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Three Essays on Financial Distress and Valuation

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University of Connecticut, [2017]

This dissertation consists of three essays examining issues related to financial distress and its impact on stock prices and future firm performance. In the first essay, we explore the impact of economic conditions on the valuation of bank discretionary loan loss provisions and expect to find a strong conditional effect. Driven by fluctuations in lending standards over the business cycle, we show that during good times increases in discretionary loan loss provisions are used to support loan growth and are associated with higher stock returns. In contrast, during periods of economic turmoil discretionary loan loss provisions are expected to indicate deeper problems in the loan portfolio and are negatively valued by the market.

In the second essay, I identify an external financing channel capable of generating significant overvaluation among distressed firms' stocks and explaining their puzzlingly low returns (i.e., the distress anomaly). Specifically, the decision of a distressed firm to raise external capital generates a large dispersion of investor beliefs. Consistent with predictions that prices will only reflect optimists' valuations in the presence of short-sale constraints, I find distressed firms' stocks earn comparable returns to healthy firms' stocks when prior year external financing activity is low but underperform significantly when external financing activity is high. This underperformance is concentrated around earnings announcements, as optimistic investors are disappointed on average upon observing actual performance outcomes.

The third essay examines the relation between takeover activity and the performance of distressed company stocks while exploring two competing explanations. The *risk-based explanation* predicts

distressed firms with a high probability of being acquired will earn lower returns, because the possibility of acquisition makes them less risky. Conversely, the *managerial alignment explanation* predicts low returns for distressed firms with low probability of being acquired, because without the disciplining effect of a possible takeover, self-interested managers have an incentive to "play it safe" and avoid risky investments. I find evidence consistent with the latter hypothesis, as distressed firms with low takeover exposure earn lower future returns while investing less, reducing leverage, and earning lower profits.

Three Essays on Financial Distress and Valuation

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Chapter 1

Discretionary Loan Loss Provisions: A Sign of Prosperity or a Sign of Problems?

1.1 Introduction

In theory, when bank management determines it is unlikely to collect all amounts due according to the contractual terms of its loan agreements, a loan loss provision expense is recorded in the current period equal to the expected loss. This increases the bank's loss reserves, which are used to absorb future loan defaults. Thus, under regulatory guidance an unusually large loan loss provision expense should reflect management's expectations of elevated lending losses and convey this information to investors. Despite this seemingly adverse news, however, prior research generally documents a positive relation between the discretionary component of loan loss provisions (DLLP) 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.

In this study, we examine the market's reaction to discretionary loan loss provisions over several business cycles and expect to find a strong conditional valuation effect that is dependent on the state of the economy, because the motivation for recording excess provision expenses varies dramatically with overall economic conditions. In particular, there is substantial evidence that lending standards vary considerably over the business cycle, with loose credit policies implemented in 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). Thus, when the economy is strong and relatively few borrowers are expected to default, many banks aim to grow their loan portfolios while pursuing higher loan yields. Bank managers who decide to implement such growth strategies are likely to record high DLLP in order to support new loans made under looser underwriting standards.[1] With low default rates expected to persist in good states of the economy, this leads to expectations of higher future earnings for these banks and results in a positive market valuation of DLLP.

In contrast, during economic downturns banks tighten their underwriting standards and become averse to granting higher-risk loans. Further, bank earnings tend to be depressed; therefore, managers only record discretionary loan loss provisions as needed to cover the losses associated with loans nearing default. Thus, based on management's private information about its loan port-

[1] Evidence of this effect is supported by comments from bank analysts and executives. http://www.wsj.com/articles/banks-bet-on-consumers-is-getting-riskier-1469221959

folio, high DLLP indicates to the market which banks are facing the most severe default problems, thereby causing a negative market valuation of DLLP in bad economic times.

Using a broad panel of publicly traded U.S. bank holding companies (BHCs) over the period 1997–2013, we test the conditional valuation hypothesis and show that, consistent with prior findings, DLLP expenses are positively valued by the market but only during "good times". In contrast, stock returns are significantly lower for banks with large discretionary provision expenses when economic prospects are bleak. We attribute this to more widespread economic turmoil in the market resulting in increased investor skepticism and a greater likelihood that high DLLP reflects management's inside knowledge of a deteriorating loan portfolio rather than plans to increase lending.

The adoption of more aggressive lending policies by high DLLP banks during good times is expected to generate an increase in lending activity and provide a boost to earnings. Consistent with our predictions, DLLP recorded during good economic times is associated with higher earnings in the following year, which is driven primarily by an increase in net interest income from higher interest rate loans and loan growth. However, no such relation is found during periods when the economy is weak. As a result, while DLLP recorded during good economic times is associated with increased earnings potential, in bad economic times DLLP's only impact is to reduce current period earnings.

We choose to focus on loan loss provisions for two primary reasons. First, loan loss provisions represent what is by far the most economically significant accrual for banking institutions. The median loan loss provision (LLP) expense as a percentage of earnings prior to taxes and LLP expenses is 12.51% in our sample, and in 5.43% of bank-years this ratio exceeds 100% illustrating its substantial impact on earnings. Additionally, the importance of accruals, including their effect on asset pricing, has been well documented in the literature (e.g., Sloan, 1996; Bhojraj et al., 2009).

Second, the nature of the loan loss provision expense is such that it is based on management estimates and is highly subjective. FAS 114, which stipulates how creditors are to assess troubled loans, directly 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."[2] Consequently, the flexibility

[2]Additional reserves are set aside for pools of relatively homogeneous loans under the guidance of FAS 5.

that management is granted in determining an appropriate reserve for bank loan portfolios coupled with the economic impact of the LLP expense make it necessary for both investors and regulators to evaluate the information content of loan loss provisions carefully.

In order to separate the non-discretionary component of loan loss provisions from the discretionary component, we control for the most essential determinants of bank loan loss provisions such as the bank's allowance for loan losses, non-performing loans, change in non-performing loans, and net charge-offs. Further, we also consider variables reflecting loan portfolio composition as well as changes in portfolio composition, which are frequently ignored in prior studies. We find the majority of these control variables are significant in predicting loan loss provisions with coefficients of varying magnitudes, suggesting that it is important to take this information into account when estimating DLLP.

Our study makes three main contributions to the literature. First, we document a strong conditional valuation effect of DLLP in our panel of BHCs using a set of variables reflecting market-wide economic conditions including real GDP growth, industry Tobin's Q, official business cycle dates, and consumer sentiment. We provide evidence that not only do discretionary loan loss provisions no longer convey positive information to investors when the economy is weak, but that during the financial crisis when economic concerns intensified the stocks of banks with high DLLP were severely punished by the market.

Second, we provide evidence that DLLP is associated with significant differences in future operating performance. Consistent with high DLLP banks relaxing underwriting standards when the economy is strong, these banks experience both higher loan growth and higher overall earnings compared to other banks in the following year, which is driven by increased net-interest income. In contrast, during bad economic times high DLLP banks have similar future loan growth and earnings performance to other banks but sustain a hit to current period earnings from increased provision expenses. These results are consistent with the conditional valuation hypothesis and indicate what value-relevant information DLLP provides to the market.

Third, we address potential endogeneity concerns often ignored by prior studies. We create a matched sample between banks in the top quintile of DLLP and comparable banks with lower levels of DLLP. This helps ensure the market's reaction to DLLP is not confounded by differences in other return determinants and aids in quantifying the economic magnitude of the effect. We

also examine the return performance of high DLLP banks compared to low DLLP banks around events that altered the perceived health of financial institutions. The results add support to our conditional valuation hypothesis, as high DLLP banks earned significantly lower returns around the IndyMac bank failure, which represented the largest commercial bank failure in nearly two decades and intensified default concerns, while this group of banks also experienced the most positive returns upon the announcement of the Troubled Asset Relief Program (TARP) intended to help alleviate financial distress.

Our paper is related to the literature on lending cycles, which play a key role in driving fluctuations in loan loss provisions over time. For instance, Asea and Blomberg (1998) explore a dataset consisting of over two million commercial and industrial loans and show that credit policies fluctuate systematically over the business cycle, with lax lending polices implemented during expansions and tighter policies in recessions, which influences the overall health of the economy. Additionally, Bassett et al. (2014) study credit supply shocks using survey data comprised of bank-level responses on lending standards. They note the most commonly cited reasons for banks to alter lending standards are changes in the economic outlook and shifts in risk tolerance. This is consistent with our evidence and helps explain why banks record DLLP when implementing more aggressive lending strategies during economic booms while only recording additional provision expenses as needed to cover losses during downturns.

Our study is also closely related to the literature on the market recognition of accounting discretion and bank valuation. Huizinga and Laeven (2012) offer evidence that the use of accounting discretion was widespread in 2008, as investors placed significant discounts on bank assets whose value was likely to be overstated. Our results are consistent with their findings in the sense that investors punish high DLLP bank valuations during market downturns when fundamentals and underlying asset quality are likely 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 is closely related due to the dynamics in lending and appears to be of first order importance in explaining the DLLP valuation effect.

One possible concern is that the conditional valuation of DLLP could create an incentive for all banks to record higher DLLP in good times and lower DLLP in bad times with the goal of increasing their valuations; however, recording higher DLLP is costly since it reduces both current

earnings and Tier 1 capital. Such a reduction in a bank's financial ratios can lead to higher external financing costs, higher insurance premiums, and higher supervisory risk ratings, thereby limiting the incentives for banks to record high DLLP when it is unnecessary. In contrast, there are far lower costs associated with under-reporting loan loss provisions, since in addition to being associated with higher valuations in bad times, it also increases bank earnings and Tier 1 capital, which is particularly valuable given the higher external financing costs during downturns. This highlights the need for regulators to scrutinize loan loss provisions more heavily during bad times, as this is when banks have the greatest incentive to overstate their true financial condition.

As noted in Beatty and Liao (2014), few studies utilizing a broad panel of banking institutions have examined the valuation effects of DLLP subsequent to the mid 1990s. More recent studies have tended to focus on a subset of banks such as those audited by the largest accounting firms (Kanagaretnam et al., 2009) or those utilizing derivatives (Kilic et al., 2013). One possible explanation for this is that when failing to condition on a measure of economic outlook, we find the estimated impact of DLLP on returns to be negative and insignificant. Our study helps to fill this gap in the literature while providing an explanation for the strong conditional valuation effect.

The rest of this paper is organized as follows. Section 1.2 reviews the existing literature on DLLP valuation and credit cycles and also outlines our hypotheses. Section 1.3 describes the data and provides summary statistics. Section 1.4 outlines our methodology and the empirical tests that follow. Section 1.5 presents the results and discusses our findings. Section 1.6 offers a series of robustness tests. Section 1.7 concludes.

1.2 Hypothesis Development

1.2.1 *Background*

A number of studies have explored the valuation implications of loan loss provisions because of their significant impact on bank financial statements in addition to the large degree of information asymmetry between bank management and market participants. The *traditional view* predicts a negative relation between DLLP and stock returns, because investors are unlikely to be fully informed about the health of bank loan portfolios. As a result, positive DLLP reveals to market participants that expected loan defaults are higher than anticipated based on portfolio characteristics,

which elicits a negative stock price response. However, Beaver et al. (1989) provide initial evidence on this topic and document a surprising positive relation between a bank's allowance for loan losses, which reflects total accumulated reserves (provisions) for loan losses, and its market-to-book ratio. They reason that an observed increase in the allowance for loan losses account may be seen as positive news, because it conveys that the bank is able to absorb the "hit to earnings" associated with recording additional provision expenses. Elliott et al. (1991) offer a similar explanation suggesting the market interprets increased loan loss provisions as a sign of a bank's willingness to deal with problem loans, thus, creating a positive stock price reaction in response to loan loss reserve announcements. This argument assumes that investors are not negatively surprised by the extent of predicted loan losses for high DLLP banks and that loan loss provisions are associated with beneficial management actions that mitigate risk. Consistent with the traditional view we expect investors will not typically be fully informed about the extent of bank loan losses, leading to a negative stock price reaction to DLLP when the economy is weak and default levels are elevated.

