subsequent analyses evaluate this possibility. Hereafter, we refer to the regression residuals of each specification as an estimate of *DLLP*, since the residuals represent the portion of loan loss provision expenses unexplained by economic, loan portfolio, and bank-specific characteristics, and the fitted values from our regressions are referred to as *NDLLP*. We winsorize the *DLLP* estimates at the 2.5$^{\text{th}}$ and 97.5$^{\text{th}}$ percentiles to mitigate the effect of outliers.[18]

5.2. The Relation Between DLLP, Stock Returns, and Bank Valuation

Table 3 reports the estimation results from Equation 4, which tests for a conditional relation between *DLLP* and abnormal bank stock returns with the results presented for each of our six *DLLP* estimates. We find strong and consistent support for the conditional valuation hypothesis, as *DLLP* enters with a significantly negative coefficient and the *DLLP-HighGDP* interaction enters with a significantly positive coefficient in all specifications. This provides strong support for the conditional valuation hypothesis. Additionally, the marginal impact on returns during good economic states, as indicated by the sum of the β_1 and β_2 coefficients, is positive and significant at the one percent level in all six specifications with a p-value that is zero to three decimal places. We also report tests that evaluate the difference between the *DLLP* and *NDLLP* coefficients in both good and bad economic states. We find *DLLP* has a more positive impact on returns than *NDLLP* in good economic states where the difference is positive in all specifications and significant at the ten percent level of better in all five specifications that capture variation in discretion both within and across banks. All specifications include year fixed effects to control for time-specific factors, and we double-cluster standard errors by bank and year to address the possibility that regression residuals may be correlated across time for the same bank holding company or across banks within the same year. This is expected to yield relatively conservative standard error estimates throughout our analyses.

[18]We find similar results when winsorizing at the 1$^{\text{st}}$ and 99$^{\text{th}}$ or 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles.

DeBoskey and Jiang (2012) and Kanagaretnam et al. (2010) provide evidence that bank auditors have greater ability to constrain negative, income-increasing *DLLP* than positive, income-decreasing *DLLP*. Using our primary *DLLP* measure we separately evaluate the relations of positive and negative *DLLP* with excess bank stock returns in Appendix B. We find consistent coefficient signs in both instances, and the observed conditional return relation is stronger for positive *DLLP* consistent with prior evidence of banks having greater leeway to over-reserve than under-reserve. Although the negative coefficient on $DLLP^{-}$ is not statistically significant, in both instances the *DLLP-HighGDP* interaction term and the marginal *DLLP* impact during good economic states is positive and significant. Given the qualitatively similar patterns, our remaining analyses focus on the overall *DLLP* measure which takes both positive and negative values.

Table 4 displays the results for tests of the conditional relation between our primary *DLLP* measure and risk-adjusted returns using alternate proxies of economic conditions based on the banking industry Tobin's Q, official business cycle dates, and consumer sentiment index. For all three proxies we obtain consistent results, as *DLLP* again enters with a significantly negative coefficient while the *DLLP* interaction term enters with a significantly positive coefficient.[19] Additionally, the marginal impact of *DLLP* during good states of the economy is positive and significant when using the industry Tobin's Q and consumer sentiment proxies but close to zero and statistically insignificant when using the business cycle indicator variable, *BOOM*. This latter result reflects the fact that official recessions are infrequent and most time periods are classified as expansions even when the strength of the economy is below average. Consistent with the business cycle proxy only isolating periods of extreme economic distress, the coefficient on *DLLP* is more negative when only recessions are defined as bad economic states.

In Table 5, we examine whether the cash flow news provided by *DLLP* is associated with higher bank valuations, all else equal. We use each bank's Tobin's Q at the start of the subsequent holding period to capture the relative pricing of bank assets. Overall, the valuation tests yield con-

[19] In Appendix C, we repeat the analysis using continuous measures of GDP growth, industry Tobin's Q, and the Consumer Sentiment Index. Overall, we find qualitatively similar results.

sistent results with those reported for risk-adjusted returns, as *DLLP* enters with a coefficient that is negative and insignificant, whereas the *DLLP-HighGDP* interaction is positive and significant at the five percent level or better in all specifications. Additionally, the estimated marginal impact of *DLLP* on valuations during good economic states is positive and significant at the one percent level in all specifications. Altogether these results provide strong support for the conditional valuation hypothesis.

5.3. DLLP and Future Bank Performance

Table 6 presents our dynamic panel estimation results that evaluate the relation between *DLLP* and future bank performance as reflected by earnings (*EBTP*), net interest income (*NII*), loan growth (*LoanGr*), and changes in non-performing loans (Δ*NPL*). Similar to prior studies, we find two lags are sufficient to capture the persistence of profitability (see, e.g., Glen et al., 2001) as well as that of our other performance measures. Consistent with Hypothesis 2, we find that in good economic states *DLLP* is associated with higher earnings in the following year. The *DLLP-HighGDP* interaction coefficient is positive and significant in predicting overall earnings as well as net interest income, which reflects the core component of earnings directly related to bank lending. We also find a positive and significant relation between *DLLP* and future loan growth during good economic times that appears to drive the increase in net interest income and overall earnings. In contrast, *DLLP* is associated with lower future earnings and significant subsequent increases in non-performing loans when the economy is weak. Thus, during bad economic states *DLLP* is indicative of future loan portfolio deterioration beyond what is already reflected in bank financial statements.

Our results also indicate that all System GMM specification tests are satisfied. As expected, the AR(1) tests reject the null of no first-order autocorrelation in the first-differenced residuals that occurs as a result of differencing, but we cannot reject the null of zero second-order autocorrelation with the AR(2) test *p*-values ranging from 0.11 to 0.69. Further, the Hansen test of over-identifying restrictions reveals that we cannot reject that our instruments are valid, and the difference-in-Hansen test indicates that we cannot reject that the instruments included in our levels equations are exogenous. Altogether, these results provide strong support for our second hypothesis regarding the conditional predictive power of *DLLP*.

5.4. Impact of the Financial Crisis

Table 7 presents tests of the association between *DLLP* and excess bank stock returns during the 2008 financial crisis. Consistent with prior results, *DLLP* enters with a negative coefficient that is significant at the one percent level for both specifications implying that our results are not driven by the financial crisis. Thus, *DLLP* is not associated with higher returns even during times of relative economic weakness in contrast to findings in prior studies that focus on shorter and earlier time periods. As predicted by the CVH, the *DLLP-HighGDP* interaction term is positive and significant at the one percent level in both specifications. The marginal impact of *DLLP* on returns in good states of the economy is also positive and significant at the one percent level. Consistent with our hypothesis that *DLLP* primarily conveys loan default information when the economy is weak and lending standards are tight, we find evidence of a significant incremental effect of *DLLP* recorded during the financial crisis beyond the negative return impact during periods of relative economic weakness. The *DLLP-CRISIS* interaction coefficient is negative and significant at the one percent level in both specifications resulting in a pronounced negative marginal effect ($\beta_1 + \beta_3$). Overall, the results support our hypotheses and reflect that growing loan portfolio quality issues are expected to drive managerial decisions to record higher *DLLP* during times of crisis.

6. Robustness

6.1. Assessing different treatments of charge-offs

In their overview of the empirical literature on financial accounting in the banking industry, Beatty and Liao (2014) highlight the lack of a consensus for how to best model discretionary loan loss provisions. In particular, they note that some studies control for charge-offs, because charge-offs directly affect the allowance for loan losses; however, they also highlight the very high correlation between charge-offs and provision expenses as a primary reason why other studies do not include charge-offs, as doing so may explain away too much of the variation of provisions.

Our primary approach for estimating *DLLP* adjusts reported loan loss provisions by net charge-offs in order to account for the relation between *LLP* and *NCO* without estimating a mechanical relation. Given that *ALLP* is constructed as the difference of the two variables, a potential concern is that it may tend to take larger (smaller) values for banks with lower (higher) net charge-offs. To ensure this does not drive our results, Appendix D includes *NCO* as well as its interaction with the *HighGDP* indicator in our second-stage return regression to control for the possibility that differences in net charge-offs explain the observed return relation. We also include all controls from our main specification in Table 3. Consistent with our earlier analyses, the coefficient on *DLLP* is negative and significant while the *DLLP-HighGDP* interaction is positive and significant in all specifications. Additionally, the estimated marginal impact of *DLLP* on returns during good economic states is positive and significant at the five percent level or better in all specifications.[20]

Next, we explore several alternate *DLLP* estimation procedures with different treatments of loan charge-offs. First, in Appendix E, Panel A, we re-estimate the same set of models as in Table 2; however, we only undo the effect of bank recoveries by defining the dependent variable, *ALLP**, as loan loss provisions plus recoveries, and we include gross charge-offs (*GCO*) in our set of controls. This alternate estimation procedure allows the coefficient on gross charge-offs to be freely estimated consistent with the approach used in several prior studies (Kanagaretnam et al., 2010; Beck and Narayanamoorthy, 2013; Basu et al., 2020).[21] Panel B presents the associated conditional return tests using the alternate *DLLP* estimates (i.e. *ALT1DLLP*) derived from predicting *ALLP**. Overall, we find similar results that add additional support to our CVH, as the *ALT1DLLP* coefficient is negative and significant while the *ALT1DLLP-HighGDP* coefficient is positive and significant. We also find the estimated marginal effect of *ALT1DLLP* on returns during good economic states is positive and significant at the ten percent level or better in all specifications and

[20]The full sample correlation between *ALLP* and *NCO* is 0.024, and the correlation between our primary *DLLP* measure and *NCO* is 0.048. This further suggests that high *DLLP* banks do not benefit from lower charge-offs as the result of our estimation procedure.

[21]The reported coefficients are multiplied by 100 for readability, so a charge-off coefficient of 100 implies a one-to-one relation. We cannot reject that the *GCO* coefficient is 100 in the first three specifications and the value is near 100 for all specifications which provides added support for our primary measure of loan loss provisions. The robustness tests, however, highlight that the CVH results also hold when allowing the coefficient to be freely estimated.

at the five percent level or better in 11 of 12 specifications. Panel C repeats the analysis with our alternate proxies of economic conditions and yields consistent results.

A number of prior studies exclude *NCO* from the estimation of expected loan loss provisions (Liu and Ryan, 2006; Beatty and Liao, 2011; Bushman and Williams, 2012, 2015). Additionally, Beatty and Liao (2020) highlight that the decision to include or exclude *NCO* involves a trade-off between Type 1 and Type 2 errors and that models controlling for *NCO* may understate reporting discretion. As a result, Panel D re-estimates our models using unadjusted *LLP* as the dependent variable with loan charge-offs excluded as an independent variable, and Panel E reports the corresponding valuation tests. We again find that the coefficient on our alternate DLLP measure (*ALT2DLLP*) is negative and significant while the *ALT2DLLP-HighGDP* interaction is positive and significant in all specifications. This provides added support for our conditional valuation hypothesis. Additionally, although the estimated marginal effect of *ALT2DLLP* on returns during high growth periods is not significantly different from zero in columns 1 through 6, the estimates become positive and significant across all specifications in columns 7 through 12 when controlling for any direct association between reported charge-offs and bank stock returns. Panel F repeats these analyses with the alternate economic state proxies, and we document consistent results. Altogether, the results provide strong support for the conditional valuation hypothesis and highlight how *DLLP's* information content is highly dependent upon economic conditions.

6.2. Subperiod Analysis

To ensure the results are consistent with our hypotheses across the full sample period, we estimate separate regressions for five different subperiods using our primary *DLLP* estimate. The results presented in Table 8 add support to the CVH despite reduced statistical power from the limited number of observations per regression. The estimated relation between *DLLP* and *EXRET* is positive during the late 1990s and mid 2000s – the two subperiods with the strongest economic growth – but negative during the early 2000s, the financial crisis, and in the period following the financial crisis. Most prior studies evaluating the valuation of *DLLP* explore periods prior to 2006, and our results are in agreement with a generally positive market response during this period of relatively strong economic conditions. Overall, our subperiod results highlight that the value-relevant information embedded in *DLLP* is highly dependent upon the state of the economy.

6.3. Major Events of the Financial Crisis

Next, we exploit two plausibly exogenous events during the 2008 financial crisis to further evaluate *DLLP*'s valuation implications. We first sort banks into quintile portfolios based on their value of *DLLP*, and we define the portfolios *DLLPQ5* and *DLLPQ1* as banks in the top and bottom quintiles, respectively. We then evaluate how the returns of each portfolio responded to major events that impacted the market's expectations of loan losses and consumer confidence in the banking sector. Table 9 displays the results with cumulative event-window returns computed from one trading day before the event until one day after the event.

Panel A presents returns around the seizure of IndyMac Bank by federal regulators on July 11, 2008, which was triggered by a substantial increase in mortgage defaults and represents one of the largest bank failures in U.S. history. During the event-window, high *DLLP* banks returned -4.41% relative to the S&P 500 compared to -1.48% for low *DLLP* banks with the difference significant at the five percent level. This result is consistent with investor fears over loans defaults driving a more negative *DLLP* response when the economy is struggling.[22] In contrast, Panel B explores returns around the enactment of the Housing and Economic Recovery Act, which was designed to provide support for subprime borrowers and bring stability to the secondary mortgage market during the financial crisis. We find the stock prices of high *DLLP* banks returned 2.72% relative to the S&P 500 during this event-window compared to -1.26% for low *DLLP* banks. This suggests the market anticipated a greater program benefit to banks perceived as having more distressed assets and adds further support to the CVH.

[22]In unreported results, we also find similar return patterns around the date Washington Mutual was seized and placed into receivership in September 2008, although significance levels are somewhat lower.

6.4. *Matched Sample Analysis*

To limit endogeneity concerns and ensure differences in *DLLP* drive our results, we conduct a matched sample analysis with the results presented in Table 10. We form our sample by taking each bank in the top quintile of *DLLP* each year and matching it to a highly similar bank not in the top *DLLP* quintile. Matches are identified using nearest neighbor matching based on the computed Mahalanobis distance where the matching characteristics include *NDLLP*, earnings before taxes and provisions, prior loan growth, log size, log book-to-market, and tier 1 capital.

Panel A presents mean characteristic values for high *DLLP* banks as well as all other banks prior to creating a matched sample. The values are presented separately for years when real GDP growth is high (*HighGDP* = 1) and low (*HighGDP* = 0), since we aim to measure *DLLP*'s impact on stock returns separately during these periods. Many significant differences exist between high and low *DLLP* banks in both sub-samples, as indicated by the reported *p*-values from difference-in-means tests. Panel B reports the average characteristic values for the high *DLLP* banks and their corresponding matches which indicates that the matching procedure is effective at minimizing characteristic differences. Banks no longer exhibit a significant difference along any of the matching variables in periods of high or low GDP growth, which allows for a cleaner evaluation of the association between *DLLP* and bank stock returns. Consistent with the CVH predictions, Panel C suggests that during good economic times high *DLLP* banks earn 3.70% higher annual risk-adjusted returns than otherwise similar banks with lower levels of *DLLP*. In contrast, high *DLLP* banks earn 7.48% lower annual risk-adjusted returns than comparable banks during bad economic states. Both estimates are statistically significant and consistent with our hypotheses. In unreported tests, we find the results are robust to the use of alternate matching mechanisms such as propensity score matching.

6.5. *Removal of Banks with Non-positive LLP*

Last, we repeat the main analyses but with all bank-year observations containing non-positive loan loss provisions removed. Such cases are unlikely to have a large impact due to their limited number and generally smaller values for our test variables, but we repeat the analyses with their exclusion to ensure the results hold. Appendix F reveals that the coefficients and significance levels are similar to those reported in our main analyses. Altogether, the results are consistent with *DLLP*'s information content being highly dependent upon the state of the economy.

7. Conclusions

Prior research finds that discretionary loan loss provisions are associated with higher stock returns and valuations but has failed to explain what drives this surprising finding while relying on relatively short sample periods. In contrast, we hypothesize that the value-relevant information conveyed by DLLP is dependent upon the state of the economy, motivated by evidence of substantial variation in lending standards over the business cycle. Our results offer strong support for the conditional valuation hypothesis, as DLLP is associated with significantly lower abnormal returns during periods of economic distress when banks tighten lending standards and use provisions to address rising loan impairment but more positive abnormal returns and bank valuations in good economic states when banks relax underwriting standards to stimulate loan growth.

We first propose a new adjusted-LLP measure to estimate DLLP while overcoming the mechanical relation between loan loss provisions and net charge-offs, and we enhance the reliability of our results by re-estimating DLLP using a variety of specifications and estimation procedures. The conditional return relation holds across all DLLP estimates derived using our adjusted-LLP measure. We also confirm our results are robust to the choice of proxy for economic conditions and when examining a matched sample that compares otherwise similar banks with significant differences in DLLP. In robustness tests, we explore alternate treatments of loan charge-offs when estimating DLLP given differing approaches used in prior studies. Our results provide consistent evidence of a significant negative DLLP-return relation in bad economic states with a significantly more positive relation in good economic states across all estimates.

Next, using dynamic panel models that account for persistence in measures of bank performance, we evaluate whether DLLP is conditionally related to future bank performance outcomes as predicted by our hypotheses. Consistent with bank managers utilizing DLLP to support increased lending activity in good states of the economy, we find DLLP is predictive of significantly higher one-year-ahead earnings, net interest income, and loan growth. Conversely, during bad states of the economy DLLP is negatively related to future earnings but displays a strong positive relation with future changes in non-performing loans. This suggests that in bad economic states DLLP is not only used to cover losses on existing problem loans but also signifies more widespread portfolio weakness and future credit quality issues.

In subsequent analyses, we explore the market's assessment of DLLP during the 2008 financial crisis. Adding further support to our hypotheses, we find the conditional DLLP-return relation holds when isolating the effect of the financial crisis, and we document an incremental negative impact on returns consistent with heightened default concerns driving the negative market response. With banks transitioning to the current expected credit losses (CECL) model, banks should be able to more readily build reserves during good economic states when underwriting standards are less stringent in order to better withstand future downturns. Yet, with an even greater degree of managerial judgment and discretion permitted bank regulators must ensure the informativeness of bank loss reserves is maintained. Our findings suggest particularly strong scrutiny is required during downturns when understating expected loan losses both overstates earnings and capital and avoids significant stock price declines.

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Table 1
Summary statistics.

Panel A: Accounting Data

	Mean	Median	Stdev	P1	P5	P95	P99
LLP	0.6901	0.3823	0.9985	-0.2711	0.0000	2.4968	5.1440
ALLP	0.1128	0.0810	0.4562	-1.2143	-0.4248	0.7280	1.7051
ALLP*	0.8050	0.4835	1.0288	-0.0468	0.0597	2.7214	5.3584
EBTP	0.0432	0.0275	0.2523	-0.0273	0.0043	0.0573	0.1540
Tier1	0.1777	0.1282	0.5993	0.0734	0.0899	0.2332	0.6439
ALL	0.0153	0.0136	0.0073	0.0036	0.0080	0.0286	0.0440
NPL	0.0144	0.0080	0.0186	0.0000	0.0009	0.0507	0.0886
Δ*NPL*	0.0019	0.0004	0.0150	-0.0322	-0.0136	0.0216	0.0513
RE	0.6993	0.7330	0.1828	0.0466	0.3603	0.9343	0.9859
Δ*RE*	0.0882	0.0570	0.1657	-0.1640	-0.0770	0.3447	0.7140
CI	0.1684	0.1456	0.1155	0.0008	0.0306	0.3882	0.5900
Δ*CI*	0.0183	0.0098	0.0532	-0.0898	-0.0367	0.0955	0.2041
CONS	0.0852	0.0488	0.1009	0.0005	0.0034	0.2622	0.4774
Δ*CONS*	0.0044	-0.0003	0.0355	-0.0580	-0.0236	0.0463	0.1222
NCO	0.0058	0.0029	0.0088	-0.0010	0.0000	0.0224	0.0440
GCO	0.0069	0.0039	0.0093	0.0000	0.0003	0.0248	0.0471
RECO	0.0011	0.0007	0.0015	0.0000	0.0001	0.0035	0.0073
NII	0.0618	0.0564	0.0416	0.0315	0.0379	0.0937	0.1479
LoanGr	0.1170	0.0816	0.2130	-0.2203	-0.1044	0.4443	0.9418

Panel B: Market Data

	Mean	Median	Stdev	P1	P5	P95	P99
EXRET	0.0153	0.0035	0.3428	-0.9542	-0.4714	0.5459	0.8990
Log(Size)	12.5468	12.1696	1.8488	9.6447	10.2288	16.4219	18.1528
Log(BTM)	-0.0569	-0.0461	0.0955	-0.2690	-0.1751	0.0391	0.0634

The sample contains 5,675 bank-year observations and 734 unique bank holding companies (BHCs) over the period 1997–2013. This table reports the mean, median, standard deviation, 1st percentile, 5th percentile, 95th percentile, and 99th percentile values for the primary variables used in our regression analyses. Panel A reports statistics for accounting variables, which are scaled by total loans at the end of year *t−1*. *LLP* is the loan loss provision expense multiplied by 100 for readability. *ALLP* and *ALLP** denote loan loss provisions adjusted by net charge-offs and recoveries, respectively. *EBTP* is earnings before taxes and provision for loan loss expense. *Tier1* is the lagged value of bank Tier 1 capital. *ALL* is the lagged value of the allowance for loan losses account. *NPL* is the lagged value of non-performing loans comprised of loans 90 days or more delinquent and any loans that are in nonaccrual status. *RE*, *CI*, and *CONS* are measured as lagged total real estate, commercial and industrial loans, and consumer loans, respectively. Δ*RE*, Δ*CI*, and Δ*CONS* represent first differences between years *t* and *t-1* for real estate, commercial and industrial, and consumer loans, respectively. *NCO* is the amount of net charge-offs computed as gross charge-offs (*GCO*) minus recoveries (*RECO*). *NII* is net interest income, measured as the difference between interest income and interest expense scaled by total loans. *LoanGr* is the annual percentage loan growth. Panel B reports statistics on stock market data. *EXRET* is a BHC's annual stock return less the return predicted by the Fama-French 3-factor model. *Log(Size)* is the log of a bank's market value of equity computed as the price multiplied by the number of shares outstanding. *Log(BTM)* is the log of the book value of assets divided by the market value of assets.

Table 2
Estimation of bank loan loss provisions.

Model:		(1)		(2)		(3)		(4)		(5)		(6)	
Variable	Predicted Sign	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat	Coef.	*t*-stat
$ALL_{i,t-1}$	-	-17.35***	-7.14	-21.07***	-7.36	-20.80***	-7.40	-38.07***	-13.67	-21.23***	-7.36	-34.66***	-11.08
$NPL_{i,t-1}$	+	0.32	0.38	2.54**	2.59	3.26***	3.18	7.06***	3.27	5.80**	2.18	5.11***	3.19
$\Delta NPL_{i,t}$	+	10.90***	6.62	12.25***	8.79	13.93***	9.14	15.35***	13.21	18.31***	14.19	13.35***	8.26
$RE_{i,t-1}$	+	0.27***	5.57	0.30***	3.89	0.25***	3.15	0.39	1.54	0.25***	2.84	0.19	0.70
$CI_{i,t-1}$	+	0.55***	5.85	0.66***	5.98	0.61***	5.54	1.01***	3.98	0.66***	5.12	0.74**	2.01
$CONS_{i,t-1}$	+	0.27***	3.48	0.20*	1.76	0.16	1.34	0.47	1.46	0.23**	2.01	0.17	0.39
$\Delta RE_{i,t}$	+	0.14	1.74	0.17***	3.21	0.09	0.59	-0.08	-0.73	0.07	0.53	0.13	1.49
$\Delta CI_{i,t}$	+	0.09	0.46	0.44**	2.72	0.38*	1.92	0.25	0.95	0.21	0.75	0.23	0.94
$\Delta CONS_{i,t}$	+	0.12	0.39	-0.30	-0.74	0.04	0.11	0.09	0.32	0.08	0.21	-0.20	-0.66
$EBTP_{i,t}$	+					0.25	0.85	0.24	1.70	0.26	0.82		
$Tier1_{i,t-1}$	+					-0.10	-0.96	-0.27**	-2.90	-0.10	-0.93		
$Beta_{i,t-1}$	+					-0.02	-0.88	-0.02	-1.01	-0.02	-0.80		
$\Delta NPL^2_{i,t}$	?					-14.24	-1.36	-26.17**	-2.60	-36.37***	-2.86		
$\Delta RE^2_{i,t}$	?					0.08	0.67	0.17*	1.85	0.11	0.93		
$\Delta CI^2_{i,t}$	?					0.24	0.35	0.48	0.64	0.52	0.75		
$\Delta CONS^2_{i,t}$	?					-1.80**	-2.13	-1.69***	-3.27	-1.89*	-1.92		
$GDPR_t$	-									0.01	0.49		
$GDPR_t * NPL_{i,t-1}$	-							-0.68	-0.80	-1.16	-1.05		
$GDPR_t * \Delta NPL_{i,t}$	-							-1.46***	-5.11	-1.79***	-4.82		
$ALLP_{i,t-1}$	?											0.13***	4.11
$ALLP_{i,t-2}$	?											0.04*	1.70
Cross-Sectional		Yes		No		No		No		No		AR(1): p=0.00	
Year FE		No		Yes		Yes		Yes		No		AR(2): p=0.93	
Bank FE		No		No		No		Yes		No		Hansen overid: p=0.27	
Adjusted R^2				0.428		0.434		0.513		0.423		Diff-in-Hansen: p=0.16	
Average R^2		0.374											