Subsequently, researchers attempted to offer more direct evidence for why investors seemed to value provision expenses positively, as it contradicts the traditional view that loan loss provisions simply reflect expected future losses. Along these lines, Wahlen (1994) shows that when conditioning on unexpected non-performing loans and unexpected charge-offs, discretionary provisions are associated with both higher stock returns and higher future cash flows. Although this study fails to identify the mechanism leading to stronger future performance among banks with increased provisions, it highlights that there is a discretionary component of loan loss provisions that provides investors with unique value-relevant information. Liu et al. (1997), however, show that these positive valuation implications only hold for low regulatory capital banks in the fourth fiscal quarter. Although their results are consistent with prior theories offered in the literature, such as loss provisions reflecting management's commitment to resolving problem loans which is important for low capital banks, they are also consistent with provisions mechanically helping to alleviate capital constraints in the pre-BASEL period when bank reserves were counted as part of Tier 1 capital.[3] As a result, there is insufficient evidence to draw strong conclusions from their work regarding the source of positive information discretionary provisions provided to the market and whether this

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

relation should be expected to persist under the revised (current) capital standards. For the same reason, we advise readers to use caution when comparing our results with studies on the valuation of loan loss provisions in the pre-1989 period, as the positive mechanical impact of loan loss provisioning on bank capital in this earlier regime may or may not outweigh the negative information content of DLLP during downturns.

Beatty and Liao (2014) highlight that most studies examining the valuation effects of loan loss provisions utilized samples concentrated in the pre-BASEL period, and "were only focused on the signaling hypothesis of loan loss provisions without considering the valuation of other properties of provisions." Additionally, subsequent research has utilized small subsamples to address specific questions regarding the information content of loan loss provisions without exploring DLLP valuation more broadly. For instance, Kanagaretnam et al. (2009) predict that discretionary provisions will be more informative for banks audited by one of the Big 5 auditing firms in their sample and particularly so if the auditing firm was a leader in the banking industry. Consistent with this they find discretionary provisions are positively and significantly valued primarily for banks audited by one of these firms; however, they do not attempt to determine what actions high DLLP banks take to enhance shareholder value. One possible benefit of recording provisions early is noted in Beatty and Liao (2011) who show banks that build-up sufficient reserves during good times to absorb the credit losses in subsequent downturns are forced to cut lending less significantly in recessions and can avoid having to raise additional capital when it is most costly. Likewise, Laeven and Majnoni (2003) claim that "a prudent bank should show a positive association between the amount of loan loss provisions and the growth rate of its loan portfolio." Similarly, our work suggests banks benefit by building up reserves to support loan growth in times of expansion. We focus on providing a better understanding of the information content of DLLP and how it varies with overall economic conditions.

1.2.2 *Impact of Credit Cycles*

A related body of work within the finance literature that motivates our hypotheses explores credit cycles – the notion that banks and other institutions ease lending standards in boom periods when expected defaults are low while greatly tightening lending standards in downturns when expected defaults are high. Such variation in credit policies is directly related to loan loss provi-

sioning, since it is associated with both the riskiness of new loans as well as the likelihood of default on existing loans. Highlighting these periodic shifts in lending practices, Ruckes (2004) presents a model that ties variation in credit policies to changing economic conditions over the business cycle. His model demonstrates that when the economy enters a boom phase banks have less incentive to evaluate borrowers thoroughly since screening is costly and the average quality of borrowers is high. This leads to price competition among lenders and even higher risk borrowers are funded, because default is gauged to be unlikely. In contrast, during severe recessions the average quality of borrowers is low, and banks rationally choose not to spend significant resources on screening and instead implement restrictive lending policies. In our context, the model suggests that when the economy is weak, DLLP should be highest for banks experiencing loan portfolio quality issues, consistent with the traditional view of loan loss provisioning. In contrast, when the economy is strong and expected defaults are low, banks have an incentive to use DLLP to support loan growth facilitated by relaxed underwriting standards, which can lead to higher earnings and a positive market response as was found in the prior literature.

Evidence of countercyclical lending standards has also been demonstrated empirically. Asea and Blomberg (1998) study a sample of commercial and industrial loans and find that banks provide credit to borrowers on more lenient terms during expansions, whereas they charge higher risk premia on loans and increase collateral requirements during recessions. Dell'Ariccia et al. (2012) also provide evidence that mortgage denial rates were lower in high credit growth areas and lenders placed less weight on applicants' loan-to-income ratios in these regions. This suggests that new loans are granted more freely when economic growth is strong and near-term default risk is low in order to boost earnings. Further, Bassett et al. (2014) develop a unique credit supply indicator using the Federal Reserve's Loan Officer Opinion Survey, which queries banks about changes in lending standards for major loan types. Macroeconomic factors and shifts in risk tolerance are among the most commonly cited reasons for tightened lending standards, and their figures suggest credit access was most restricted during the 2001 recession and 2007–2009 financial crisis. As anticipated, 2008 represented the peak in lending tightness. Consequently, our study focuses on the related impact on bank loan loss provisioning and its valuation effects, as the information content of DLLP should vary substantially with underwriting standards and default expectations.

It is conceivable that some banks could attempt to relax their credit standards when the economy

is strong without recording heightened loan loss provisions; however, there are two primary factors that are likely to prevent this from occurring. First, although loan loss provisioning practices are based on the "incurred-loss" model, which only requires that reserves are made for losses that are probable and can be reasonably estimated, remarks from Dugan (2009) of The Office of the Comptroller of the Currency suggest regulators encouraged bankers to use "judgment that takes into account other forward-leaning factors, such as changes in underwriting standards and changes in the economic environment that would have an impact on loan losses." This indicates that regulatory pressures encourage banks to build-up reserves through reporting discretion when they plan to increase their risk-taking.

Additionally, several papers document benefits to recording timely provisions during expansions rather than waiting until substantial losses begin to materialize during downturns. For example, Beatty and Liao (2011) provide evidence that banks that record more timely provisions are forced to reduce lending less during recessions and are less subject to capital crunches, and Bushman and Williams (2012) note that forward-looking provisioning is associated with enhanced risk-taking discipline. Bushman and Williams (2015) and Andreou et al. (2017) also indicate that failing to establish sufficient reserves during good times subjects banks to increased crash risk and greater capital inadequacy concerns in recessions. Such benefits are consistent with DLLP being associated with higher market valuations in good times, as was typically found in the early literature.

In a related study, Thakor (2016) develops a theoretical model to explain how shifts in risk assessment can occur within the banking industry, which contributes to lax lending policies in expansions and tight policies in recessions. In this model, a series of successfully repaid loans causes market participants, including investors and regulators, to increase their beliefs about bankers' skill levels and risk management abilities enabling banks to take on riskier lending until creditors realize that favorable outcomes were based on chance or until defaults increase leading to an eventual crash. As a consequence of this cyclical variation in risk assessment and lending standards, we expect to find a strong conditional valuation of discretionary loan loss provisions.

In particular, banks that loosen their underwriting standards during economic booms in search of higher yields and loan growth rates will tend to increase loan loss provisions (reserves) to protect against an increase in default risk. As a result, investors will expect higher profits for these banks due to higher net interest margins on risky loans and lower default rates in boom periods, thereby

leading to a positive market reaction to discretionary loan loss provisions. In contrast, during recessions banks reduce overall lending and only provide credit to the lowest credit risk borrowers, so increases in discretionary loan loss provisions will predominantly reflect the impaired credit quality of existing loans and higher expected default rates. This results in a negative valuation of loss provisions. Essentially, discretionary loan loss provisions in bad times reveal to the market which banks have been most adversely impacted by the downturn. This leads to our main hypothesis:

Conditional Valuation Hypothesis (CVH). Investors value discretionary loan loss provisions positively in good economic times but negatively in bad economic times.

This view that the information revealed by discretionary loan loss provisions is conditional on economic conditions is also in agreement with recent statements from bank executives that while the economy remains strong overall, "some lenders are lowering credit-score requirements and taking on riskier customers." As a result, additions to loan loss reserves reflect efforts to increase loan volume.[4] By relaxing their underwriting standards, banks are looking to increase revenues at a time when conservative loans offer relatively low margins. This leads us to our second hypothesis:

Hypothesis 2. Banks that record higher discretionary loan loss provisions during good economic times will experience higher future earnings and loan growth. Conversely, when the economy is weak increased loss provisions will offer no information related to future bank performance.

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 also reflect this view, and by accounting for the variation in lending standards over the business cycle we are able to evaluate what information the market gains from the discretionary (unexpected) portion of loan loss provisions. In summary, when times are good the expectations of future loan losses are minimal and the discretionary component of loan loss provisions is associated with bank efforts to enhance loan volume. Conversely, during economic downturns management's expectation of future

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

loan losses is the dominant component of DLLP and serves to inform market participants about the extent of banks' expected loan defaults.

1.3 Data and Summary Statistics

1.3.1 *Data Description*

Bank holding company data is obtained from the Bank Regulatory database, which maintains data collected from the FR Y-9C consolidated financial statements of bank holding companies. We form our sample by taking all bank holding companies with non-missing annual data on LLP expenses and the control variables necessary to predict the expected level of LLP in addition to available 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 found in CRSP.[5]

Our sample period spans from 1997 to 2013, which successfully captures the expansionary period leading up to the dot-com bubble in which economic concerns were limited as well as both the 2001 and 2007–2009 recessions. The data in Bank Regulatory is incomplete before 2000, so we merge in data from the Federal Reserve Bank of Chicago on non-performing loans for financial statements filed between 1996 (to account for lagged predictors) and 1999 by matching year and rssdid.[6]. 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 767 unique BHCs and 6,046 bank-year observations.

In constructing the explanatory variables for estimating DLLP, we scale all accounting variables by prior year-end total assets. This helps to mitigate issues with skewness and accounts for differences in size. Additionally, we lag accounting data from bank regulatory filings by four months to ensure all information is publicly available. Cumulative stock returns are then computed over the corresponding twelve months.

To examine the impact of business conditions on DLLP valuation, we generate several indicator variables that reflect the strength of the overall economy. For our first measure we define the

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

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

variable, LowGDP, which is equal to one if the growth in real GDP was below its time series median and zero otherwise. Growth in real GDP is a primary variable used in Bassett et al. (2014) to capture the state of the economy and provides a good indication of overall economic activity.

For our second measure, following Wang et al. (2010), we proxy for the perceived strength of the economy using the industry median Tobin's Q, computed as the market value of assets scaled by the book value of assets. In theory, when investors expect good times ahead, they will be willing to pay more for the assets of the bank resulting in a higher value of Q. At the end of each year we construct the variable QLow, which takes the value one when the median bank Tobin's Q is below its time series median and zero otherwise.

Next, we generate a recession dummy, REC, which is equal to one if the economy was determined to be in a recession at the end of the annual holding period according to the National Bureau of Economic Research (NBER) business dating cycle and zero otherwise. By doing so, we define the holding periods ending in 2001, 2008, and 2009 as recessionary periods. Although analyzing years according to the NBER recession definition provides a way to study the market's reaction to DLLP conditional on economic conditions, its usefulness may be limited since relatively few periods are considered to be official recessions. Further, there may exist times when the economy was relatively weak and market participants had significant concerns related to expected defaults despite these periods not being defined as official recessions. For these reasons we expect recessionary periods to capture times of extreme economic weakness but fail to isolate times of economic strength.