This table presents regressions used to estimate the expected level of loan losses and decompose bank loan loss provisions into a discretionary and non-discretionary component. The dependent variable, *ALLP*, is calculated as loan loss provisions less net charge-offs for bank *i* in year *t*, scaled by total loans at year-end *t-1*. We multiply this ratio by 100 to enhance the readability of coefficients. The first specification estimates cross-sectional regressions for each year and reports the average coefficient estimates with *t*-statistics based on the standard deviation of cross-sectional estimates. Specifications two through four use pooled regressions with either year fixed effects, bank fixed effects, or both to control for unobservable factors. Specification five includes the real GDP growth rate in each year (*GDPR*) and its interaction with several predictors. The final specification includes the first two lags of *ALLP* and is estimated using System GMM. Standard errors for panel regressions are double-clustered by bank and year with the corresponding *t*-statistics reported in the adjacent column. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3
Conditional relation between DLLP and bank stock returns.

	Dependent Variable = $EXRET_{i,t}$					
DLLP Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$DLLP_{i,t}$	-0.108***	-0.130***	-0.124***	-0.102**	-0.109**	-0.130***
	(-3.83)	(-2.92)	(-2.69)	(-2.07)	(-2.29)	(-3.29)
$DLLP_{i,t} * HighGDP_t$	0.213***	0.232***	0.222***	0.175***	0.202***	0.239***
	(5.63)	(4.48)	(4.17)	(3.23)	(3.80)	(4.36)
$NDLLP_{i,t}$	-0.163***	-0.168***	-0.177***	-0.163***	-0.186***	-0.134***
	(-2.58)	(-3.76)	(-3.60)	(-3.49)	(-3.51)	(-2.72)
$NDLLP_{i,t} * HighGDP_t$	0.195***	0.168**	0.180**	0.212***	0.207**	0.114
	(2.67)	(2.11)	(2.23)	(2.83)	(2.51)	(1.64)
$LoanGr_{i,t}$	0.201***	0.212***	0.215***	0.203***	0.218***	0.250***
	(2.75)	(2.86)	(2.89)	(2.87)	(2.87)	(2.64)
$LoanGr_{i,t} * HighGDP_t$	-0.147	-0.151*	-0.155*	-0.158*	-0.165*	-0.249**
	(-1.63)	(-1.70)	(-1.75)	(-1.82)	(-1.84)	(-2.50)
$EBTP_{i,t}$	0.340*	0.344*	0.358*	0.330	0.360*	0.296
	(1.69)	(1.72)	(1.78)	(1.64)	(1.79)	(1.60)
$Tier1_{i,t-1}$	-0.127*	-0.127*	-0.134*	-0.124*	-0.133*	-0.108*
	(-1.81)	(-1.83)	(-1.92)	(-1.81)	(-1.92)	(-1.65)
$Log(Size)_{i,t-1}$	-0.010	-0.010	-0.010	-0.010	-0.010	-0.006
	(-1.07)	(-1.05)	(-1.06)	(-1.15)	(-1.04)	(-0.74)
$Log(BTM)_{i,t-1}$	0.100	0.102	0.105	0.079	0.112	0.175
	(0.75)	(0.76)	(0.78)	(0.59)	(0.84)	(1.24)
F-test: $\beta_1 + \beta_2 = 0$	0.105	0.102	0.098	0.073	0.093	0.108
[p-value]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
F-test: $\beta_1 - \beta_3 = 0$	0.054	0.038	0.053	0.061	0.077	0.004
[p-value]	[0.234]	[0.167]	[0.137]	[0.215]	[0.086]	[0.863]
F-test: $\beta_1 + \beta_2 - (\beta_3 + \beta_4) = 0$	0.072	0.102	0.095	0.024	0.071	0.128
[p-value]	[0.030]	[0.053]	[0.072]	[0.657]	[0.091]	[0.003]

This table presents regressions that examine the stock market response (*EXRET*) to discretionary loan loss provisions (*DLLP*) conditional on the state of the economy. Each specification uses an alternate estimate of *DLLP* corresponding to the Table 2 regressions, and *DLLP* is interacted with an indicator variable, $HighGDP_t$, that is set equal to one in years when real GDP growth was above its time series median and zero otherwise. Year fixed effects are included in all specifications to control for the level of bank stock returns in a given year and other time specific factors. The sample period is 1997 to 2013. Standard errors are double-clustered by bank and year with the corresponding *t*-statistics reported below in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 4
Conditional relation between DLLP and bank stock returns using alternate proxies of economic conditions.

Panel A: Industry Tobin's Q

	$DLLP_t$	$HighQ_t$ x $DLLP_t$	$NDLLP_t$	$HighQ_t$ x $NDLLP_t$	$LoanGr_t$	$HighQ_t$ x $LoanGr_t$	$EBTP_t$	$Tier1_{t-1}$	$Log\ Size_{t-1}$	$Log\ BTM_{t-1}$
Coefficient	-0.114***	0.182***	-0.164**	0.172**	0.225**	-0.162	0.345*	-0.128*	-0.010	0.101
t-statistic	(-3.79)	(3.98)	(-2.50)	(2.15)	(2.55)	(-1.64)	(1.73)	(-1.85)	(-1.09)	(0.74)

F-tests: $\beta_1 + \beta_2$ = 0.067, p-value = 0.020; $\beta_1 - \beta_3$ = 0.050, p-value = 0.294; $\beta_1 + \beta_2 - (\beta_3 + \beta_4)$ = 0.060, p-value = 0.073

Panel B: Business Cycle Dating

	$DLLP_t$	$BOOM_t$ x $DLLP_t$	$NDLLP_t$	$BOOM_t$ x $NDLLP_t$	$LoanGr_t$	$BOOM_t$ x $LoanGr_t$	$EBTP_t$	$Tier1_{t-1}$	$Log\ Size_{t-1}$	$Log\ BTM_{t-1}$
Coefficient	-0.150***	0.119*	-0.222***	0.120	0.155*	-0.011	0.345*	-0.129*	-0.010	0.085
t-statistic	(-2.74)	(1.85)	(-4.72)	(1.53)	(1.95)	(-0.10)	(1.73)	(-1.87)	(-1.13)	(0.69)

F-tests: $\beta_1 + \beta_2$ = -0.030, p-value = 0.432; $\beta_1 - \beta_3$ = 0.072, p-value = 0.000; $\beta_1 + \beta_2 - (\beta_3 + \beta_4)$ = 0.072, p-value = 0.101

Panel C: Consumer Sentiment

	$DLLP_t$	$SENT_t$ x $DLLP_t$	$NDLLP_t$	$SENT_t$ x $NDLLP_t$	$LoanGr_t$	$SENT_t$ x $LoanGr_t$	$EBTP_t$	$Tier1_{t-1}$	$Log\ Size_{t-1}$	$Log\ BTM_{t-1}$
Coefficient	-0.114***	0.199***	-0.165***	0.193***	0.233***	-0.186**	0.331*	-0.123*	-0.010	0.103
t-statistic	(-3.98)	(4.94)	(-2.61)	(2.66)	(2.93)	(-2.04)	(1.67)	(-1.78)	(-1.11)	(0.77)

F-tests: $\beta_1 + \beta_2$ = 0.085, p-value = 0.000; $\beta_1 - \beta_3$ = 0.051, p-value = 0.263; $\beta_1 + \beta_2 - (\beta_3 + \beta_4)$ = 0.057, p-value = 0.077

This table presents regressions that examine the relation between discretionary loan loss provisions (*DLLP*) and excess bank stock returns (*EXRET*) conditional on the state of the economy using our primary *DLLP* measure. In each panel, *DLLP* is interacted with an indicator variable that takes a value of one in the good state of the economy and zero otherwise. Specifically, *HighQ* takes the value one when the median bank Tobin's Q is above its time series median and zero otherwise; *BOOM* is set equal to one if the NBER determined the economy was in a period of expansion and zero in recession; and *SENT* is set equal to one when the Consumer Sentiment Index is above its time series median and zero otherwise. Year fixed effects are included in all specifications to control for time specific factors that influence the returns of all bank stocks in a given year. The sample period is 1997 to 2013. Standard errors are double-clustered by firm and year with the corresponding t-statistics reported below in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 5
DLLP and bank valuation.

	Dependent Variable = Bank Tobin's Q					
DLLP Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$DLLP_{i,t}$	-0.764	-0.641	-0.392	-0.475	-0.077	-0.513
	(-0.93)	(-0.73)	(-0.47)	(-0.82)	(-0.10)	(-0.58)
$DLLP_{i,t} * HighGDP_t$	3.089***	3.717***	3.469***	1.778**	2.837***	3.513***
	(3.09)	(3.94)	(3.90)	(2.37)	(3.35)	(3.26)
$NDLLP_{i,t}$	-1.721***	-2.241***	-2.628***	-1.821**	-2.685***	-1.645**
	(-2.81)	(-3.22)	(-3.32)	(-2.55)	(-3.86)	(-2.13)
$NDLLP_{i,t} * HighGDP_t$	2.860***	2.084	2.233	4.141***	3.076**	1.265
	(2.75)	(1.44)	(1.57)	(3.83)	(2.33)	(1.04)
$LoanGr_{i,t}$	0.017*	0.021**	0.022**	0.018*	0.022**	0.026**
	(1.74)	(2.15)	(2.33)	(1.87)	(2.36)	(2.05)
$LoanGr_{i,t} * HighGDP_t$	-0.005	-0.005	-0.006	-0.010	-0.009	-0.019
	(-0.37)	(-0.38)	(-0.44)	(-0.79)	(-0.68)	(-1.32)
$EBTP_{i,t}$	0.114*	0.114*	0.117*	0.109*	0.117*	0.092*
	(1.86)	(1.88)	(1.94)	(1.79)	(1.93)	(1.82)
$Tier1_{i,t-1}$	-0.025	-0.025	-0.026	-0.023	-0.026	-0.016
	(-0.99)	(-1.00)	(-1.06)	(-0.92)	(-1.05)	(-0.74)
$Log(Size)_{i,t-1}$	0.013***	0.013***	0.013***	0.013***	0.013***	0.012***
	(6.28)	(6.34)	(6.32)	(6.19)	(6.31)	(5.73)
F-test: $\beta_1 + \beta_2 = 0$	2.326	3.076	3.078	1.303	2.760	3.000
[p-value]	[0.001]	[0.000]	[0.000]	[0.004]	[0.000]	[0.000]
F-test: $\beta_1 - \beta_3 = 0$	0.957	1.600	2.237	1.346	2.608	1.131
[p-value]	[0.082]	[0.062]	[0.006]	[0.013]	[0.000]	[0.142]
F-test: $\beta_1 + \beta_2 - (\beta_3 + \beta_4) = 0$	1.187	3.232	3.473	-1.016	2.368	3.379
[p-value]	[0.084]	[0.044]	[0.019]	[0.363]	[0.104]	[0.007]

This table examines the valuation effects of bank discretionary loan loss provisions (*DLLP*) conditional on overall economic conditions by regressing a measure of bank Tobin's Q at the start of year *t+1*, computed as the sum of the market value of equity and book value of liabilities divided by the book value of assets, on *DLLP*, the interaction of *DLLP* and a business cycle indicator equal to one when GDP growth is above its time series median and zero otherwise, and a set of control variables. The analysis is repeated for each set of *DLLP* and *NDLLP* values estimated in Table 2. All regressions include year fixed effects with standard errors double clustered by bank and year. *t*-statistics are reported below the regression coefficients in parentheses with ***, **, and * used to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6
DLLP and future bank performance.

Dependent Variable	System GMM $EBTP_{i,t}$	$NII_{i,t}$	$LoanGr_{i,t}$	$\Delta NPL_{i,t}$
$DLLP_{i,t-1}$	-1.157***	-0.180*	-2.884	0.740***
	(-2.75)	(-1.83)	(-1.44)	(3.00)
$DLLP_{i,t-1} * HighGDP_{t-1}$	6.047**	0.576**	8.775**	-0.860***
	(2.26)	(2.25)	(2.08)	(-2.86)
$NDLLP_{i,t-1}$	-0.097	-0.013	-2.172***	0.185***
	(-0.81)	(-0.14)	(-3.56)	(2.61)
$NDLLP_{i,t-1} * HighGDP_{t-1}$	-1.267	0.163	-6.181*	-0.213*
	(-1.59)	(0.81)	(-1.72)	(-1.94)
$LoanGr_{i,t-1}$	-0.006	0.013		0.008***
	(-1.25)	(0.98)		(3.28)
$LoanGr_{i,t-1} * HighGDP_{t-1}$	0.011	-0.055**		-0.006**
	(1.57)	(-2.26)		(-2.14)
$NPL_{i,t-1}$	-0.022	-0.037	-0.429	-0.387***
	(-0.32)	(-0.64)	(-1.05)	(-6.41)
$\Delta NPL_{i,t-1}$	0.111	-2.120**	-2.322***	
	(0.79)	(-2.26)	(-5.74)	
$Loans_{i,t-1}$	-0.029***	-0.009	-0.042	0.004
	(-3.33)	(-1.31)	(-0.53)	(0.42)
$Log(Size)_{i,t-1}$	0.000	0.001	-0.007	0.002***
	(0.05)	(0.94)	(-0.59)	(2.67)
$Tier1_{i,t-1}$	0.004	0.002	0.229**	-0.003
	(0.39)	(0.86)	(2.15)	(-1.03)
$DepVar_{i,t-1}$	0.452***	0.706***	0.492***	-0.234***
	(9.53)	(10.01)	(4.72)	(-4.44)
$DepVar_{i,t-2}$	0.070*	-0.030	0.017	0.055
	(1.77)	(-0.99)	(0.60)	(1.61)
AR(1) test [p-value]	[0.00]	[0.00]	[0.00]	[0.00]
AR(2) test [p-value]	[0.69]	[0.25]	[0.11]	[0.18]
Hansen test of over-identification [p-value]	[0.20]	[0.20]	[0.35]	[0.12]
Diff-in-Hansen tests of exogeneity [p-value]	[0.23]	[0.12]	[0.28]	[0.15]

This table reports dynamic panel estimation results that evaluate the relation between discretionary loan loss provisions and future bank performance where the dependent variable is either one-year ahead earnings before taxes and provision for loan loss expenses (*EBTP*), net interest income (*NII*), loan growth (*LoanGr*), or the change in non-performing loans (Δ*NPL*). AR(1) and AR(2) are tests for first-order and second-order autocorrelation in the first-differenced residuals with a null of zero autocorrelation. The Hansen test of over-identification is based on the null hypothesis that the instruments are valid, and the Diff-in-Hansen test of exogeneity is under the null that the instruments used for the equations in levels are exogenous. The instruments included consist of the first lag of all predictor variables (i.e. *t-2* values) as well as the second lag of the lagged dependent variable, non-performing loans, the ratio of loans to assets, and log bank size to allow for tests of over-identification. In all specifications, the year indicators are treated as strictly exogenous. *t*-statistics are reported below in parentheses and are based on robust standard errors with the Windmeijer (2005) finite-sample correction. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Loan loss provisions and the financial crisis.

	$DLLP_{i,t}$	$HighGDP_t$ x $DLLP_{i,t}$	$CRISIS_t$ x $DLLP_{i,t}$	$NDLLP_{i,t}$	$HighGDP_t$ x $NDLLP_{i,t}$	$CRISIS_t$ x $NDLLP_{i,t}$	$LoanGr_{i,t}$	$HighGDP_t$ x $LoanGr_{i,t}$	$EBTP_{i,t}$	$Tier1_{i,t-1}$	Log $Size_{i,t-1}$	Log $BTM_{i,t-1}$
Coefficient	-0.096***	0.184***	-0.210***	-0.126**			0.187***	-0.074	0.343*	-0.130*	-0.010	0.080
t-statistic	(-3.40)	(5.24)	(-7.28)	(-2.40)			(2.62)	(-0.92)	(1.71)	(-1.85)	(-1.11)	(0.62)
F-tests:	$\beta_1 + \beta_2$ = 0.088, p-value = 0.000; $\beta_1 - \beta_4$ = 0.031, p-value = 0.399; $\beta_1 + \beta_2 - \beta_4$ = 0.215, p-value = 0.000											
Coefficient	-0.097***	0.202***	-0.214***	-0.154**	0.187**	-0.351***	0.204***	-0.151*	0.337*	-0.125*	-0.009	0.102
t-statistic	(-3.40)	(5.34)	(-7.33)	(-2.43)	(2.54)	(-7.29)	(2.82)	(-1.68)	(1.67)	(-1.78)	(-1.04)	(0.77)
F-tests:	$\beta_1 + \beta_2$ = 0.105, p-value = 0.000; $\beta_1 - \beta_4$ = 0.057, p-value = 0.199; $\beta_1 + \beta_2 - (\beta_4 + \beta_5)$ = 0.072, p-value = 0.000; $\beta_1 + \beta_3 - (\beta_4 + \beta_6)$ = 0.193, p-value = 0.000											

This table introduces a dummy variable, *CRISIS*, which is equal to one for the annual holding period ending in 2008, and zero otherwise. The dependent variable in each specification is the annual bank stock return in excess of the return predicted by the Fama-French 3-factor model (*EXRET*). All regressions include year fixed effects. Standard errors are double-clustered by bank and year with the corresponding *t*-statistics reported below in parentheses.. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Sub-period analysis of the market reaction to DLLP.

PERIOD	1997 – 1999	2000 – 2002	2003 – 2005	2006 – 2008	2009 – 2013
	$EXRET_{i,t}$	$EXRET_{i,t}$	$EXRET_{i,t}$	$EXRET_{i,t}$	$EXRET_{i,t}$
$DLLP_{i,t}$	0.055	-0.109**	0.132***	-0.161***	-0.111**
	(0.76)	(-2.35)	(3.21)	(-4.42)	(-2.16)
$NDLLP_{i,t}$	0.019	-0.222***	0.026	-0.206***	-0.163***
	(0.18)	(-3.20)	(0.55)	(-4.06)	(-4.04)
$LoanGr_{i,t}$	0.031	0.167***	0.108**	0.000	0.460***
	(0.56)	(2.80)	(2.16)	(0.00)	(4.73)
$EBTP_{i,t}$	0.221	0.857***	1.644***	0.048	0.534
	(1.08)	(4.34)	(3.70)	(0.22)	(1.15)
$Tier1_{i,t-1}$	-0.048	-0.230***	-0.625***	-0.062	-0.217
	(-0.74)	(-3.77)	(-3.44)	(-0.60)	(-1.07)
$Log(Size)_{i,t-1}$	-0.021***	-0.011**	-0.013***	0.022***	-0.011*
	(-3.11)	(-2.36)	(-2.94)	(4.56)	(-1.70)
$Log(BTM)_{i,t-1}$	0.094	0.328**	0.792***	-0.445**	0.516**
	(0.42)	(2.32)	(4.40)	(-2.46)	(2.16)
Year FE	Y	Y	Y	Y	Y
Observations	947	1,091	1,159	973	1,494
Real GDP Growth	4.69	1.71	3.50	0.50	1.58

This table presents regressions for the five different sub-periods listed in the first row of the table. The dependent variable in each specification is the annual bank stock return in excess of the corresponding return predicted by the Fama-French 3-factor model (*EXRET*). All columns include year fixed effects, and *t*-statistics computed using clustered standard errors are reported below in parentheses. Real GDP Growth represents the average annual growth rate across the years in the subperiod. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Table 9
Shocks to consumer confidence.

Panel A: IndyMac Bank Seized by FDIC (7/11/08)					
Portfolio	Return	Obs	Diff	t	p
*DLLPQ*5	-4.41	63	-2.93	-2.47	0.015
*DLLPQ*1	-1.48	64			
Panel B: Housing and Economic Recovery Act (7/30/08)					
Portfolio	Return	Obs	Diff	t	p
*DLLPQ*5	2.72	63	3.98	2.76	0.007
*DLLPQ*1	-1.26	64			

This table evaluates the difference in return performance around significant economic events between banks with high and low levels of discretionary loan loss provisions (*DLLP*). Specifically, we compare the performance of banks in the top quintile of *DLLP* (*DLLPQ5*) to banks in the bottom quintile of *DLLP* (*DLLPQ1*) around both the date that IndyMac bank was seized by the FDIC and the date the Housing and Economic Recovery Act was passed. Return represents the cumulative bank return from one day before the announcement date until one day after the announcement date (i.e., *t-1, t+1*) relative to the corresponding return for the S&P 500 index. *Obs* represents the number of banks in each portfolio. The table also reports the difference in average returns for the two portfolios with corresponding *t*-statistics and *p*-values for two-sided tests that evaluate whether the mean returns are equal.

Table 10
Matched sample analysis.

Panel A: Unmatched Sample Characteristics

	HighGDP = 1				HighGDP = 0			
Variable	Mean DLLPQ5	Mean Control	Diff.	p	Mean DLLPQ5	Mean Control	Diff.	p
$NDLLP_{i,t}$	0.0833	0.0838	-0.0005	0.96	0.1541	0.1192	0.0349	0.03
$EBTP_{i,t}$	0.0380	0.0339	0.0041	0.00	0.0266	0.0264	0.0002	0.84
$LoanGr_{i,t-1}$	0.1877	0.1571	0.0306	0.01	0.1279	0.1016	0.0263	0.00
$Log(Size)_{i,t-1}$	12.2585	12.7528	-0.4943	0.00	12.3954	12.5750	-0.1797	0.02
$Log(BTM)_{i,t-1}$	-0.0972	-0.0864	-0.0109	0.03	-0.0402	-0.0386	0.0015	0.69
$Tier1_{i,t-1}$	0.2032	0.1612	0.0420	0.11	0.1793	0.1773	0.0020	0.94