For our final proxy of economic conditions we use the Index of Consumer Sentiment obtained from the University of Michigan, which is useful for distinguishing between times of relative optimism and pessimism.[7] This measure is derived from survey responses from a representative sample of U.S. households and has a natural correlation to the business cycle, as the index value is based on the percentage of favorable versus unfavorable replies for five questions pertaining to both current and future economic conditions. To generate our indicator variable, we first record the value of the Index of Consumer Sentiment at the end of each holding period. We then compute the median index value across the full sample and define a variable, SENT, equal to one in any year when the

[7] Data available at https://data.sca.isr.umich.edu/data-archive/mine.php. Data is obtained through the Survey of Consumers, Survey Research Center, University of Michigan. This data is also available through the Federal Reserve Bank of Chicago webpage and is listed under "IBEX Consumer Sentiment."

index value is below its time series median and zero otherwise.[8]

The extent to which the Consumer Sentiment Index correlates with the business cycle can be seen in Figure 1.1. There is a distinct decline in the value of the index during each of the five recessions since its inception in 1978. This is unsurprising as individuals are expected to be more pessimistic during times of economic hardship. The index also provides a real-time tracking of sentiment levels, as its value is published monthly based on new survey responses, whereas official recession dating is not established until after the fact when the business cycle dating committee can definitively identify a peak or trough in economic activity. Finally, we note the extent of the decline in the index was more severe for deeper recessions such as the 2007–2009 recession relative to the recession of 2001, which was less extreme. This provides some assurance that the index is successful in capturing market sentiment.

1.3.2 *Summary Statistics*

Table 1.1 presents summary statistics for the variables used in estimating the discretionary and non-discretionary components of bank LLP expenses. The statistics are based on the full sample containing 6,046 bank-year observations. Our main variable of interest, LLP, is computed as the ratio of bank loan loss provision expenses in year t to total assets from year-end t–*1*. To enhance the readability of coefficients in our later regression analysis, we multiply this value by 100, which converts it to a percentage of the BHC's total assets as of the beginning of the year.[9] The median bank-year involves a loan loss provision expense equal to approximately 0.25% of total assets. While it may be difficult to judge the economic significance of the LLP expense based solely on this ratio, when compared to the median ratio of bank income before loan loss provision and tax expenses to total assets (EBTP) of 1.82%, it is clear that it often has a material impact on bank performance.

Further, there is substantial variation among BHCs in regard to the amount of loan loss expenses they incur in a given year, as evidenced by LLP's standard deviation of 0.70%. There are many factors that contribute to such variation including bank risk taking, loan portfolio composition, regulatory scrutiny, and overall economic conditions. For instance, highly elevated levels of LLP

[8] We also looked at changes in the index value, which has a positive correlation with the index level; however, we expect the index level to perform better since there may be some periods where economic conditions are improving but still relatively poor. This is the case in several years at the end of our sample period.

[9] Details on variable construction can be found in Appendix Table A1.1.

expenses are expected during years in which the economy is struggling and borrower default is more likely. Also worth noting is that the median value of bank allowance for loan losses (ALL), which acts as a reserve account for future losses, is equal to 0.91% of total assets. This suggests the typical bank in our sample has sufficient reserves set aside to absorb several years worth of average sized loan losses.

It is also clear that loans represent an important asset for the vast majority of BHCs in our sample. Within bank loan portfolios, real estate loans tend to represent the largest component. The variable computed as real estate loans to total assets, RE, has a mean (median) value of 46.86% (47.93%). Commercial and Industrial loans, CI, represent a large but less substantial portion of total assets with a mean (median) value of 10.99% (9.45%). We also compute the value of all other loans, which has a mean (median) value of 7.94% (5.81%). This segment consists primarily of consumer loans, including loans for automobiles, education, and credit cards, and is pooled together as it represents a small portion of the typical balance sheet. Also reported are statistics for changes in each loan segment as a percentage of total assets. These variables indicate that the percentage of funds loaned out was generally increasing during our sample period as the means and medians for all three loan segment growth variables are greater than zero.

Panel B of Table 1.1 presents data on bank stock returns and control variables that are known predictors of stock returns. EXRET represents the annual bank stock return in excess of the one-year risk-free rate.[10] The mean (median) annual excess return during our sample is 8.23% (6.20%). Also included are statistics for the log of bank market value of equity (Log(Size)) and log book-to-market (Log(BTM)). These variables are used to control for the well-known effects of size and value, respectively.

1.4 Methodology

1.4.1 *Estimating Discretionary Loan Loss Provisions (DLLP)*

To test our conditional valuation hypothesis, it is first necessary to partition bank loan loss provision expenses into a discretionary and non-discretionary component. It has been well documented that a large degree of estimation and subjectivity is involved in determining the loan loss

[10] Data on risk-free returns used in the construction of this variable are obtained from Ken French's Data Library.

provision expense, but while it is undeniable that room for managerial discretion exists, there are also many factors that necessitate additional loan loss provisions. For instance, a BHC with a large increase in non-performing loans, in which borrowers are failing to make payments in accordance with the terms of their loan contracts, would require a large loan loss provision to cover the higher expected losses.[11]

Following prior literature, we estimate a bank's required level of loan loss provision (LLP) expenses by taking the fitted value from a regression model that controls for known determinants of LLP. Most of the control variables have clear theoretical motivation and are used widely in prior research, while others such as the loan type variables are infrequently used but reflect important differences in risk exposure. Our LLP estimation equation is shown below in equation 1.1.

$$\begin{aligned} LLP_{i,t} = {} & \beta_0 + \beta_1 ALL_{i,t-1} + \beta_2 NPL_{i,t-1} + \beta_3 \Delta NPL_{i,t} + \beta_4 RE_{i,t-1} + \beta_5 \Delta RE_{i,t} \\ & + \beta_6 CI_{i,t-1} + \beta_7 \Delta CI_{i,t} + \beta_8 OtherLoans_{i,t-1} + \beta_9 \Delta OtherLoans_{i,t} \\ & + \beta_{10} NetCO_{i,t} + Time_t + \epsilon_{i,t} \end{aligned} \tag{1.1}$$

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 a greater level of reserves to begin the year. An LLP expense is used to replenish the value of this account as losses materialize and as loss expectations change; therefore, a higher beginning of year value implies less need to increase reserves further.

There are also many controls used to capture important loan portfolio characteristics that affect the level of expected losses. We control for both the lagged value of non-performing loans (NPL) as well as the change in non-performing loans (ΔNPL) during year *t*. The expected sign on each is positive; however, we expect the coefficient for ΔNPL to be greater in magnitude, because previously identified non-performing loans may not require additional reserves to the extent that sufficient reserves were made, and provision expenses incurred, in prior periods.

Further, we control for the lagged values of real estate loans (RE), commercial and industrial loans (CI), and other loans (OtherLoans). Banks engaged in a greater level of lending activity are likely to incur more loan related losses, so we expect positive coefficients on each of these controls.

Most prior studies have ignored loan segment variables when estimating the discretionary and

[11]Non-performing loans is computed as the sum of loans 90 days or more delinquent and still in accrual status, plus any loans that have been placed in non-accrual status (items bhck5525 and bhck5526).

non-discretionary components of LLP; however, failure to include them could result in an inaccurate estimation of the LLP components since, for example, a residential real estate loan may have a different expected loss than a business loan of equal value. As estimation procedures have become more refined some studies have incorporated loan type variables (e.g., Cornett et al., 2009; Kanagaretnam et al., 2010; DeBoskey and Jiang, 2012); however, in our estimation we go one step further and also include variables reflecting changes in loan portfolio composition: ΔRE, ΔCI, and ΔOtherLoans.

Additionally, we control for net charge-offs (NetCO), which is the amount of bank loans charged-off in year t less any recoveries. This should have a strong positive relation to LLP, as the relation is, to an extent, mechanical. A loan charge-off reflects the materialization of a loan loss and directly reduces the value of a bank's allowance for loan losses (ALL). Consequently, high levels of loan charge-offs result in the need to replenish the ALL account. While it is possible that some discretion could also be utilized in regards to the timing of the charge-off decision, failing to control for charge-offs would confound our measure of DLLP, as banks that experience higher realizations of loan defaults would be likely to have higher DLLP values. Additionally, the degree of discretion in the charge-off decision is less substantial, and if anything, controlling for it should produce more conservative estimates.

Lastly, we include year indicator variables to control for the impact of changes in the regulatory environment, overall economic conditions, and other time specific factors. This also accounts for the average economic expectations among managers, which can influence their estimates of future losses.[12]

Although we do not include them as predictors in our main specification, we also explore the impact of controlling for earnings before taxes and LLP expenses (EBTP) in year t and the lagged level of bank Tier 1 capital (Tier1). There is some debate in the literature on whether the effect of these terms on bank LLP reflects managerial discretion or relevant underlying loan portfolio characteristics.[13] Most studies have interpreted a positive coefficient on EBTP and Tier1 as evidence of earnings management and capital management, respectively. For instance, a positive

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

[13]Among many others, Kim and Kross (1998), Ahmed et al. (1999), Fonseca and González (2008), Cornett et al. (2009), DeBoskey and Jiang (2012), and Dolar (2016) explore the use of DLLP to achieve managerial objectives and provide mixed evidence.

coefficient on EBTP is consistent with banks recording more LLP expenses in years when their earnings are high because they can greater afford to, and banks under-reporting LLP expenses when their earnings are low in order to boost reported income, thus, effectively smoothing income over time. Likewise banks may be more willing to record LLP expenses when they have sufficiently high amounts of Tier 1 capital but become more hesitant as capital is depleted.[14] This is the position we adopt here, and we interpret positive coefficients on these variables as evidence of the aforementioned managerial biases. Additionally, there are many other reasons why management may choose to record discretionary provision expenses, which we do not explicitly test for.

By omitting the EBTP and Tier1 variables from our main specification, we will effectively be capturing these discretionary influences in the error term of equation 1, which is our intent. All other factors including plans to pursue aggressive loan growth strategies and other private information not reflected in the financial statements will also be captured in the error term. That is, we effectively decompose LLP into two components as shown below in equations 1.2 and 1.3, where the non-discretionary component of loan loss provisions (NDLLP) is the predicted value of LLP from equation 1, and the discretionary component of loan loss provisions (DLLP) is the difference between actual loan loss provisions and predicted loan loss provisions.

$$NDLLP = \widehat{LLP} \tag{1.2}$$

$$DLLP = LLP - \widehat{LLP} \tag{1.3}$$

1.4.2 *Testing the Conditional Market Valuation of DLLP*

Having estimated the discretionary component of loan loss provisions, we can now test our hypothesis that the information it conveys to the market is conditional on the state of the economy (CVH). The prior literature has generally found DLLP to be associated with higher bank stock returns; however, when the economy is struggling borrower defaults occur more frequently, and loan losses represent a major concern. Thus, we expect that DLLP recorded in bad economic states primarily reflect management's inside information about a deteriorating loan portfolio leading to a negative stock price response. Further, during economic downturns most financial institutions

[14] As noted earlier, this would not hold for the pre-BASEL period; however, our sample begins after the regulatory changes that resulted in the allowance for loan losses being excluded from Tier 1 capital.

tighten their credit standards, making it unlikely that extra provision expenses are recorded to support more aggressive lending policies. To test our conditional valuation hypothesis, we estimate the following regression:

$$\begin{aligned} EXRET_{i,t} = \beta_0 + \beta_1 DLLP_{i,t} + \beta_2 LowGDP_t * DLLP_{i,t} + \beta_3 NDLLP_{i,t} \\ + \beta_4 LowGDP_t * NDLLP_{i,t} + \beta_5 EBTP_{i,t} + \beta_6 Log(Size)_{i,t-1} \\ + \beta_7 Log(BTM)_{i,t-1} + \beta_8 Tier1_{i,t-1} + Time_t + \epsilon_{i,t}. \end{aligned} \tag{1.4}$$

We regress a BHC's excess return in year t (EXRET) on DLLP, NDLLP, interactions of LowGDP with each LLP component, and several controls for known determinants of stock returns. Our primary coefficients of interest are β_1 and β_2. A positive value of the coefficient β_1 supports our hypothesis that the markets value discretionary loss provisions positively when the economy is strong and a subset banks record excess provisions to support their increased lending efforts. However, we expect to find a negative value of the coefficient β_2, implying that the positive reaction only occurs during "good times", and the market instead views extra loan loss provisions as a source of negative information when the economy is struggling. We repeat this analysis by interacting each of our four different proxies for economic conditions with DLLP and expect to find consistent results in each instance.