Panel B: Matched Sample Characteristics

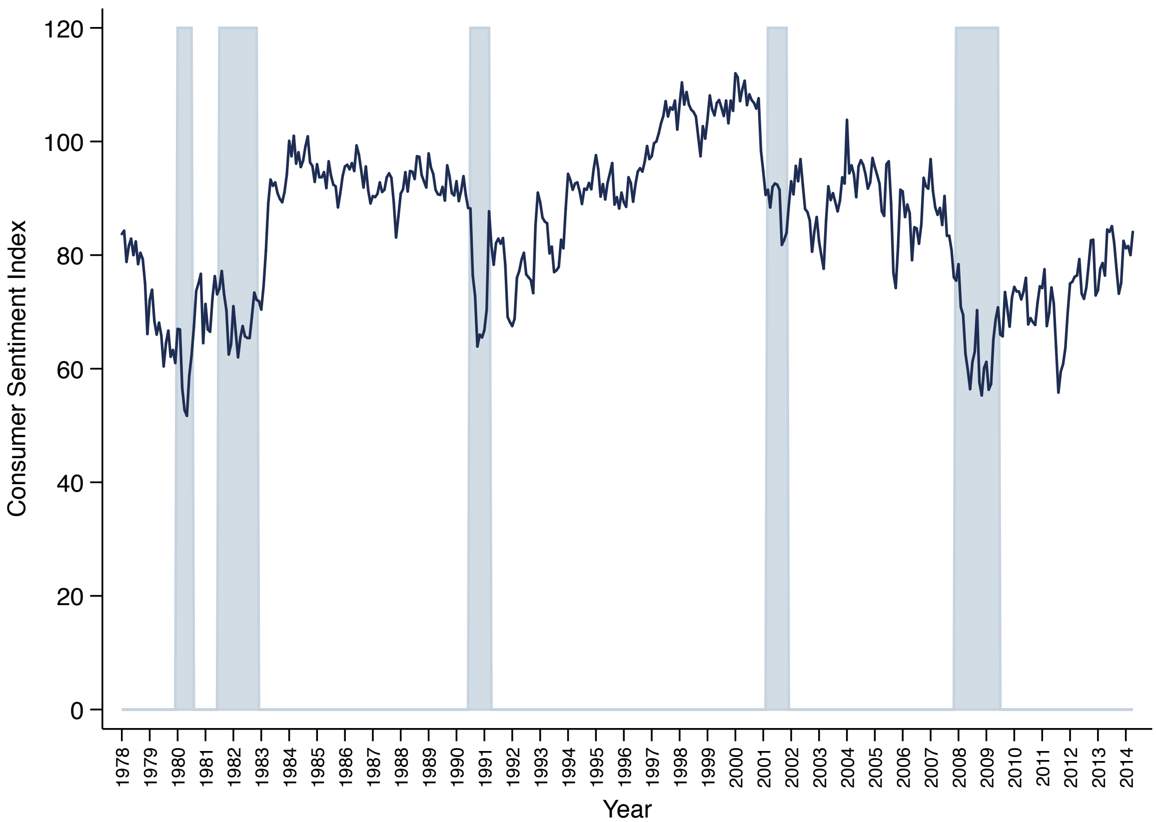
	HighGDP = 1				HighGDP = 0			
Variable	Mean DLLPQ5	Mean Control	Diff.	p	Mean DLLPQ5	Mean Control	Diff.	p
$NDLLP_{i,t}$	0.0833	0.0841	0.0008	0.95	0.1541	0.1466	0.0075	0.71
$EBTP_{i,t}$	0.0380	0.0368	0.0012	0.16	0.0266	0.0260	0.0005	0.69
$LoanGr_{i,t-1}$	0.1877	0.1700	0.0176	0.20	0.1279	0.1221	0.0059	0.57
$Log(Size)_{i,t-1}$	12.2585	12.2503	0.0082	0.93	12.3954	12.3552	0.0401	0.68
$Log(BTM)_{i,t-1}$	-0.0972	-0.0882	-0.0090	0.22	-0.0402	-0.0432	0.0031	0.66
$Tier1_{i,t-1}$	0.2032	0.1553	0.0479	0.18	0.1793	0.2126	-0.0333	0.46

Panel C: Average Treatment Effect on the Treated (ATET)

	HighGDP = 1			HighGDP = 0		
Variable	ATET	S.E.	p	ATET	S.E.	p
$EXRET_{i,t}$	0.0370	0.0187	0.048	-0.0748	0.0202	0.000

This table evaluates the impact of reporting high discretionary loan loss provisions on excess bank stock returns using an indicator variable, *DLLPQ5*, which is set equal to one if a bank's estimated value of *DLLP* is within the top quintile in a given year and zero otherwise. Using nearest neighbor matching, we match each bank with a *DLLPQ5* value of 1 to a control bank with a value of 0 based on the mahalanobis distance computed from bank characteristic values. The sample is divided into years of high real GDP growth (*HighGDP* = 1) and low real GDP growth (*HighGDP* = 0). Panel A reports the average characteristic values for the treatment group, *DLLPQ5*, and all other banks (Control) as well as p-values based on two-sample t-tests that evaluate whether there is a significant difference in means between the two groups. Panel B repeats this analysis, however, the control group includes only those banks selected by the matching procedure. Panel C reports the average effect of being in the high *DLLP* treatment group on the annual bank excess stock return (*EXRET*).

Figure 1
Index of consumer sentiment and NBER business cycle dates.



The figure displays the Consumer Sentiment Index over time since its inception. The graph is constructed using monthly values from January 1978 through April 2014. The shaded regions correspond to the periods defined as recessions by the NBER Business Cycle Dating Committee.

Appendix A

Variable names and descriptions.

Name	Description
LLP	Provision for loan losses (BHCK4230) multiplied by 100 and scaled by lagged total loans (BHCK2122).
ALLP	Provision for loan losses (BHCK4230) minus gross charge-offs (BHCK4635) plus bank recoveries (BHCK4605) with the result multiplied by 100 and scaled by lagged total loans (BHCK2122).
*ALLP**	Provision for loan losses (BHCK4230) plus bank recoveries (BHCK4605) with the sum multiplied by 100 and scaled by lagged total loans (BHCK2122).
ALL	Allowance for loan losses (BHCK3123) scaled by total loans (BHCK2122).
NPL	Loans past due 90 days or more and still accruing (BHCK5525) plus loans in nonaccrual status (BHCK5526) scaled by total loans (BHCK2122).
RE	Loans secured by real estate (BHCK1410) scaled by total loans (BHCK2122).
CI	Commercial and industrial loans (BHCK1763 + BHCK1764) scaled by total loans (BHCK2122).
CONS	Total consumer loans (BHCK2008 + BHCK 2011 through year 2000, BHCKB538 + BHCKB539 + BHCK2011 from 2001 until 2010, and BHCKB538 + BHCKB539 + BHCKK137 + BHCKK207 from 2011 until end of sample period) scaled by total loans (BHCK2122).
NCO	Gross charge-offs (BHCK4635) minus recoveries (BHCK4605) scaled by lagged total loans (BHCK2122).
GCO	Gross charge-offs (BHCK4635) scaled by lagged total loans (BHCK2122).
RECO	Recoveries (BHCK4605) scaled by lagged total loans (BHCK2122).
EBTP	Earnings before taxes and provisions (BHCK4300 + BHCK4230 + BHCK4302) scaled by lagged total loans (BHCK2122).
Tier1	Tier 1 capital (BHCK8274) scaled by total loans (BHCK2122).
Loans	Total loans (BHCK2122) scaled by total assets (BHCK2170).
NII	Net interest income (BHCK4074) scaled by lagged total loans (BHCK2122).
LoanGr	Percentage growth rate in total loans (BHCK2122).
GDPR	Real GDP growth rate as reported by the U.S. Bureau of Economic Analysis.
DLLP	Residual value from a regression model used in explaining loan loss provisions.
NDLLP	Fitted value from a regression model used in explaining loan loss provisions.
EXRET	Annual return from May 1st to April 30th less the corresponding return predicted based on the Fama-French 3-Factor model.
Size	Stock price (prc) multiplied by the number of shares outstanding (shrout).
BTM	Book value of assets scaled by the market value of assets.

Appendix B

Conditional relations of positive and negative DLLP with bank stock returns.

Panel A: Positive DLLP

	$DLLP^{+}_{i,t}$	$HighGDP_t$ x $DLLP^{+}_{i,t}$	$NDLLP_{i,t}$	$HighGDP_t$ x $NDLLP_{i,t}$	$LoanGr_{i,t}$	$HighGDP_t$ x $LoanGr_{i,t}$	$EBTP_{i,t}$	$Tier1_{i,t-1}$	$Log\ Size_{i,t-1}$	$Log\ BTM_{i,t-1}$
Coefficient	-0.239***	0.397***	-0.161***	0.195***	0.204***	-0.159*	0.338*	-0.125*	-0.010	0.108
t-statistic	(-5.13)	(6.43)	(-2.77)	(2.80)	(2.88)	(-1.79)	(1.68)	(-1.77)	(-1.07)	(0.81)
F-tests:	$\beta_1 + \beta_2$ = 0.158, p-value = 0.000;	$\beta_1 - \beta_3$ = -0.078, p-value = 0.301;	$\beta_1 + \beta_2 - (\beta_3 + \beta_4)$ = 0.124, p-value = 0.047							

Panel B: Negative DLLP

	$DLLP^{-}_{i,t}$	$HighGDP_t$ x $DLLP^{-}_{i,t}$	$NDLLP_{i,t}$	$HighGDP_t$ x $NDLLP_{i,t}$	$LoanGr_{i,t}$	$HighGDP_t$ x $LoanGr_{i,t}$	$EBTP_{i,t}$	$Tier1_{i,t-1}$	$Log\ Size_{i,t-1}$	$Log\ BTM_{i,t-1}$
Coefficient	-0.027	0.151**	-0.160**	0.183**	0.200***	0.137	0.336*	-0.124*	-0.010	0.094
t-statistic	(-0.32)	(2.49)	(-2.45)	(2.47)	(2.77)	(-1.53)	(1.68)	(-1.79)	(-1.15)	(0.73)
F-tests:	$\beta_1 + \beta_2$ = 0.124, p-value = 0.011;	$\beta_1 - \beta_3$ = 0.132, p-value = 0.000;	$\beta_1 + \beta_2 - (\beta_3 + \beta_4)$ = 0.100, p-value = 0.004							

This table separately evaluates the relations of positive discretionary loan loss provisions ($DLLP^{+}$) and negative discretionary loan loss provisions ($DLLP^{-}$) with excess bank stock returns (*EXRET*). $DLLP^{+}$ is set equal to *DLLP* if *DLLP* is positive and zero otherwise, and $DLLP^{-}$ is set equal to *DLLP* if *DLLP* is negative and zero otherwise. The dependent variable is the annual bank stock return in excess of the return predicted by the Fama-French 3-factor model (*EXRET*). The independent variables in Panel A include $DLLP^{+}$, an interaction term between $DLLP^{+}$ and the high GDP growth indicator (*HighGDP*), the non-discretionary component of the loan loss provision expense (*NDLLP*), an interaction term between *NDLLP* and *HighGDP*, loan growth (*LoanGR*) and its interaction with *HighGDP*, earnings before taxes and provision for loan loss expenses (*EBTP*), bank Tier 1 capital (*Tier1*), the log of bank market value of equity (*Log(Size)*), and the log of the book value of assets scaled by market value of assets (*Log(BTM)*). Panel B repeats the analysis with $DLLP^{-}$ and its interaction with *HighGDP* as the primary test variables. All regressions are for the period 1997 to 2013 and include year fixed effects. Standard errors are double-clustered by bank and year with the corresponding *t*-statistics reported below in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Appendix C

Assessing the conditional relation between DLLP and bank stock returns using continuous business cycle variables.

Panel A: Real GDP Growth

	$DLLP_{i,t}$	$GDPR_t$ x $DLLP_{i,t}$	$NDLLP_{i,t}$	$GDPR_t$ x $NDLLP_{i,t}$	$LoanGr_{i,t}$	$GDPR_t$ x $LoanGr_{i,t}$	$EBTP_{i,t}$	$Tier1_{i,t-1}$	$Log\ Size_{i,t-1}$	$Log\ BTM_{i,t-1}$
Coefficient	-0.096**	0.026**	-0.174***	0.035*	0.199*	-0.024	0.342*	-0.127*	-0.009	0.097
t-statistic	(-2.56)	(2.14)	(-2.46)	(1.74)	(1.87)	(-0.83)	(1.71)	(-1.82)	(-1.05)	(0.72)

Panel B: Industry Tobin's Q

	$DLLP_{i,t}$	Q_t x $DLLP_{i,t}$	$NDLLP_{i,t}$	Q_t x $NDLLP_{i,t}$	$LoanGr_{i,t}$	Q_t x $LoanGr_{i,t}$	$EBTP_{i,t}$	$Tier1_{i,t-1}$	$Log\ Size_{i,t-1}$	$Log\ BTM_{i,t-1}$
Coefficient	-2.209***	2.094***	-2.324**	2.160**	2.291	-2.052	0.348*	-0.130*	-0.010	0.107
t-statistic	(-5.53)	(5.49)	(-2.29)	(2.27)	(1.45)	(-1.38)	(1.75)	(-1.86)	(-1.12)	(0.78)

Panel C: Consumer Sentiment

	$DLLP_{i,t}$	$SENTc_t$ x $DLLP_{i,t}$	$NDLLP_{i,t}$	$SENTc_t$ x $NDLLP_{i,t}$	$LoanGr_{i,t}$	$SENTc_t$ x $LoanGr_{i,t}$	$EBTP_{i,t}$	$Tier1_{i,t-1}$	$Log\ Size_{i,t-1}$	$Log\ BTM_{i,t-1}$
Coefficient	-0.469***	0.005***	-0.485**	0.005**	0.644	-0.006	0.338*	-0.127*	-0.010	0.090
t-statistic	(-2.90)	(2.71)	(-2.42)	(2.07)	(1.51)	(-1.27)	(1.68)	(-1.79)	(-1.13)	(0.69)

This table presents regressions that examine the relation between discretionary loan loss provisions (*DLLP*) and excess bank stock returns (*EXRET*) conditional on the state of the economy using continuous variables to capture the general movements in the business cycle. The three variables include *GDPR*, *Q*, and *SENTc*, which reflect the percentage growth rate in real GDP, the cross-sectional median Tobin's Q of all banks, and the level of the consumer sentiment index, respectively. Year fixed effects are included in all specifications to control for the level of stock returns in a given year and other time specific factors. The sample period is 1997 to 2013. Standard errors are double-clustered by firm and year with the corresponding *t*-statistics reported below in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Appendix D

DLLP and bank stock returns with additional controls.

	Dependent Variable = $EXRET_{i,t}$					
DLLP Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$DLLP_{i,t}$	-0.090***	-0.124***	-0.096**	-0.081**	-0.091**	-0.103***
	(-3.43)	(-3.45)	(-2.51)	(-2.08)	(-2.04)	(-3.35)
$DLLP_{i,t} * HighGDP_t$	0.201***	0.208***	0.186***	0.144***	0.182***	0.208***
	(4.80)	(3.72)	(3.91)	(2.67)	(3.39)	(4.05)
$NDLLP_{i,t}$	-0.092	-0.334*	-0.405	-0.113**	-0.305***	0.447*
	(-1.20)	(-1.80)	(-1.60)	(-2.38)	(-3.31)	(1.96)
$NDLLP_{i,t} * HighGDP_t$	0.144*	0.089	0.168***	0.183***	0.128*	0.085
	(1.90)	(0.74)	(2.62)	(3.19)	(1.70)	(1.38)
$NCO_{i,t}$	-0.058***	-0.056***	-0.060***	-0.060***	-0.057***	-0.066***
	(-4.12)	(-3.16)	(-4.17)	(-3.88)	(-3.68)	(-4.07)
$NCO_{i,t} * HighGDP_t$	-0.009	-0.028	-0.005	-0.003	-0.015	0.005
	(-0.44)	(-0.89)	(-0.30)	(-0.17)	(-0.77)	(0.19)
$LoanGr_{i,t}$	0.216	0.218*	0.227*	0.223*	0.222*	0.211*
	(1.58)	(1.87)	(1.82)	(1.79)	(1.75)	(1.68)
$LoanGr_{i,t} * HighGDP_t$	-0.084	-0.207**	-0.087	-0.095	-0.077	-0.173**
	(-1.02)	(-2.21)	(-1.09)	(-1.21)	(-1.03)	(-2.08)
$EBTP_{i,t}$	0.371*	0.359**	0.431*	0.356*	0.413*	0.322*
	(1.74)	(2.32)	(1.82)	(1.68)	(1.89)	(1.76)
$Tier1_{i,t-1}$	-0.132*	-0.188***	-0.156*	-0.126*	-0.149*	-0.108*
	(-1.75)	(-2.69)	(-1.88)	(-1.68)	(-1.95)	(-1.66)
$Log(Size)_{i,t-1}$	-0.008	-0.149***	-0.009	-0.009	-0.009	-0.005
	(-0.85)	(-4.75)	(-0.85)	(-0.91)	(-0.86)	(-0.57)
$Log(BTM)_{i,t-1}$	0.207	1.027***	0.217	0.193	0.220	0.321*
	(1.17)	(3.20)	(1.16)	(1.05)	(1.17)	(1.66)
$ALL_{i,t-1}$	2.187*	-4.923	-4.140	2.288	-2.445	20.025**
	(1.66)	(-1.35)	(-0.73)	(1.43)	(-1.10)	(2.48)
$NPL_{i,t-1}$	-1.687***	-1.937*	-0.927	-1.633***	-1.136**	-4.771***
	(-3.37)	(-1.96)	(-1.39)	(-2.82)	(-2.02)	(-3.16)
$\Delta NPL_{i,t}$	-1.899***	1.248	1.946	-1.542**	1.056	-8.787***
	(-2.95)	(0.51)	(0.61)	(-2.17)	(0.70)	(-2.76)
$RE_{i,t-1}$	-0.008	-0.019	0.073	-0.010	0.055	-0.106
	(-0.09)	(-0.06)	(0.72)	(-0.14)	(0.76)	(-1.16)
$CI_{i,t-1}$	0.088	-0.006	0.279	0.081	0.243**	-0.220
	(0.74)	(-0.02)	(1.57)	(0.85)	(2.15)	(-1.20)
$CONS_{i,t-1}$	0.099	0.149	0.148*	0.105	0.157*	0.046
	(1.10)	(0.47)	(1.69)	(1.28)	(1.90)	(0.55)
$\Delta RE_{i,t}$	-0.016	0.104	0.025	-0.021	0.008	-0.020
	(-0.11)	(0.93)	(0.17)	(-0.17)	(0.06)	(-0.17)
$\Delta CI_{i,t}$	-0.266	-0.392*	-0.141	-0.260	-0.202	-0.358
	(-1.24)	(-1.81)	(-0.55)	(-1.32)	(-0.99)	(-1.48)
$\Delta CONS_{i,t}$	-0.266	-0.338	-0.366*	-0.267	-0.320	-0.079
	(-1.32)	(-1.31)	(-1.74)	(-1.27)	(-1.46)	(-0.38)
F-test: $\beta_1 + \beta_2 = 0$	0.111	0.084	0.090	0.063	0.092	0.105
[p-value]	[0.000]	[0.026]	[0.001]	[0.041]	[0.001]	[0.010]
F-test: $\beta_1 - \beta_3 = 0$	0.001	0.210	0.309	0.032	0.215	-0.550
[p-value]	[0.982]	[0.196]	[0.239]	[0.542]	[0.029]	[0.015]
F-test: $\beta_1 + \beta_2 - (\beta_3 + \beta_4) = 0$	0.059	0.330	0.327	-0.006	0.269	-0.427
[p-value]	[0.358]	[0.123]	[0.214]	[0.915]	[0.035]	[0.079]

This table examines the relation between discretionary loan loss provisions (*DLLP*) and excess bank stock returns (*EXRET*) conditional on the state of the economy. *DLLP* estimates reflect the values derived from Table 2, and all loan loss predictors from the primary specification in Table 2 are included as controls as well as net charge-offs and its interaction with a high GDP growth indicator set equal to one if real GDP growth is above its time series median. Year fixed effects are included in all specifications to control for time specific factors that impact all bank stocks in a given year. The sample period is 1997 to 2013. Standard errors are double-clustered by bank and year with the corresponding t-statistics reported below in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Appendix E

Assessing the impact of alternate treatments of loan charge-offs on DLLP estimation and the conditional relation with bank stock returns.

Panel A: Estimation of bank loan loss provisions adjusted by recoveries (first alternate DLLP measures)

Dependent Variable = $ALLP^*_t = LLP_t + RECO_t$

Model:		(1)		(2)		(3)		(4)		(5)		(6)	
Variable	Predicted Sign	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
$ALL_{i,t-1}$	-	-18.67***	-9.89	-23.64***	-8.47	-23.38***	-8.45	-39.74***	-13.83	-23.87***	-8.10	-33.33***	-8.40
$NPL_{i,t-1}$	+	-0.41	-0.39	1.59*	1.85	2.37**	2.65	4.84***	4.21	3.11**	2.22	3.26**	2.13
$\Delta NPL_{i,t}$	+	9.94***	8.26	11.67***	8.44	13.46***	9.66	14.03***	11.63	16.26***	12.01	11.90***	10.85
$RE_{i,t-1}$	+	0.28***	5.94	0.31***	4.16	0.26***	3.43	0.34	1.33	0.25***	3.01	0.24	0.85
$CI_{i,t-1}$	+	0.52***	6.12	0.65***	5.88	0.60***	5.13	0.98***	3.88	0.65***	5.14	0.86**	2.27
$CONS_{i,t-1}$	+	0.29***	4.05	0.13	1.09	0.08	0.69	0.44	1.34	0.17	1.47	-0.06	-0.13
$\Delta RE_{i,t}$	+	0.18**	2.60	0.19***	4.00	0.13	0.88	-0.02	-0.21	0.15	1.04	0.11	1.37
$\Delta CI_{i,t}$	+	0.09	0.44	0.46**	2.81	0.42*	2.11	0.32	1.27	0.29	1.21	0.26	1.20
$\Delta CONS_{i,t}$	+	0.11	0.35	-0.36	-0.83	-0.03	-0.09	0.11	0.33	0.05	0.13	-0.37	-1.35
$GCO_{i,t}$	+	101.27***	30.80	105.33***	30.54	105.53***	30.22	109.64***	31.20	111.20***	33.87	109.78***	41.78
$EBTP_{i,t}$	+					0.23	0.78	0.25*	1.82	0.23	0.73		
$Tier1_{i,t-1}$	+					-0.09	-0.89	-0.27***	-3.10	-0.09	-0.81		
$Beta_{i,t-1}$	+					-0.02	-1.08	-0.02	-0.99	-0.03	-1.21		
$\Delta NPL^2_{i,t}$	?					-15.47	-1.48	-26.68**	-2.86	-34.85***	-3.22		
$\Delta RE^2_{i,t}$	?					0.05	0.39	0.14	1.39	0.06	0.48		
$\Delta CI^2_{i,t}$	?					0.12	0.18	0.39	0.52	0.42	0.61		
$\Delta CONS^2_{i,t}$	?					-1.72**	-2.15	-1.58***	-3.21	-1.77**	-2.14		
$GDPR_t$	-									0.01	1.50		
$GDPR_t * NPL_{i,t-1}$	-							0.07	0.12	-0.36	-0.48		
$GDPR_t * \Delta NPL_{i,t}$	-							-0.99***	-4.21	-1.21***	-4.12		
$GDPR_t * GCO_{i,t}$	-							-2.63*	-1.97	-2.53**	-2.01		
$ALLP^*_{i,t-1}$	?											0.03*	1.71
$ALLP^*_{i,t-2}$	?											-0.02	-1.19
Cross-Sectional		Yes		No		No		No		No		AR(1): p=0.00	
Year FE		No		Yes		Yes		Yes		No		AR(2): p=0.68	
Bank FE		No		No		No		Yes		No		Hansen overid: p=0.48	
Adjusted R^2				0.889		0.890		0.909		0.890		Diff-in-Hansen: p=0.19	
Average R^2		0.813											