The non-discretionary component of earnings, NDLLP, is expected to be negatively associated with returns regardless of the state of the economy given that it represents higher losses directly related to loan portfolio characteristics. Although it is unclear whether the magnitude of its coefficient would differ during periods of strong versus weak growth, we interact this variable with the LowGDP indicator as well to empirically test this possibility.

We also include year indicator variables in all specifications to alleviate the concern that the results are driven by abnormally high or low bank stock returns in a particular year.[15] Given that we are studying firms from only one industry, the returns for most of our observations tend to be relatively high or relatively low within a given year; therefore, year controls are used to capture the market performance of the banking sector.

[15]We do not include the LowGDP indicator variable in the same specification, as it cannot be estimated due to collinearity with the year indicator variables.

1.4.3 *Effect of the Financial Crisis on DLLP Valuation*

The 2008 financial crisis represents a period of economic weakness when lending standards tightened significantly and bank loan portfolios were highly distressed. Consequently, our hypotheses suggest the market will value DLLP even more negatively during this period than in less severe downturns, as loan loss provisions were expected to be recorded almost exclusively to cover losses on existing problem loans. Additionally, there may be some concern that the financial crisis is solely responsible for the conditional valuation effect. In order to ensure this is not the case and to test our hypothesis, we generate a dummy variable, CRISIS, which takes the value of one during the holding periods ending in 2008 and 2009 and zero otherwise. We add an additional interaction term between this indicator variable and DLLP with the regression equation displayed below.

$$\begin{aligned} EXRET_{i,t} = \beta_0 &+ \beta_1 DLLP_{i,t} + \beta_2 LowGDP_t * DLLP_{i,t} + \beta_3 CRISIS_t * DLLP_{i,t} \\ &+ \beta_4 NDLLP_{i,t} + \beta_5 LowGDP_t * NDLLP_{i,t} + \beta_6 CRISIS_t * DLLP_{i,t} + \beta_7 EBTP_{i,t} \\ &+ \beta_8 Log(Size)_{i,t-1} + \beta_9 Log(BTM)_{i,t-1} + \beta_{10} Tier1_{i,t-1} + Time_t + \epsilon_{i,t} \end{aligned} \tag{1.5}$$

We expect to find a positive value for β_1 as before; however, this specification allows us to test if there is a differential impact of how the market values DLLP when the economy is relatively weak compared to when it is experiencing a severe recession. Given that the banking industry as a whole tightens lending standards during periods of economic weakness, we expect negative values for both β_2 and β_3. This is consistent with DLLP being more reflective of loan default problems than plans to implement loan growth strategies when the economy is relatively weak and implies the valuation effect is even more negative during the crisis when loan defaults became a major concern. Alternatively, if the crisis period is completely driving the conditional valuation of DLLP, then the significance of β_2 will be subsumed by the crisis interaction term and only β_3 will be significantly negative, suggesting that DLLP is positively valued aside from times of severe financial crisis.

1.5 Results

1.5.1 *Discretionary Loan Loss Provisions (DLLP) Estimation*

In this section, we begin by estimating the discretionary and non-discretionary components of loan loss provisions to test our conditional valuation hypothesis. Table 1.2 presents the results from regressions of bank loan loss provisions on a set of control variables used to determine a bank's expected loan losses. We focus primarily on the results of our baseline model from equation 1.1, which are reported in the first column.

As expected, the allowance for loan losses (ALL) has a significantly negative effect on LLP expenses. For each additional dollar of loss reserves in the ALL at the end of the prior year, approximately 24.7 fewer cents are expected to be expensed. This is unsurprising because, all else equal, a higher ALL balance implies the bank has greater reserves already built up to absorb future losses. Further, we find a significantly positive coefficient on each of our loan type variables, and the coefficients are significantly different from one another reflecting the varying risk levels associated with different loan types. For instance, the coefficient on CI is 0.742, which is greater than the coefficient on RE or OtherLoans, reflecting the higher risk associated with commercial lending.

Net charge-offs (NetCO) enters with a coefficient of 106.65 suggesting that for every $1 of loans charged-off, approximately $1.07 is expensed. In other words, banks contribute roughly one additional dollar to the allowance for loan losses account for each dollar of loans deemed uncollectible to replenish its value. The fact that our coefficient exceeds one may be a reflection of the use of historical loss ratios by banks to estimate future losses; thus, resulting in higher reserves following periods of elevated losses.

Finally, we include year indicator variables in our baseline specification to capture industry-wide, time-varying effects. Although unreported, many year indicators are significant, with 2008 and 2009 having the most positive coefficients. This is a product of the heightened loan losses during the financial crisis resulting in the need for substantial provision expenses. Column 2 is the only specification where we omit year controls. We find the R-squared value declines and many of the coefficients change noticeably when omitting these as right-hand side variables suggesting it is important to control for time effects.

In columns 3 through 5, we add controls for either earnings before taxes and provision expenses (EBTP), the level of Tier 1 capital, or both. In column 3, EBTP enters with a positive but statistically insignificant coefficient, and in column 4 Tier1 has a positive and significant coefficient. This implies the extent to which most banks used DLLP to engage in income smoothing in our sample period was somewhat limited but is consistent with prior findings of capital management. In column 5, we include both EBTP and Tier1 and find the coefficient on EBTP becomes negative, albeit insignificant, while Tier1 is still positive and significant at the five percent level. This suggests the management of bank capital levels is one additional factor that may cause banks to bias their loan loss estimates; however, it does not generate predictions consistent with our hypotheses, as its effect on valuation should be similar in all states of the economy.

It is worth mentioning that our main specification in column 1, which will be used for the remainder of the analyses, has a very high R-squared value of 0.893. This is substantially higher than what is typical in prior literature predicting the level of LLP.[16] While much of this may be due to the use of a broader sample with more variation as well as differences in sample periods, we have also included many important predictors in estimating the levels of DLLP and NDLLP that were often omitted in earlier studies. This is crucial because failure to accurately partition LLP will limit the power and reliability of our tests. The fact that we can explain the majority (89.3%) of the variation is expected given that there are many observable loan portfolio quality indicators that have a sizable impact on loan loss provisions. Going forward, the regression residuals are referred to as DLLP, since they represent provision expenses unexplained by loan portfolio characteristics reported in the financial statements, and the fitted values from our regression are referred to as NDLLP. We also winsorsize the DLLP variable at the 2.5$^{\text{th}}$ and 97.5$^{\text{th}}$ percentiles to mitigate the effect of outliers.[17]

In addition, the results from Table 1.2 reveal the inclusion of EBTP and Tier1 has a minimal impact on the regression R-squared value, and when reported to three decimal places the R-squared values are the same. This is consistent with the non-discretionary determinants of loan loss pro-

[16]For reference, Huizinga and Laeven (2012) report an R^2 ranging from 0.357 to 0.515 but use quarterly LLP. Kanagaretnam et al. (2009) obtain an adjusted R^2 of 0.3659 while using a smaller sample of 837 bank-year observations that is likely to exhibit much less variation. Ahmed et al. (1999) report an adjusted R^2 ranging from 0.20 to 0.24 with annual data but fail to control for the level of net charge-offs and ALL, and they include a time regime dummy rather than year dummies, all of which are found to be important predictors.

[17]We examine the results when winsorizing instead at the 1$^{\text{st}}$ and 99$^{\text{th}}$ or 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles and find the results are robust.

visions explaining more of the overall variation than the discretionary components, although other factors captured in the error term, such as management's private information about its loan portfolio and plans to alter credit standards, are expected to have a stronger impact than EBTP or Tier1.

1.5.2 *Conditional Valuation of DLLP*

Having estimated both discretionary and non-discretionary loan loss provisions, we now explore the valuation of DLLP and test our main hypothesis (CVH). We expect to find a strong conditional valuation of DLLP, as the factors that drive managers' decisions of whether to record extra loss provisions depend highly on the state of the economy. Specifically, when overall economic activity is increasing, managers have an incentive to loosen underwriting standards in order to grow their loan portfolios and boost earnings as suggested by Ruckes (2004), which can produce a positive market response given that expected defaults are low. However, when economic growth slows, banks lend more conservatively, thereby reducing the risk associated with new loans being granted. At the same time, the likelihood that existing borrowers default increases making it necessary for managers of troubled institutions to record extra loss provisions to cover looming defaults, resulting in a negative valuation of DLLP recorded in bad economic times. To test the CVH, we regress annual bank excess returns on the value of each component of provision expenses, DLLP and NDLLP, an interaction of each component with one of our four proxies for economic conditions, earnings before taxes and provision expenses, EBTP, and other known determinants of stock returns. Table 1.3 presents the results.

In Panel A, we test our hypothesis using the indicator for low real GDP growth as a proxy for the overall state of the economy. The primary coefficients of interest are on DLLP and the LowGDP-DLLP interaction term. As predicted, we find the estimate of DLLP's impact on returns is positive during periods of strong economic growth but negative during times when the economy is weak. A Wald test on the sum of the β_1 and β_2 coefficients confirms the marginal effect of DLLP during periods of low growth is negative and significant at the one percent level, thus, highlighting that investors perceived loan portfolio weakness as the primary driver of DLLP in bad states of the economy.[18]

[18]We also repeat the analysis focusing separately on investor reactions to banks that over-reserve (positive DLLP)

Panel B repeats the analysis using the industry median Tobin's Q, measured as the average ratio of market value of assets to book value of assets, as an alternate proxy for economic conditions. We obtain results that are qualitatively similar to before with DLLP being positively valued during good times, when average bank Q values are high, and negatively valued during bad times. The coefficient on DLLP is positive and significant at the five percent level while the interaction term is negative and significant at the one percent level.

In Panel C, we interact the recession indicator based on the NBER's business cycle dates with DLLP. As predicted, we find the estimate of DLLP's impact on returns is positive during periods of expansion but negative during recessions. It is worth noting, however, that the coefficient on DLLP is small and statistically insignificant, which highlights the shortcomings of the recession indicator. The REC variable succeeds in identifying the years of greatest economic concern, as evidenced by the significantly negative coefficient on the REC-DLLP interaction, but classifies relatively few years as official recessions even when the economy is relatively weak. This results in a much smaller and insignificant coefficient on DLLP.

For our final proxy of economic conditions we use the consumer sentiment index with the results presented in Panel D. Our findings are similar to before in terms of the signs of the coefficients, and DLLP once again enters with a significantly positive coefficient. This suggests that in years when the level of consumer sentiment was high, investors viewed banks with higher levels of DLLP favorably, as these institutions were expected to increase their lending efforts more substantially.

Additionally, all of the control variables enter with the expected signs. The non-discretionary component of loan loss provisions, NDLLP, has a negative and significant coefficient in all specifications as predicted given that this variable reflects the amount of distress in bank loan portfolios based on financial statements. Further, its effect does not seem to be greatly impacted by economic conditions, as the coefficient on its interaction term is small in magnitude and only statistically significant in Panels B and C. Our controls for earnings, size, book-to-market, and Tier 1 capital are also significant at the one percent level, and in all panels we include year dummy variables. Although unreported, many of the year controls enter significantly as well. Because individual banks appear in our sample over multiple years, we cluster standard errors at the bank level, which

compared to those that under-reserve (negative DLLP) for future loan losses with the results reported in Appendix Table A1.2. We find the general results are consistent in both cases, although the market reaction to positive DLLP is stronger, consistent with banks having greater leeway to over-reserve than under-reserve.

addresses the concern that regression residuals may be correlated across time for the same bank holding company.