Panel B: First alternate DLLP measures and bank stock returns												
	Dependent Variable = $EXRET_{i,t}$											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DLLP Specification:	1	2	3	4	5	6	1	2	3	4	5	6
$ALT1DLLP_{i,t}$	-0.084***	-0.098***	-0.092***	-0.085***	-0.084**	-0.075***	-0.089***	-0.104***	-0.099***	-0.088***	-0.094**	-0.085***
	(-3.57)	(-3.26)	(-2.90)	(-2.81)	(-2.31)	(-2.69)	(-3.62)	(-3.15)	(-2.73)	(-2.76)	(-2.37)	(-2.70)
$ALT1DLLP_{i,t} * HighGDP_t$	0.197***	0.198***	0.184***	0.132***	0.165***	0.180***	0.207***	0.208***	0.197***	0.152***	0.183***	0.211***
	(5.37)	(4.73)	(4.25)	(3.06)	(3.58)	(3.82)	(5.34)	(4.54)	(4.08)	(3.20)	(3.63)	(3.59)
$ALT1NDLLP_{i,t}$	-0.072***	-0.070***	-0.072***	-0.071***	-0.072***	-0.073***	-0.159***	-0.174***	-0.185***	-0.153***	-0.169***	-0.155***
	(-6.48)	(-6.99)	(-7.25)	(-7.34)	(-6.96)	(-7.13)	(-3.23)	(-5.05)	(-5.93)	(-4.67)	(-5.19)	(-4.04)
$ALT1NDLLP_{i,t} * HighGDP_t$	0.019	0.015	0.017	0.026*	0.012	0.035*	0.173***	0.161***	0.181***	0.196***	0.171***	0.193**
	(0.90)	(0.98)	(1.20)	(1.85)	(0.82)	(1.86)	(2.61)	(2.86)	(3.37)	(3.78)	(2.89)	(2.48)
$NCO_{i,t}$							0.099**	0.115***	0.126***	0.096***	0.113***	0.096***
							(2.13)	(3.89)	(4.42)	(3.16)	(3.87)	(2.82)
$NCO_{i,t} * HighGDP_t$							-0.180***	-0.166***	-0.186***	-0.202***	-0.182***	-0.192**
							(-2.96)	(-3.18)	(-3.54)	(-4.04)	(-3.31)	(-2.40)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test: $\beta_1 + \beta_2 = 0$	0.113	0.100	0.092	0.047	0.082	0.105	0.118	0.104	0.098	0.063	0.089	0.126
[p-value]	[0.000]	[0.000]	[0.000]	[0.062]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.032]	[0.001]	[0.003]
F-test: $\beta_1 - \beta_3 = 0$	-0.012	-0.028	-0.021	-0.014	-0.012	-0.002	0.070	0.070	0.086	0.065	0.076	0.070
[p-value]	[0.637]	[0.305]	[0.462]	[0.580]	[0.705]	[0.942]	[0.105]	[0.001]	[0.001]	[0.005]	[0.002]	[0.001]
F-test: $\beta_1 + \beta_2 - (\beta_3 + \beta_4) = 0$	0.166	0.156	0.146	0.091	0.141	0.143	0.104	0.117	0.101	0.021	0.087	0.088
[p-value]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.021]	[0.004]	[0.022]	[0.652]	[0.091]	[0.047]

Panel C: First alternate DLLP measures and bank stock returns using alternate proxies of economic conditions												
Economic Conditions Proxy: Industry Tobin's Q												
	$ALT1DLLP_{i,t}$	$HighQ_t$ x $ALT1DLLP_{i,t}$	$ALT1NDLLP_{i,t}$	$HighQ_t$ x $ALT1NDLLP_{i,t}$	$NCO_{i,t}$	$HighQ_t$ x $NCO_{i,t}$	$LoanGr_{i,t}$	$HighQ_t$ x $LoanGr_{i,t}$	$EBTP_{i,t}$	Log $Tier1_{i,t-1}$	Log $Size_{i,t-1}$	$BTM_{i,t-1}$
Coefficient	-0.089***	0.164***	-0.073***	0.016			0.109*	-0.021	0.371*	-0.131*	-0.005	0.153
t-statistic	(-3.48)	(3.88)	(-6.39)	(0.86)			(1.89)	(-0.30)	(1.69)	(-1.68)	(-0.52)	(0.92)
F-tests:	$\beta_1 + \beta_2$ = 0.075, p-value = 0.011; $\beta_1 - \beta_3$ = -0.017, p-value = 0.528; $\beta_1 + \beta_2 - (\beta_3 + \beta_4)$ = 0.132, p-value = 0.000											
Coefficient	-0.094***	0.173***	-0.159***	0.151**	0.100**	-0.157**	0.151**	-0.082	0.371*	-0.131*	-0.005	0.157
t-statistic	(-3.51)	(3.93)	(-3.10)	(2.25)	(2.15)	(-1.03)	(2.03)	(-2.46)	(1.68)	(-1.68)	(-0.51)	(0.95)
F-tests:	$\beta_1 + \beta_2$ = 0.079, p-value = 0.009; $\beta_1 - \beta_3$ = 0.066, p-value = 0.146; $\beta_1 + \beta_2 - (\beta_3 + \beta_4)$ = 0.087, p-value = 0.038											
Economic Conditions Proxy: Business Cycle Dating												
	$ALT1DLLP_{i,t}$	$BOOM_t$ x $ALT1DLLP_{i,t}$	$ALT1NDLLP_{i,t}$	$BOOM_t$ x $ALT1NDLLP_{i,t}$	$NCO_{i,t}$	$BOOM_t$ x $NCO_{i,t}$	$LoanGr_{i,t}$	$BOOM_t$ x $LoanGr_{i,t}$	$EBTP_{i,t}$	Log $Tier1_{i,t-1}$	Log $Size_{i,t-1}$	$BTM_{i,t-1}$
Coefficient	-0.139***	0.133**	-0.051***	-0.023**			0.078	0.025	0.376*	-0.132*	-0.005	0.146
t-statistic	(-2.83)	(2.33)	(-8.57)	(-1.98)			(0.97)	(0.28)	(1.68)	(-1.68)	(-0.54)	(0.89)
F-tests:	$\beta_1 + \beta_2$ = -0.006, p-value = 0.843; $\beta_1 - \beta_3$ = -0.088, p-value = 0.046; $\beta_1 + \beta_2 - (\beta_3 + \beta_4)$ = 0.069, p-value = 0.017											
Coefficient	-0.140***	0.130**	-0.174***	0.047	0.167***	-0.110*	0.132	-0.007	0.379*	-0.134*	-0.006	0.133
t-statistic	(-2.93)	(2.28)	(-5.00)	(0.75)	(4.32)	(-1.72)	(1.56)	(-0.07)	(1.69)	(-1.70)	(-0.57)	(0.84)
F-tests:	$\beta_1 + \beta_2$ = -0.010, p-value = 0.759; $\beta_1 - \beta_3$ = 0.034, p-value = 0.277; $\beta_1 + \beta_2 - (\beta_3 + \beta_4)$ = 0.117, p-value = 0.002											
Economic Conditions Proxy: Consumer Sentiment												
	$ALT1DLLP_{i,t}$	$SENT_t$ x $ALT1DLLP_{i,t}$	$ALT1NDLLP_{i,t}$	$SENT_t$ x $ALT1NDLLP_{i,t}$	$NCO_{i,t}$	$SENT_t$ x $NCO_{i,t}$	$LoanGr_{i,t}$	$SENT_t$ x $LoanGr_{i,t}$	$EBTP_{i,t}$	Log $Tier1_{i,t-1}$	Log $Size_{i,t-1}$	$BTM_{i,t-1}$
Coefficient	-0.091***	0.187***	-0.072***	0.018			0.121**	-0.043	0.371*	-0.131*	-0.005	0.159
t-statistic	(-3.78)	(5.12)	(-6.40)	(0.95)			(2.24)	(-0.65)	(1.67)	(-1.66)	(-0.51)	(0.95)
F-tests:	$\beta_1 + \beta_2$ = 0.097, p-value = 0.000; $\beta_1 - \beta_3$ = -0.018, p-value = 0.460; $\beta_1 + \beta_2 - (\beta_3 + \beta_4)$ = 0.151, p-value = 0.000											
Coefficient	-0.096***	0.198***	-0.166***	0.181***	0.107**	-0.191***	0.169***	-0.117	0.375*	-0.131*	-0.005	0.173
t-statistic	(-3.84)	(5.14)	(-3.25)	(2.74)	(2.22)	(-3.09)	(2.61)	(-1.52)	(1.68)	(-1.67)	(-0.52)	(1.03)
F-tests:	$\beta_1 + \beta_2$ = 0.102, p-value = 0.000; $\beta_1 - \beta_3$ = 0.070, p-value = 0.129; $\beta_1 + \beta_2 - (\beta_3 + \beta_4)$ = 0.086, p-value = 0.043											

Panel D: Estimation of bank loan loss provisions excluding NCO as a predictor (second alternate DLLP measures)

Dependent Variable = LLP_t

Model:		(1)		(2)		(3)		(4)		(5)		(6)	
Variable	Predicted Sign	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
$ALL_{i,t-1}$	-	15.57**	2.22	17.86**	2.54	16.68**	2.37	-2.38	-0.40	16.23**	2.40	-16.75*	-1.67
$NPL_{i,t-1}$	+	15.96***	9.44	20.02***	6.37	19.10***	5.79	25.28***	3.75	26.03***	3.27	17.55***	3.11
$\Delta NPL_{i,t}$	+	20.89***	4.76	23.65***	5.70	23.22***	5.07	24.60***	6.08	34.41***	7.40	43.79***	5.29
$RE_{i,t-1}$	+	0.10	1.38	0.08	0.46	0.05	0.27	0.23	0.48	0.08	0.39	-0.01	-0.01
$CI_{i,t-1}$	+	0.62***	3.42	0.81***	3.21	0.74**	2.63	0.99*	1.77	0.84***	2.82	0.33	0.31
$CONS_{i,t-1}$	+	1.16***	5.10	1.22***	3.49	1.19***	3.26	0.93	1.55	1.25***	3.57	-0.46	-0.26
$\Delta RE_{i,t}$	+	-0.52	-1.63	-0.12	-0.57	-0.71*	-1.82	-0.97***	-2.94	-0.91**	-2.15	-1.44*	-1.82
$\Delta CI_{i,t}$	+	0.11	0.38	0.06	0.20	-0.34	-1.04	-0.46	-0.87	-1.03	-1.55	-1.09	-0.41
$\Delta CONS_{i,t}$	+	0.91**	2.63	0.53	0.77	1.03	1.46	0.84	1.70	1.05	1.44	2.70	0.92
$EBTP_{i,t}$	+					0.74	1.71	0.41*	1.85	0.76	1.36		
$Tier1_{i,t-1}$	+					-0.31*	-2.01	-0.39***	-3.18	-0.32	-1.56		
$Beta_{i,t-1}$	+					0.04	0.66	-0.02	-0.34	0.03	0.49		
$\Delta NPL^2_{i,t}$	?					6.40	0.28	-7.61	-0.31	-40.56	-1.20		
$\Delta RE^2_{i,t}$	?					0.63**	2.54	0.76***	3.36	0.76***	2.66		
$\Delta CI^2_{i,t}$	?					2.14*	2.02	2.52*	1.94	3.13**	2.37		
$\Delta CONS^2_{i,t}$	?					-3.54	-1.33	-3.54	-1.63	-3.67	-1.12		
$GDPR_t$	-									-0.04	-1.56		
$GDPR_t * NPL_{i,t-1}$	-							-1.58	-0.69	-2.46	-0.72		
$GDPR_t * \Delta NPL_{i,t}$	-							-2.02	-1.73	-2.75**	-2.17		
$LLP_{i,t-1}$	?											0.39**	2.88
$LLP_{i,t-2}$	?											0.06	1.04
Cross-Sectional		Yes		No		No		No		No			AR(1): p=0.00
Year FE		No		Yes		Yes		Yes		No			AR(2): p=0.19
Firm FE		No		No		No		Yes		No			Hansen overid: p=0.91
Adjusted R^2				0.486		0.495		0.572		0.443			Diff-in-Hansen: p=0.92
Average R^2		0.338											

Panel E: Second alternate DLLP measures and bank stock returns												
	Dependent Variable = $EXRET_{i,t}$											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
DLLP Specification:	1	2	3	4	5	6	1	2	3	4	5	6
$ALT2DLLP_{i,t}$	-0.085***	-0.078***	-0.075***	-0.065***	-0.066***	-0.067***	-0.109***	-0.089***	-0.089***	-0.089***	-0.075**	-0.050*
	(-5.33)	(-4.82)	(-4.56)	(-3.23)	(-3.84)	(-4.18)	(-3.95)	(-3.38)	(-3.26)	(-2.72)	(-2.45)	(-1.66)
$ALT2DLLP_{i,t} * HighGDP_t$	0.079***	0.071***	0.072***	0.059***	0.061***	0.098***	0.196***	0.170***	0.167***	0.158***	0.149***	0.164**
	(3.60)	(3.19)	(3.50)	(2.76)	(2.99)	(2.73)	(4.88)	(4.79)	(4.70)	(4.15)	(4.07)	(2.39)
$ALT2NDLLP_{i,t}$	-0.092***	-0.107***	-0.112***	-0.104***	-0.113***	-0.083***	-0.114***	-0.116***	-0.125***	-0.127***	-0.120***	-0.072***
	(-8.82)	(-8.83)	(-7.50)	(-7.43)	(-7.10)	(-7.61)	(-6.52)	(-8.31)	(-9.62)	(-5.73)	(-7.35)	(-4.88)
$ALT2NDLLP_{i,t} * HighGDP_t$	0.036	0.025	0.021	0.052**	0.022	0.021	0.171***	0.169**	0.149**	0.159***	0.139**	0.105
	(0.98)	(0.63)	(0.51)	(2.35)	(0.50)	(0.61)	(3.53)	(2.57)	(2.32)	(4.16)	(2.13)	(1.53)
$NCO_{i,t}$							0.026	0.011	0.015	0.027	0.010	-0.017
							(1.43)	(0.62)	(0.90)	(1.58)	(0.52)	(-0.91)
$NCO_{i,t} * HighGDP_t$							-0.147***	-0.123***	-0.116***	-0.121***	-0.108***	-0.087*
							(-4.54)	(-4.64)	(-4.47)	(-5.87)	(-4.25)	(-1.95)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test: $\beta_1 + \beta_2 = 0$	-0.006	-0.007	-0.002	-0.006	-0.004	0.030	0.087	0.081	0.078	0.069	0.073	0.114
[p-value]	[0.642]	[0.647]	[0.859]	[0.504]	[0.711]	[0.327]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.056]
F-test: $\beta_1 - \beta_3 = 0$	0.007	0.029	0.038	0.039	0.047	0.016	0.005	0.027	0.036	0.038	0.045	0.022
[p-value]	[0.637]	[0.130]	[0.078]	[0.076]	[0.020]	[0.197]	[0.752]	[0.171]	[0.113]	[0.236]	[0.060]	[0.252]
F-test: $\beta_1 + \beta_2 - (\beta_3 + \beta_4) = 0$	0.050	0.075	0.089	0.046	0.086	0.092	0.030	0.029	0.053	0.036	0.055	0.081
[p-value]	[0.185]	[0.088]	[0.038]	[0.020]	[0.052]	[0.015]	[0.314]	[0.601]	[0.310]	[0.156]	[0.296]	[0.045]

Panel F: Second alternate DLLP measures and bank stock returns using alternate proxies of economic conditions

Economic Conditions Proxy: Industry Tobin's Q

	$ALT2DLLP_{i,t}$	$HighQ_t$ x $ALT2DLLP_{i,t}$	$ALT2NDLLP_{i,t}$	$HighQ_t$ x $ALT2NDLLP_{i,t}$	$NCO_{i,t}$	$HighQ_t$ x $NCO_{i,t}$	$LoanGr_{i,t}$	$HighQ_t$ x $LoanGr_{i,t}$	$EBTP_{i,t}$	$Log\ Tier1_{i,t-1}$	$Log\ Size_{i,t-1}$	$BTM_{i,t-1}$
Coefficient	-0.087***	0.068***	-0.091***	0.022			0.111*	-0.019	0.371*	-0.131*	-0.006	0.156
t-statistic	(-5.11)	(2.99)	(-8.77)	(0.62)			(1.94)	(-0.28)	(1.69)	(-1.69)	(-0.64)	(0.92)
F-tests	$\beta_1+\beta_2$ = -0.020, p-value = 0.144; $\beta_1-\beta_3$ = 0.003, p-value = 0.846; $\beta_1+\beta_2-(\beta_3+\beta_4)$ = 0.049, p-value = 0.145											
Coefficient	-0.114***	0.164***	-0.114***	0.129**	0.029	-0.118***	0.127**	-0.068	0.365*	-0.127*	-0.006	0.174
t-statistic	(-3.88)	(3.76)	(-6.11)	(2.53)	(1.47)	(-3.46)	(2.24)	(-0.99)	(1.67)	(-1.65)	(-0.57)	(1.04)
F-tests	$\beta_1+\beta_2$ = 0.050, p-value = 0.081; $\beta_1-\beta_3$ = 0.000, p-value = 0.992; $\beta_1+\beta_2-(\beta_3+\beta_4)$ = 0.035, p-value = 0.209											

Economic Conditions Proxy: Business Cycle Dating

	$ALT2DLLP_{i,t}$	$BOOM_t$ x $ALT2DLLP_{i,t}$	$ALT2NDLLP_{i,t}$	$BOOM_t$ x $ALT2NDLLP_{i,t}$	$NCO_{i,t}$	$BOOM_t$ x $NCO_{i,t}$	$LoanGr_{i,t}$	$BOOM_t$ x $LoanGr_{i,t}$	$EBTP_{i,t}$	$Log\ Tier1_{i,t-1}$	$Log\ Size_{i,t-1}$	$BTM_{i,t-1}$
Coefficient	-0.068*	-0.002	-0.079***	-0.012			0.081	0.025	0.379*	-0.135*	-0.006	0.142
t-statistic	(-1.95)	(-0.06)	(-15.14)	(-0.72)			(0.99)	(0.27)	(1.69)	(-1.71)	(-0.65)	(0.83)
F-tests	$\beta_1+\beta_2$ = -0.070, p-value = 0.000; $\beta_1-\beta_3$ = 0.011, p-value = 0.737; $\beta_1+\beta_2-(\beta_3+\beta_4)$ = 0.021, p-value = 0.293											
Coefficient	-0.153***	0.099	-0.146***	0.071**	0.105***	-0.123***	0.124	-0.025	0.375*	-0.132*	-0.006	0.151
t-statistic	(-2.91)	(1.60)	(-6.72)	(1.97)	(3.69)	(-3.33)	(1.47)	(-0.27)	(1.66)	(-1.67)	(-0.63)	(0.91)
F-tests	$\beta_1+\beta_2$ = -0.054, p-value = 0.113; $\beta_1-\beta_3$ = -0.007, p-value = 0.839; $\beta_1+\beta_2-(\beta_3+\beta_4)$ = 0.021, p-value = 0.304											

Economic Conditions Proxy: Consumer Sentiment

	$ALT2DLLP_{i,t}$	$SENT_t$ x $ALT2DLLP_{i,t}$	$ALT2NDLLP_{i,t}$	$SENT_t$ x $ALT2NDLLP_{i,t}$	$NCO_{i,t}$	$SENT_t$ x $NCO_{i,t}$	$LoanGr_{i,t}$	$SENT_t$ x $LoanGr_{i,t}$	$EBTP_{i,t}$	$Log\ Tier1_{i,t-1}$	$Log\ Size_{i,t-1}$	$BTM_{i,t-1}$
Coefficient	-0.085***	0.066***	-0.092***	0.036			0.121**	-0.043	0.370*	-0.131*	-0.007	0.163
t-statistic	(-5.07)	(2.79)	(-8.89)	(1.14)			(2.30)	(-0.63)	(1.67)	(-1.68)	(-0.66)	(0.96)
F-tests	$\beta_1+\beta_2$ = -0.019, p-value = 0.231; $\beta_1-\beta_3$ = 0.007, p-value = 0.668; $\beta_1+\beta_2-(\beta_3+\beta_4)$ = 0.037, p-value = 0.266											
Coefficient	-0.111***	0.180***	-0.116***	0.168***	0.028	-0.144***	0.137***	-0.100	0.363*	-0.126*	-0.006	0.183
t-statistic	(-3.90)	(4.45)	(-6.62)	(3.93)	(1.55)	(-4.86)	(2.72)	(-1.56)	(1.65)	(-1.63)	(-0.58)	(1.09)
F-tests	$\beta_1+\beta_2$ = 0.069, p-value = 0.006; $\beta_1-\beta_3$ = 0.004, p-value = 0.810; $\beta_1+\beta_2-(\beta_3+\beta_4)$ = 0.017, p-value = 0.537											

This table re-estimates discretionary loan loss provisions (*DLLP*) using different treatments of loan charge-offs and then re-evaluates the conditional *DLLP*-return relation. Panel A displays the expected loan loss provision estimation results using a dependent variable, *ALLP**, defined as the bank's reported loan loss provisions plus recoveries scaled by prior year-end total loans, and gross charge-offs are included as an independent variable. Panel B presents the results for tests of the conditional relation between these alternate DLLP estimates (*ALT1DLLP*) and excess bank stock returns, and Panel C reports similar tests using alternate proxies of economic conditions. Panel D repeats the estimation of expected loan loss provisions using the unadjusted value of loan loss provisions (*LLP*) as the dependent variable with net-charge offs (*NCO*) excluded from the set of independent variables. Panel E reports the associated tests of a conditional *DLLP*-return relation using the DLLP estimates derived from the specifications in Panel D (*ALT2DLLP*), and Panel F reports the results for similar tests using alternate proxies of economic conditions. *Controls* indicates the inclusion of *LoanGr, LoanGr*HighGDP, EBTP, Tier1, Log(Size), and year fixed effects*. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Appendix F
Association of DLLP with bank stock returns excluding non-positive LLP banks.

	Dependent Variable = $EXRET_{i,t}$					
DLLP Specification:	(1)	(2)	(3)	(4)	(5)	(6)
$DLLP_{i,t}$	-0.095***	-0.105***	-0.099***	-0.090***	-0.096***	-0.088***
	(-4.30)	(-3.69)	(-3.24)	(-3.09)	(-2.77)	(-3.96)
$DLLP_{i,t} * HighGDP_t$	0.174***	0.177***	0.168***	0.145***	0.152***	0.168***
	(5.17)	(4.56)	(4.08)	(3.16)	(3.44)	(3.56)
$NDLLP_{i,t}$	-0.082***	-0.080***	-0.081***	-0.081***	-0.081***	-0.081***
	(-6.99)	(-7.78)	(-8.29)	(-8.27)	(-7.83)	(-7.15)
$NDLLP_{i,t} * HighGDP_t$	0.028	0.024	0.027	0.032**	0.020	0.040**
	(1.03)	(1.36)	(1.62)	(2.03)	(1.08)	(2.00)
$LoanGr_{i,t}$	0.095**	0.099**	0.098**	0.095*	0.097**	0.138**
	(2.01)	(2.02)	(2.00)	(1.92)	(2.00)	(2.36)
$LoanGr_{i,t} * HighGDP_t$	-0.007	-0.016	-0.015	-0.015	-0.012	-0.124**
	(-0.10)	(-0.23)	(-0.21)	(-0.20)	(-0.17)	(-1.97)
$EBTP_{i,t}$	0.605*	0.617*	0.603*	0.591*	0.607*	0.729
	(1.74)	(1.76)	(1.71)	(1.70)	(1.73)	(1.63)
$Tier1_{i,t-1}$	-0.205	-0.208	-0.202	-0.199	-0.203	-0.263
	(-1.60)	(-1.62)	(-1.56)	(-1.56)	(-1.58)	(-1.50)
$Log(Size)_{i,t-1}$	-0.004	-0.004	-0.004	-0.004	-0.004	-0.001
	(-0.35)	(-0.35)	(-0.35)	(-0.39)	(-0.36)	(-0.12)
$Log(BTM)_{i,t-1}$	0.301	0.308*	0.309*	0.288	0.307*	0.442**
	(1.61)	(1.66)	(1.66)	(1.55)	(1.65)	(2.20)
F-test: $\beta_1 + \beta_2 = 0$	0.079	0.072	0.069	0.055	0.057	0.080
[p-value]	[0.001]	[0.001]	[0.002]	[0.060]	[0.016]	[0.025]
F-test: $\beta_1 - \beta_3 = 0$	-0.013	-0.025	-0.018	-0.009	-0.015	-0.007
[p-value]	[0.581]	[0.351]	[0.519]	[0.708]	[0.603]	[0.760]
F-test: $\beta_1 + \beta_2 - (\beta_3 + \beta_4) = 0$	0.133	0.128	0.122	0.104	0.117	0.121
[p-value]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

This table examines the relation between discretionary loan loss provisions (*DLLP*) and excess bank stock returns (*EXRET*) conditional on the state of the economy after removing all observations with loan loss provisions less than or equal to zero. Year fixed effects are included in all specifications to control for the level of bank stock returns in a given year and other time specific factors. The sample period is 1997 to 2013. Standard errors are double-clustered by bank and year with the corresponding t-statistics reported below in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.