1.5.3 *DLLP and Future Bank Performance*

There is much theoretical and empirical evidence that bank lending standards vary dramatically over the business cycle (Asea and Blomberg, 1998; Ruckes, 2004; Dell'Ariccia et al., 2012; Bassett et al., 2014). As a result, the factors that cause managers to record discretionary loan loss provisions are expected to vary as well. We have already seen that investors value discretionary loan loss provisions positively when economic growth is strong but negatively when economic growth is weak, and we now test our second hypothesis that DLLP will be associated with higher future earnings growth and lending activity in good states of the economy.

In Table 1.4, we partition our sample period based on whether the predictor variables, including DLLP, are measured during years of above or below median real GDP growth. Next, we regress various measures of future bank performance on current period values of DLLP, NDLLP, and a set of control variables.

Consistent with our hypothesis, we find that during periods when the economy is strong, as reflected in high real GDP growth, DLLP is associated with significantly higher earnings before taxes and provision expenses in the following year. Further, when examining specific components of earnings as the outcome variable, we observe that DLLP has a significantly positive relation with next period net interest income (NII) but is not significantly related to non-interest income (NonII) or non-interest expenses (NonIE). This adds support to the theory that these high DLLP banks relax lending standards in order to obtain higher yielding loans, as the impact is manifested in observable outcomes. Finally, in the last column we see that DLLP is positively related to future loan growth, although the relation is only marginally significant. Overall, these results support our hypothesis that when the economy is healthy and borrowers are less likely to default, bank managers who set aside excess reserves do so to establish a cushion for potential losses as they pursue loan growth strategies that include higher interest rate loans. Therefore, the extra provision expenses serve as an indication of the bank's increased future earnings potential.

Conversely, when economic growth is low we find no relation between DLLP and future earnings or loan growth. The coefficient on DLLP is insignificant at the five percent level in all of the

predictive regressions and is significantly negative in predicting net interest income at the ten percent level. This suggests that during bad economic times DLLP offers few predictions for the future performance of the bank, and as a result simply represents additional expenses taken in the current period to cover loan losses.

1.5.4 *Impact of the Financial Crisis*

Table 1.5 explores the valuation of DLLP during the 2008 financial crisis, which was a time of extreme financial distress for a large number of banks. Consistent with prior results, DLLP enters with a positive coefficient that is significant at the one percent level in all specifications. Interestingly, the interaction of DLLP and LowGDP still enters with a significantly negative coefficient even after the inclusion of the CRISIS-DLLP interaction term. Thus, we find that even during times of relative – but not extreme – economic weakness, DLLP is not valued positively by the market. In fact, the estimated marginal effect ($\beta_1 + \beta_2$) of discretionary loan loss provisions on returns is negative and significant at the ten percent level.

We also find there was a significant incremental effect of the financial crisis on the market's valuation of DLLP, as the overall effect of DLLP on returns became much more negative during this period. This is reflective of the fact that growing investor fears over underlying loan portfolio quality were the dominant force at the time. The estimated marginal effect ($\beta_1 + \beta_2 + \beta_3$) of discretionary loan loss provisions on returns during the crisis is negative and significant at the one percent level.

1.6 Robustness

This section presents a series of robustness tests to help rule out alternate explanations. Specifically, we explore the valuation of DLLP over various sub periods and around significant economic events during the financial crisis. We also form a matched sample of high and low DLLP banks to help minimize any remaining endogeneity concerns.

1.6.1 *Subperiod Analysis*

To rule out the possibility that our results are driven by a specific period of time and to shed more light on our analysis, we conduct regressions that decompose our sample into five separate subperiods with the results presented in Table 1.6. We find the market reaction to DLLP is positive during periods of expansion and strong growth such as the late 1990s and mid 2000s. The last row reports the average growth rate of real GDP, which was much higher during these two sub periods; thus, highlighting the strength of the economy in these times. During the subsample spanning 2000 to 2002, the coefficient on DLLP is negative but also small and only marginally significant. This period includes the recession following the dot-com boom; however, the recession was relatively short-lived, officially lasting only eight months, and consumer optimism was still near average levels. In contrast, the financial crisis was much more severe and coincided with a major decline in economic output, consumer confidence, and credit availability. The market reaction to DLLP during this period was extremely negative and significant at the one percent level, consistent with the market perceiving higher than expected loan loss provisions as being driven by problems in bank loan portfolios. We also find a negative but less extreme reaction to DLLP in the period following the financial crisis, as economic concerns dissipated slowly.

Most prior studies on DLLP valuation explore periods prior to 2006, and our results are in agreement with the general finding of a positive market valuation during that time. This is consistent with our explanation, as economic growth was strong during most of the 1990s through the mid-2000s. Overall, the findings of this table support the notion of a strong conditional market valuation dependent upon the health of the economy.

1.6.2 *Major Events of the Financial Crisis*

To add to the evidence of the conditional valuation of DLLP, we exploit two plausibly exogenous events that occurred during the 2008 financial crisis. We first sort banks into quintile portfolios based on their value of DLLP, and we define the portfolio DLLPQ5, which includes banks in the top quintile and DLLPQ1, which includes banks in the bottom quintile. We then study the returns of each portfolio relative to the S&P 500 index around major events that are expected to alter the level of concern regarding loan defaults and consumer confidence in the banking sector. In each

case we use a return measurement window spanning from one trading day before the event to one day after the event. Table 1.7 displays the results.

Panel A presents returns around the seizure of IndyMac Bank by federal regulators on July 11, 2008, which was driven to a large extent by a substantial increase in mortgage defaults and represented one of the largest bank failures in U.S. history. Although this event sent a shock through the entire banking sector, it is observed that high DLLP bank stock prices suffered much more, falling by 4.79% relative to the S&P 500 index compared to just 2.04% for low DLLP banks. This difference is significant at the five percent level, and is consistent with our evidence that investor fears over loan defaults result in a negative valuation of DLLP when the economy is struggling.[19]

Panel B explores returns around the announcement of the proposal for the Troubled Asset Relief Program (TARP) by then Treasury Secretary, Henry Paulson, on September 19, 2008. Although the program details were not yet known at this time, the intent to increase the liquidity of the secondary mortgage market and provide major relief to distressed financial institutions was clearly communicated. We observe that this had a major impact on bank valuations, but that stock prices for high DLLP banks increased significantly more as their average return relative to the S&P 500 was 11.91% compared to 5.38% for low DLLP banks. This suggests the market anticipated that banks with high DLLP would benefit more substantially from the bailout and that the program would help lessen the negative impact of bad assets on their financial statements.

1.6.3 *Matched Sample Analysis*

To provide assurance that bank differences in DLLP are driving the results, as opposed to bank differences along some other dimension, we conduct a matched sample analysis with the results presented in Table 1.8. To form our sample, we first take banks in the top quintile of DLLP each year based on the indicator DLLPQ5. We then match each high DLLP bank to the bank with the most similar characteristics within the same year that does not record a high level of DLLP. Specifically, we match banks using nearest neighbor matching based on their computed mahalanobis distance, which takes into account how large the differences are in their characteristic values for NDLLP, EBTP, log size, log book-to-market, and tier 1 capital.

[19] 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.

Panel A presents mean characteristic values for high DLLP banks as well as for all other banks prior to creating a matched sample. The values are presented separately for years when real GDP growth is low (LowGDP = 1) and high (LowGDP = 0), since our goal is to measure the market reaction to DLLP separately during these periods. We find that many significant differences exist between the two groups of banks as indicated by the reported p-values from tests for differences in means.

Panel B reports the average characteristic values for the high DLLP banks and their corresponding matches. Here we observe that the matching procedure is effective at minimizing characteristic differences, as the two groups no longer exhibit a significant difference along any of the key variables in periods of high or low GDP growth. This allows for a cleaner evaluation of the valuation of DLLP.

The measured effect of recording high levels of discretionary loan loss provisions is reported in Panel C. We find that during good economic times, banks with high levels of DLLP earn an annual return that is, on average, 5.58% higher than other similar banks with lower levels of DLLP. Conversely, during bad times high DLLP banks earn an annual return that is, on average, 5.49% lower than comparable banks with lower DLLP. Both estimates are statistically significant at the one percent level. This helps confirm that much information is contained in the loan loss estimates provided by banking institutions, and that economic conditions play a large role in whether investors are likely to view DLLP positively or as a major cause for concern. In unreported tests, we find the results are robust to the use of alternate matching mechanisms including propensity score matching.

1.7 Conclusions

Prior research has generally found that the market values discretionary loan loss provisions positively but has failed to reach a conclusion for what drives this finding and has relied on relatively limited sample periods. Motivated by evidence of substantial variation in lending standards over the course of the business cycle, this study explores the effect of economic conditions on the valuation of discretionary loan loss provisions and documents a strong conditional valuation effect. In particular, we show that discretionary loan loss provisions are positively valued during years of strong economic growth when banks tend to loosen underwriting standards, whereas the market reacts negatively

to DLLP recorded during economic downturns when credit policies become more restrictive. This result is robust to the choice of proxy for economic conditions and also holds when examining a matched sample in which banks only exhibit significant differences in their levels of DLLP.

Intuitively, during periods of economic growth banks tend to relax lending standards in order to increase loan volume and generate higher interest income. Bank managers who plan to implement such growth strategies can use DLLP in order to build up reserves that protect against the increased credit risk. In this case, the extra provision expenses serve as an indication to investors of the bank's increased future earning potential and defaults are expected to remain low given the health of the economy. However, when earnings are depressed and more borrowers are likely to experience financial hardship, DLLP is no longer valued positively as banks tighten their lending standards and are only expected to record extra provision expenses when many existing problem loans are nearing default. This results in a significantly negative valuation of DLLP recorded during bad states of the economy.

In addition, we find that not only did market participants respond negatively to discretionary loan loss provisions during periods of low economic growth; they also did so much more severely during the financial crisis. This is consistent with our main hypothesis, as it became increasingly clear that DLLP recorded during this period was reflective of management's private information about distress within its loan portfolio. This also suggests that bank regulators, in particular, have reason to evaluate loan loss provisions with more scrutiny during bad times, as this is when banks are able to benefit most by overstating their true financial health.

Table 1.1: Summary Statistics

The sample contains 6,046 bank-year observations and 767 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 each variable used in the regression analysis within our study. Panel A reports statistics for the accounting variables. LLP is equal to a BHC's provision for loan loss expense in year t multiplied by 100 and scaled by total assets at the end of year $t-1$. Similarly, we scale all accounting variables by prior year-end total assets. 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 OtherLoans are measured as lagged total real estate, commercial and industrial loans, and other loans, respectively. ΔRE, ΔCI, and ΔOtherLoans represent first differences between years t and t-1 for real estate, commercial and industrial, and other loans, respectively. NetCO is the amount of net charge-offs computed as total charge-offs minus recoveries. Panel B reports statistics on stock market data. EXRET is a BHC's annual stock return in excess of the one-year risk-free rate. Log(Size) is the natural 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.

Panel A: Accounting Data

	Mean	Median	Stdev	P1	P5	P95	P99
LLP	0.4642	0.2465	0.7029	-0.1437	0.0000	1.7258	3.7159
EBTP	0.0185	0.0182	0.0155	-0.0169	0.0032	0.0329	0.0505
Tier1	0.0906	0.0857	0.0383	0.0506	0.0606	0.1276	0.1869
ALL	0.0099	0.0091	0.0049	0.0008	0.0044	0.0189	0.0283
NPL	0.0092	0.0050	0.0122	0.0000	0.0005	0.0328	0.0592
ΔNPL	0.0014	0.0002	0.0098	-0.0204	-0.0086	0.0144	0.0383
RE	0.4686	0.4793	0.1570	0.0045	0.1999	0.7078	0.8039
ΔRE	0.0618	0.0386	0.1172	-0.1168	-0.0500	0.2438	0.4838
CI	0.1099	0.0945	0.0747	0.0003	0.0177	0.2500	0.3797
ΔCI	0.0125	0.0065	0.0356	-0.0548	-0.0234	0.0649	0.1390
OtherLoans	0.0794	0.0581	0.0776	0.0004	0.0049	0.2024	0.3336
ΔOtherLoans	0.0058	0.0012	0.0267	-0.0499	-0.0194	0.0428	0.1053
NetCO	0.0038	0.0018	0.0061	-0.0006	0.0000	0.0155	0.0313

Panel B: Market Data

	Mean	Median	Stdev	P1	P5	P95	P99
EXRET	0.0823	0.0620	0.3655	-0.7639	-0.4797	0.6941	1.1019
Log(Size)	12.4755	12.0899	1.8243	9.6516	10.2220	16.3168	18.0689
Log(BTM)	-0.0569	-0.0466	0.0937	-0.2646	-0.1729	0.0390	0.0640

Table 1.2: Estimation of Bank Loan Loss Provisions

This table presents regressions of annual BHC loan loss provisions (LLP) on a set of predictor variables that affect the level of loan losses. The dependent variable in each specification is LLP, which is calculated as the dollar amount of bank loan loss provisions in year t, scaled by bank total assets at year-end $t - 1$. We multiply this coefficient by 100 to transform it to a percentage, and enhance the readability of the coefficients. Independent variables are all scaled by lagged assets and include earnings before taxes and provision expenses (EBTP), Bank Tier 1 Capital (Tier1), allowance for loan losses (ALL), non-performing loans (NPL), the change in non-performing loans (ΔNPL), total real estate loans (RE), the change in real estate loans (ΔRE), total commercial and industrial loans (CI), the change in commercial and industrial loans (ΔCI), loans other than RE and CI (OtherLoans), the change in other loans (ΔOtherLoans), and net charge-offs measured as the difference between annual charge-offs and recoveries (NetCO). Columns 1, 3, 4, and 5 include year dummy variables to control for variation in LLP due to the economic conditions in different time periods. Standard errors are clustered at the firm level, with the corresponding t-statistics reported below in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
EBTP			0.221		-0.153
			(0.91)		(-0.41)
Tier1				0.224***	0.256**
				(2.96)	(2.10)
ALL	-24.665***	-26.898***	-24.726***	-24.797***	-24.773***
	(-10.25)	(-11.19)	(-10.33)	(-10.32)	(-10.35)
NPL	1.860***	1.521**	1.902***	1.892***	1.867***
	(2.63)	(2.27)	(2.69)	(2.68)	(2.66)
ΔNPL	12.316***	13.715***	12.315***	12.300***	12.299***
	(9.03)	(10.33)	(9.02)	(9.03)	(9.03)
RE	0.417***	0.442***	0.421***	0.423***	0.421***
	(12.32)	(13.34)	(12.31)	(12.35)	(12.24)
ΔRE	0.154**	0.146**	0.152**	0.152**	0.153**
	(2.07)	(2.07)	(2.03)	(2.03)	(2.03)
CI	0.742***	0.813***	0.745***	0.754***	0.754***
	(10.11)	(10.76)	(10.18)	(10.24)	(10.24)
ΔCI	0.095	0.006	0.090	0.092	0.095
	(0.43)	(0.03)	(0.41)	(0.42)	(0.43)
OtherLoans	0.211***	0.253***	0.207***	0.207***	0.209**
	(3.22)	(3.93)	(3.23)	(3.21)	(3.28)
ΔOtherLoans	0.094	0.041	0.086	0.084	0.088
	(0.52)	(0.23)	(0.48)	(0.46)	(0.49)
NetCO	106.652***	109.646***	106.678***	106.730***	106.724***
	(62.26)	(65.35)	(62.35)	(62.44)	(62.47)
Year Controls	Y	N	Y	Y	Y
R-squared	0.893	0.888	0.893	0.893	0.893

Table 1.3: Effect of Economic Conditions on DLLP Valuation

This table presents regressions that test the valuation of discretionary loan loss provisions (DLLP) conditional on the state of the economy. In each panel, DLLP is interacted with an indicator variable that takes a value of one in the down state of the economy and zero otherwise. Specifically, LowGDP is set equal to one in years real GDP growth was below its time series median, LowQ takes the value one when the median bank Tobin's Q is below its time series median, REC is set equal to one if NBER determined the economy was in recession, and SENT is set equal to one when the Consumer Sentiment Index is below its time series median. Year dummy variables 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 clustered at the firm level, with the corresponding t-statistics reported below in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Real GDP Growth								
	DLLP	LowGDP x DLLP	NDLLP	LowGDP x NDLLP	EBTP	Log Size	Log BTM	Tier1
Coefficient	0.141***	−0.263***	−0.125***	0.014	8.131***	−0.010***	0.954***	−0.827***
t-statistic	(3.06)	(-4.41)	(-8.02)	(0.80)	(11.01)	(-4.91)	(8.67)	(-5.20)
Panel B: Industry Tobin's Q								
	DLLP	LowQ x DLLP	NDLLP	LowQ x NDLLP	EBTP	Log Size	Log BTM	Tier1
Coefficient	0.093**	−0.225***	−0.138***	0.031**	8.179***	−0.010***	0.958***	−0.838***
t-statistic	(2.31)	(-3.88)	(-11.28)	(1.97)	(11.02)	(-4.86)	(8.62)	(-5.24)
Panel C: Economic Recession								
	DLLP	REC x DLLP	NDLLP	REC x NDLLP	EBTP	Log Size	Log BTM	Tier1
Coefficient	0.005	−0.269***	−0.105***	−0.038**	8.100***	−0.010***	0.951***	−0.812***
t-statistic	(0.15)	(-4.42)	(-10.94)	(-2.27)	(10.89)	(-4.73)	(8.48)	(-5.03)
Panel D: Consumer Sentiment								
	DLLP	SENT x DLLP	NDLLP	SENT x NDLLP	EBTP	Log Size	Log BTM	Tier1
Coefficient	0.113***	−0.243***	−0.134***	0.025	8.151***	−0.010***	0.957***	−0.829***
t-statistic	(2.58)	(-4.04)	(-9.13)	(1.47)	(10.94)	(-4.93)	(8.69)	(-5.22)

Table 1.4: DLLP and Future Bank Performance

This table presents results for predictive regressions where the dependent variable is either one-year ahead earnings before taxes and provision for loan loss expenses (EBTP), net interest income (NII), non-interest income (NonII), non-interest expense (NonIE), or the cumulative loan growth over the following 3-year period (LoanGr). The explanatory variables include the year t values of the discretionary component of bank loan loss provision expenses (DLLP), the non-discretionary component of the loan loss provision expenses (NDLLP), changes in non-performing loans (ΔNPL), and the lagged value of the dependent variable. All regressions also include loan controls for total real estate loans, commercial and industrial loans, and total other loans, as well as year indicator variables and firm fixed effects. The sample is divided into years of low and high real GDP growth. t-statistics are reported below in parentheses.

	High Real GDP Growth					Low Real GDP Growth				
	EBTP	NII	NonII	NonIE	LoanGr	EBTP	NII	NonII	NonIE	LoanGr
DLLP	0.35***	0.32**	-0.32	-0.32	0.13*	-0.09	-0.09*	-0.06	-0.14	-0.05
	(3.01)	(2.00)	(-1.05)	(-0.98)	(1.94)	(-0.87)	(-1.91)	(-0.58)	(-1.18)	(-1.54)
NDLLP	-0.32***	-0.44***	-0.09	-0.25	-0.15***	-0.18***	-0.12***	-0.04	-0.05	-0.09***
	(-5.13)	(-5.15)	(-0.55)	(-1.49)	(-4.60)	(-5.27)	(-7.53)	(-1.25)	(-1.44)	(-9.12)
ΔNPL	1.61	-14.49***	4.21	-9.31	-4.72***	-8.95***	-5.33***	-9.64***	-1.26	-2.16***
	(0.48)	(-3.11)	(0.48)	(-1.01)	(-2.60)	(-5.03)	(-6.57)	(-5.22)	(-0.64)	(-4.12)
Lagged Dep.	31.74***	8.74***	0.40	-2.28		18.54***	35.42***	49.02***	32.63***	
	(12.45)	(3.06)	(0.19)	(-1.00)		(9.57)	(23.95)	(25.73)	(16.35)	
Loan Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 1.5: Loan Loss Provisions and the Financial Crisis

This table introduces a dummy variable, CRISIS, which is equal to one for the annual holding periods ending in 2008 and 2009, and zero otherwise. The dependent variable in each specification is the annual bank stock return in excess of the one-year risk-free rate (EXRET). All regressions include year dummy variables. Standard errors are clustered at the firm level, with the corresponding t-statistics reported below in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

	DLLP	LowGDP x DLLP	CRISIS x DLLP	NDLLP	LowGDP x NDLLP	CRISIS x NDLLP	EBTP	Log Size	Log BTM	Tier1
Coefficient	0.174***	−0.248***	−0.233***	−0.103***	0.006	−0.056***	2.525***			
t-statistic	(3.52)	(-3.59)	(-3.41)	(-5.76)	(0.29)	(-2.93)	(3.25)			
Coefficient	0.149***	−0.231***	−0.211***	−0.115***	0.014	−0.044**	6.852***	−0.005***	0.985***	
t-statistic	(3.12)	(-3.50)	(-3.14)	(-6.97)	(0.69)	(-2.47)	(7.69)	(-2.69)	(8.27)	
Coefficient	0.142***	−0.221***	−0.207***	−0.125***	0.024	−0.039**	8.043***	−0.010***	0.950***	−0.809***
t-statistic	(3.09)	(-3.43)	(-3.06)	(-8.02)	(1.24)	(-2.16)	(10.92)	(-4.52)	(8.56)	(-5.01)
Coefficient	0.146***	−0.224***	−0.221***	−0.112***			8.070***	−0.010***	0.953***	−0.815***
t-statistic	(3.28)	(-3.54)	(-3.31)	(-14.86)			(11.04)	(-4.60)	(8.57)	(-5.10)

Table 1.6: Sub-period Analysis of DLLP Valuation

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 one-year risk-free rate (EXRET). All columns include year dummy variables, and t-statistics 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.

PERIOD	1997 – 1999	2000 – 2002	2003 – 2005	2006 – 2008	2009 – 2013
	EXRET	EXRET	EXRET	EXRET	EXRET
DLLP	0.126**	-0.092*	0.181***	-0.268***	-0.081**
	(2.36)	(-1.72)	(4.12)	(-7.29)	(-2.01)
NDLLP	-0.129***	-0.159***	-0.099***	-0.155***	-0.101***
	(-6.16)	(-6.95)	(-4.21)	(-15.21)	(-10.14)
EBTP	6.767***	7.488***	6.245***	3.284***	10.383***
	(6.76)	(9.89)	(9.33)	(6.01)	(13.87)
Log(Size)	0.004	-0.017***	-0.004	0.002	-0.004
	(1.01)	(-3.69)	(-1.18)	(0.55)	(-0.89)
Log(BTM)	0.764***	0.965***	0.891***	0.283**	2.298***
	(5.30)	(8.99)	(7.42)	(2.25)	(12.09)
Year Controls	Y	Y	Y	Y	Y
Observations	1,087	1,179	1,237	1,015	1,528
Real GDP Growth	4.69	1.71	3.50	0.50	1.58

Table 1.7: Shocks to Consumer Confidence

This table evaluates the difference in 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 initial plans for the Troubled Asset Relief Program (TARP) were announced. Return represents the cumulative bank return from 1 day before the announcement date until 1 day after the announcement date relative to the corresponding return for the S&P 500 index. *Obs* represents the number of banks in each portfolio. Also reported is 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.

Panel A: IndyMac Bank Seized by FDIC (7/11/08)					
Portfolio	Return	Obs	Diff	t	p
DLLPQ5	-4.79	65	-2.74	-2.35	0.02
DLLPQ1	-2.04	65			
Panel B: Announcement of TARP Proposal (9/19/08)					
Portfolio	Return	Obs	Diff	t	p
DLLPQ5	11.91	65	6.52	2.22	0.03
DLLPQ1	5.38	65			

Table 1.8: Matched Sample Analysis

This table evaluates the impact of reporting high discretionary loan loss provisions using a dummy 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 (LowGDP = 0) and low real GDP growth (LowGDP = 1). 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 high DLLP on the annual bank stock return (EXRET).

Panel A: Unmatched Sample Characteristics

	LowGDP = 0				LowGDP = 1			
Variable	Mean DLLPQ5	Mean Control	Diff.	p	Mean DLLPQ5	Mean Control	Diff.	p
NDLLP	0.2345	0.2700	-0.0355	0.02	0.7704	0.5451	0.2253	0.00
EBTP	0.0236	0.0209	0.0028	0.00	0.0165	0.0168	-0.0003	0.64
Log(Size)	11.9424	12.6329	-0.6905	0.00	12.1838	12.5322	-0.3484	0.00
Log(BTM)	-0.0927	-0.0860	-0.0067	0.16	-0.0311	-0.0396	0.0085	0.02
Tier1	0.0953	0.0879	0.0074	0.00	0.0951	0.0905	0.0046	0.00

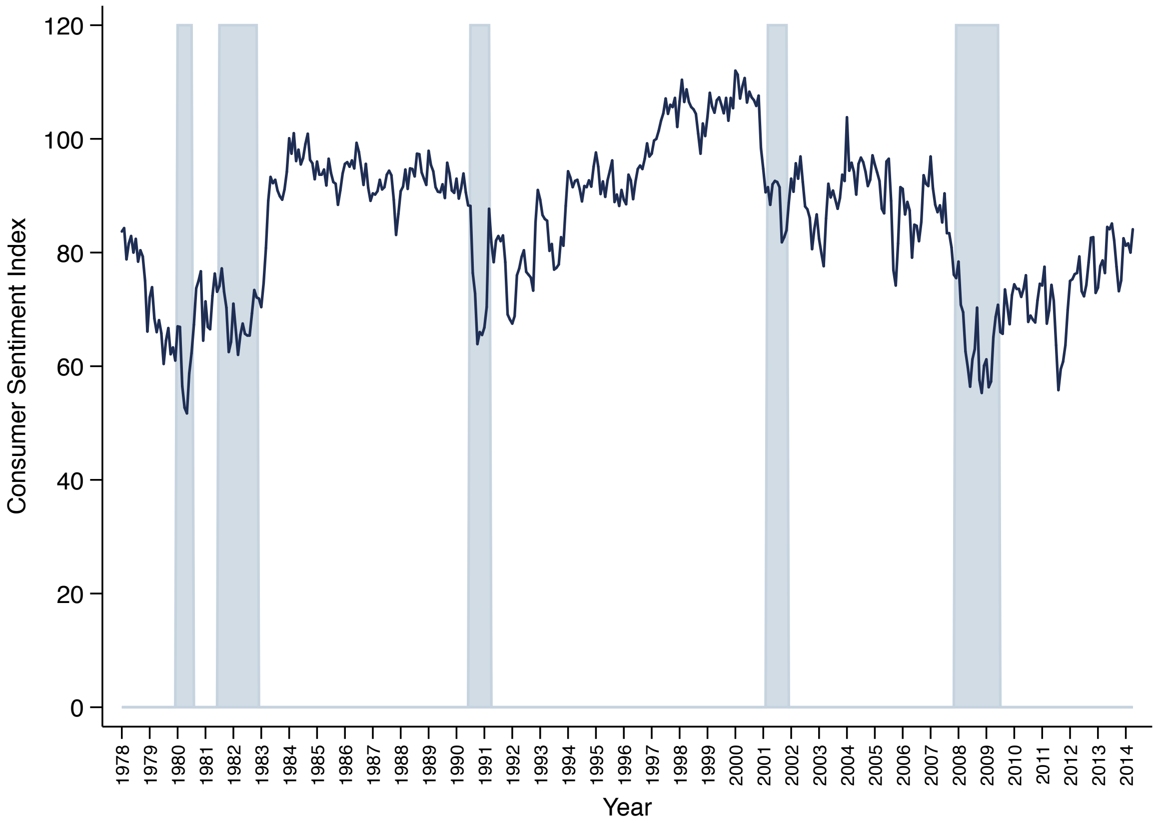
Panel B: Matched Sample Characteristics

	LowGDP = 0				LowGDP = 1			
Variable	Mean DLLPQ5	Mean Control	Diff.	p	Mean DLLPQ5	Mean Control	Diff.	p
NDLLP	0.2345	0.2406	-0.0061	0.81	0.7704	0.7356	0.0349	0.48
EBTP	0.0236	0.0221	0.0016	0.13	0.0165	0.0162	0.0003	0.75
Log(Size)	11.9424	11.9317	0.0107	0.90	12.1838	12.1758	0.0080	0.93
Log(BTM)	-0.0927	-0.0866	-0.0062	0.40	-0.0311	-0.0376	0.0065	0.14
Tier1	0.0953	0.0934	0.0019	0.56	0.0951	0.0927	0.0024	0.20

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

	LowGDP = 0			LowGDP = 1		
Variable	ATET	S.E.	p	ATET	S.E.	p
EXRET	0.0558	0.0154	0.00	-0.0549	0.0162	0.00

Figure 1.1
Index of Consumer Sentiment and NBER Business Cycle Dates.



The chart 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
Table A1.1
Variable names and descriptions.

Name	Description
LLP	Provision for Loan Losses (BHCK4230) multiplied by 100 and scaled by lagged total assets (BHCK2170).
EBTP	Earnings before taxes and provisions (BHCK4300 + BHCK4230 + BHCK4302) scaled by lagged total assets (BHCK2170).
Tier1	Tier 1 (BHCK8274) capital scaled by total assets (BHCK2170).
ALL	Allowance for Loan Losses (BHCK3123) scaled by total assets (BHCK2170).
NPL	Loans past due 90 days or more and still accruing (BHCK5525) plus loans in nonaccrual status (BHCK5526) scaled by total assets (BHCK2170).
RE	Loans secured by real estate (BHCK1410) scaled by total assets (BHCK2170).
CI	Commercial and industrial loans (BHCK1763 + BHCK1764) scaled by total assets (BHCK2170).
OtherLoans	Total loans excluding real estate and C&I loans (BHCK 2122 - BHCK1410 - BHCK1763 - BHCK1764) scaled by total assets (BHCK2170).
NetCO	Charge-offs (BHCK4635) minus recoveries (BHCK4605) scaled by total assets (BHCK2170).
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 annual return from investing in 1-month Treasury bills.
Size	Stock price (prc) multiplied by the number of shares outstanding (shrout).
BTM	Book value of equity scaled by the market value of equity.

Table A1.2: Valuation of Positive and Negative DLLP

This table reports the results for regressions that separately test the market reaction to positive discretionary loan loss provisions ($DLLP^{+}$) and negative discretionary loan loss provisions ($DLLP^{-}$). Specifically, $DLLP^{+}$ 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 one-year risk-free rate (EXRET). The independent variables in Panel A include $DLLP^{+}$, an interaction term between $DLLP^{+}$ and the low GDP growth indicator (LowGDP), the non-discretionary component of the loan loss provision expense (NDLLP), an interaction term between NDLLP and LowGDP, earnings before taxes and provision for loan loss expenses scaled by lagged total assets (EBTP), the log of bank market value of equity (Log(Size)), the log of the book value of assets scaled by market value of assets (Log(BTM)), and the lagged value of bank Tier 1 capital scaled by lagged total assets (Tier1). Panel B repeats the analysis with $DLLP^{-}$ and its interaction with LowGDP as the primary test variables. All regressions are for the period 1997 to 2013 and include year dummy variables. Standard errors are clustered at the firm level, with the corresponding t-statistics reported below in parentheses. ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Positive DLLP								
	$DLLP^{+}$	LowGDP x $DLLP^{+}$	NDLLP	LowGDP x NDLLP	EBTP	Log Size	Log BTM	Tier1
Coefficient	0.311***	−0.509***	−0.118***	0.014	2.547***			
t-statistic	(3.59)	(-4.74)	(-7.13)	(0.71)	(3.22)			
Coefficient	0.249***	−0.465***	−0.128***	0.022	6.920***	−0.006***	0.991***	
t-statistic	(2.97)	(-4.51)	(-8.18)	(1.22)	(7.70)	(-3.03)	(8.38)	
Coefficient	0.250***	−0.457***	−0.137***	0.033*	8.133***	−0.010***	0.954***	−0.830***
t-statistic	(3.05)	(-4.52)	(-9.33)	(1.90)	(11.01)	(-4.89)	(8.71)	(-5.20)

Panel B: Negative DLLP								
	$DLLP^{-}$	LowGDP x $DLLP^{-}$	NDLLP	LowGDP x NDLLP	EBTP	Log Size	Log BTM	Tier1
Coefficient	0.127**	−0.287***	−0.105***	-0.011	2.586***			
t-statistic	(1.99)	(-3.11)	(-6.19)	(-0.54)	(3.26)			
Coefficient	0.132**	−0.275***	−0.115***	-0.003	6.950***	−0.006***	0.990***	
t-statistic	(2.03)	(-3.04)	(-7.19)	(-0.14)	(7.72)	(-3.18)	(8.34)	
Coefficient	0.106*	−0.247***	−0.126***	0.010	8.180***	−0.011***	0.953***	−0.838***
t-statistic	(1.69)	(-2.80)	(-8.42)	(0.59)	(11.00)	(-5.08)	(8.62)	(-5.33)

Chapter 2

Distressed, Expanding, and Overvalued: Evidence that External Financing Activity Explains the Distress Anomaly

2.1 Introduction

A fundamental principle of finance is that investors require compensation for bearing risk. The stocks of distressed (i.e. high failure-risk) firms, however, have earned significantly lower returns over the years than stocks of healthy (i.e. low failure-risk) firms. This anomalous finding has posed challenges for asset pricing models and led to a substantial body of research (e.g., Dichev, 1998; Campbell et al., 2008; Chava and Purnanandam, 2010; Garlappi and Yan, 2011; Conrad et al., 2014; Friewald et al., 2014; Hackbarth et al., 2015). In this study, I address this long-standing puzzle and show the distress anomaly only exists among firms with high external financing activity in the prior year. Within this subsample of firms, consisting of only twenty percent of the overall sample, the underperformance of distressed stocks is extreme and persistent. What is perhaps even more surprising is that the distress anomaly appears to be non-existent in the remaining eighty percent of stocks.

I identify an external financing channel capable of generating significant overvaluation among distressed stocks and explaining their subsequent underperformance. While the existing external financing literature documents a strong negative relation between external financing activity and future returns (Ritter, 1991; Ikenberry et al., 1995; Loughran and Ritter, 1997; Spiess and Affleck-Graves, 1999; Hertzel and Li, 2010), there are two key factors I predict will make the external financing effect stronger among distressed stocks and able to explain the distress anomaly: dispersion of investor valuations and short-sale impediments. Although neither factor individually is sufficient to influence asset prices, the presence of both has been shown to be associated with overvaluation (Miller, 1977; D'Avolio, 2002; Boehme et al., 2006; Berkman et al., 2009; Daniel et al., 2016). Specifically, when short-sale limitations prevent pessimists from taking a position in a given security, its price will be determined solely by the most optimistic investors whose valuations are increasing in the dispersion of valuation beliefs.

To understand the greater strength of these two factors for distressed stocks, first consider that the decision by a distressed firm to raise external capital greatly impacts its value and long-run viability but is also associated with substantial uncertainty. On the one hand, a large cash infusion results in the firm being less cash constrained and allows it to undertake new projects that could be highly profitable. On the other hand, raising external capital is expensive for risky distressed firms

and can lead to the erosion of existing shareholder wealth if new capital projects do not pay off. This uncertainty leads to a wider dispersion in investor beliefs. In addition, Campbell et al. (2008, hereafter CHS) show that distressed companies tend to have smaller market capitalizations and more volatile stock prices, which suggests they are also more challenging to sell short. I explore additional firm characteristics that have been directly linked to short-sale limitations and find that far greater impediments to short-selling exist among distressed stocks. Specifically, I show distressed stocks have both high idiosyncratic volatility and low institutional ownership (D'Avolio, 2002; Nagel, 2005; Pontiff, 2006; Stambaugh et al., 2015). Thus, the availability of borrowable shares of distressed stocks is typically more limited given the lack of institutional holdings, and even when shares are available, the significant arbitrage risk posed by their high idiosyncratic volatility may deter short-selling. Consequently, as the dispersion of investor opinions increases distressed stock prices are expected to increase as well resulting in overvaluation.

An anecdotal example highlighting the challenges associated with valuing quickly growing distressed firms as well as the important role played by external financing is seen in the case of Intercept Pharmaceuticals. This biopharmaceutical firm which develops products designed for treating certain liver and intestinal diseases states in its 2013 annual report that, "we will continue to require additional capital to continue our clinical development and commercialization activities. Because successful development of our product candidates is uncertain, we are unable to estimate the actual funds we will require to complete research and development and commercialize our products under development." This company required significant external capital in order to undertake its projects with highly uncertain payoffs. If its products passed clinical testing and went to market, shareholders could expect to receive a large payoff; however, if its products failed, the firm would be likely to remain unprofitable and experience a decline in stock price. While a pharmaceutical company in the product development stages may seem like an extreme case, the high degree of uncertainty and wide range of potential outcomes is typical of many highly distressed companies and is expected to result in overvaluation in the presence of short-selling impediments.

The most closely related study from the external financing literature is Bradshaw et al. (2006), which develops a measure of net external financing that is associated with negative future abnormal returns and suggests the relation is driven by overly optimistic earnings expectations. While it seems surprising that the market would systematically overvalue high external financing activity

firms, the dispersion of opinion hypothesis predicts that due to the short-sale constraints associated with distressed stocks, it is only necessary for some market participants to have overly optimistic expectations to generate mispricing, rather than market participants as a whole. This more easily satisfied condition is produced whenever there is an increase in the dispersion of investor beliefs.

To test how the external financing effect varies with the level of distress, I double-sort firms into portfolios based on their *CHS* distress risk and external financing measures. Consistent with the theoretical predictions, I find a zero net-investment portfolio that buys healthy stocks and shorts distressed stocks earns a highly significant return of 1.97% per month within the top external financing quintile of firms.[20] In contrast, similarly constructed portfolios designed to measure the strength of the distress anomaly are much less profitable among the remaining stocks and earn a negative average return within the bottom two external financing quintiles.

I subsequently conduct factor model regressions using several common asset pricing models to see if previously identified risk factors can explain the underperformance of the high distress, high external portfolio. While the Hou, Xue, and Zhang (2015) q-factor model appears to have the most success in accounting for the lower returns to distressed stocks overall, it leaves large pricing errors among the portfolio of high distress, high external financing firms. Within the top external financing quintile, the distress-based long-short portfolio earns a highly significant alpha of 1.22% per month, which is driven entirely by the short leg. Conversely, within the four remaining quintiles long-short portfolio abnormal returns are small and insignificant. Overall, this evidence supports the hypothesis that high distress, high external financing firms are overvalued.

Cross-sectional Fama-MacBeth (1973) regressions present a similar picture. Predictive regressions that control for only size, book-to-market, momentum, and distress indicate that distress has a large negative impact, as is documented in prior research. However, upon the inclusion of the external financing variable and a distress, external financing interaction term, the distress variable's coefficient is reduced substantially and becomes insignificant. This suggests that by itself distress is not a strong predictor of future underperformance; rather, it serves to amplify the external financing effect by creating a greater divergence in beliefs among firms that are challenging to sell short.

[20]The long-short portfolio return is also likely to serve as an upper bound on the return that a distress-based trading strategy would generate, since short-selling limitations are expected to be severe. However, long-only investors could still benefit by avoiding underperforming stocks.

Because the divergence of opinion hypothesis implies that high distress, high external financing stocks will be owned by the most optimistic investors, it is expected that shareholders will be disappointed on average upon observing future performance outcomes, which should be more consistent with the average expectation of all market participants. I test this implication by examining the performance of the double-sorted portfolios around earnings announcement dates and find that a substantial portion of the underperformance of the high distress, high external portfolio is concentrated during these high information periods. Although it is challenging to completely rule out the possibility that unidentified risk factors can explain the results, it is unlikely that a risk-based explanation could also account for such large negative reactions to earnings news.

The dispersion of opinion theory originally developed in Miller (1977) suggests that both high dispersion of opinion and short-sale limitations are needed to generate overpricing, and the degree of overpricing will be increasing in the severity of these two conditions. Thus, while I expect distressed firms with high external financing will be overvalued in general, the extent of mispricing should be even larger for firms that are especially difficult to value or challenging to sell short. I test this by exploring the returns to distress-based long-short portfolios within subsets of high external financing firms that have low analyst coverage and a shorter time since going public (i.e. harder to value) as well as firms with high idiosyncratic volatility and low institutional ownership (i.e. greater short-sale limitations). Consistent with overvaluation being greater among these firms, the long-short portfolios earn higher returns within each of these subsets.

Many prior studies have attempted to explain the distress puzzle by incorporating previously unaccounted for sources of risk or information. For example, Chava and Purnanandam (2010), Garlappi and Yan (2011), and Friewald et al. (2014), propose models that focus on implied cost of capital, shareholder recovery, and credit risk premia implied by CDS spreads, respectively. While these studies have produced interesting new insights, they have tended to focus on proxies of firm distress other than the *CHS* measure, which is shown to have greater ability to predict firm failure and to produce much larger return spreads when conducting portfolio sorts. Additionally, data limitations on CDS spreads and the variables needed to estimate implied cost of capital greatly restrict the sample of distressed firms when utilizing either of these metrics. In this study, I use the *CHS* measure of financial distress throughout the main analysis and find distress only has a strong

negative relation to future stock performance when external financing is high.[21] As robustness, I show this finding holds over time, during periods of expansion and recession, and when extending the portfolio holding period.

The main contributions to the existing literature can be summarized as follows. First, I identify an external financing channel that can create significant overvaluation among distressed firms with high recent external financing activity. I provide evidence that short-sale constraints are far greater among distressed stocks, which allows their prices to be determined by the investors who are most optimistic that new capital projects will pay off. Consistent with this, I find the anomalously low returns to distressed stocks only exist among high external financing firms. Second, I show the underperformance of the portfolio of high distress, high external financing firms is concentrated around earnings announcements, which supports the notion that mispricing drives its low returns as shareholders are negatively surprised by earnings news. Finally, I explore the results within subsets of high external financing firms that possess characteristics making them particularly challenging to value or subject to greater short-sale limitations and find even greater underperformance among these subgroups of firms. This adds support to the dispersion of opinion hypothesis.

The rest of this paper is organized as follows. Section 2.2 reviews the existing literature and outlines the main hypotheses. Section 2.3 details the construction of the distress and external financing variables and also provides an overview of the distress anomaly. Section 2.4 tests the hypotheses and presents the empirical results. Section 2.5 discusses several robustness tests. Section 2.6 concludes.

2.2 Literature Review and Hypothesis Development

This section provides an overview of the literature on external financing activity and its impact on asset pricing. Subsequently, I describe its relation to the distress anomaly and develop a set of testable hypotheses.

[21] In unreported results, I test the predictions using Ohlson's O-score as a proxy for distress as well as long-term issuer credit rating and find qualitatively similar results.

2.2.1 *Background*

The extensive literature on external financing produces one finding with surprising regularity – a significant negative relation between capital raising events and future stock performance. The most commonly offered explanation for this finding is the market timing hypothesis, in which managers take advantage of a "window of opportunity" by issuing securities when market prices exceed fundamental values. Additionally, most studies within this strand of literature choose to focus on a specific type of external financing. For instance, Ritter (1991) explores a sample of initial public offerings (IPOs) and finds the stocks of IPO firms significantly underperform stocks of comparable firms for three years after going public. He states that the evidence is consistent with firms timing their decision to go public when investors are overly optimistic about their future prospects, as the underperformance is concentrated among young growth companies and in years of heavy IPO volume when favorable valuations are widespread. Loughran and Ritter (1995) document a similar underperformance following seasoned equity offerings (SEOs). Consistent with the view that managers tend to issue stock when they believe their securities are overpriced, Hertzel and Li (2010) decompose market-to-book ratios into misvaluation and growth option components and find the underperformance of SEOs is most severe for firms with a large misvaluation component. Overall, their results suggest decisions to raise equity capital reflect firm overvaluation in addition to financing needs.

While the majority of the external financing literature focuses on equity issuance, a number of studies have also explored the relation between the decision to raise debt capital and future performance. For example, Billett et al. (2006) show that although firms experience positive average announcement stock returns upon obtaining bank loans, they also suffer large negative abnormal returns over the following three years. A similar pattern of small positive announcement returns followed by severe long-run underperformance is documented in Chandra and Nayar (2008) for private debt placements. They provide evidence that firms manage reported earnings upward prior to the issuance of private debt using discretionary accruals, which results in temporary overvaluation to the extent that investors fail to see through biased earnings figures. Finally, Spiess and Affleck-Graves (1999) report substantial long-run underperformance following both straight and convertible debt offerings, and they suggest overvalued firms are more likely to offer securities of any type to

take advantage of mispricing. In contrast to these studies, I focus on explaining why the external financing effect is expected to have a larger effect on the performance of distressed stocks and why overvaluation persists beyond security issuance announcement dates.

Given the expansive literature documenting negative abnormal returns following the issuance of different security types, Bradshaw et al. (2006) develop a measure of net external financing, which is the approach I use here. This measure aggregates total funds raised net of dividends, repurchases, and funds used to pay down debt and is found to be a stronger predictor of future underperformance than individual components of external financing. Bradshaw et al. also find that large increases in external financing are associated with lower future profitability suggesting that the returns to new projects often do not outweigh the cost of capital. This should be of particular concern to investors in distressed companies given their higher external financing costs; however, negative abnormal returns following issuance events imply prices do not adequately reflect this possibility. The following section explains why investors may consistently overpay for high external financing firms and why the degree of overpricing is expected to be far greater among distressed stocks.

2.2.2 *Hypothesis Development*

The timing hypothesis asserts that firms issue securities when they are overvalued according to management's public and private information. While timing factors could explain why the issuance of debt and equity securities tends to coincide with overvaluation, several important questions are left unanswered. Specifically, why do low returns following issuance events persist for a year or more rather than security prices fully adjusting at the time of announcement? Why do sophisticated investors not fully exploit these opportunities given the severity of the average underperformance? Are external financing effects more pronounced for distressed companies because of their high costs of external capital and large degree of uncertainty? If so, do external financing effects explain the distress anomaly?

This section develops a set of hypotheses aimed at answering these questions by building on the theoretical predictions offered initially in Miller (1977) and explored further in various settings (Diether et al., 2002; Boehme et al., 2006; Berkman et al., 2009; Lam and Wei, 2011; Daniel et al., 2016). The central concept is that in the presence of market imperfections that limit or restrict

short selling, stocks with a greater divergence of investor valuation opinions will trade at a higher price. This price is above the mean valuation of all market participants, as the market price is effectively determined by what the most optimistic investors are willing to pay while pessimistic investors are prevented from trading against them. Individuals who hold lower valuations than the market price simply do not take a position in the stock given the high costs and limitations associated with short-selling.

In the case of distressed firms with significant external financing activity both the dispersion of opinions and short-sale constraints are generally substantial. First, consider that for all firms, healthy or distressed, the decision to raise external capital is expected to create an increased dispersion of opinions among investors given the uncertainty associated with new projects and rapid growth. Consistent with this, Chandra and Schneible (2013) document increased abnormal trading activity, a common proxy for differing investor opinions, for up to three years following external financing events, which is increasing in the amount of capital raised. The effect on the dispersion of opinions is also expected to be particularly large for distressed issuers because their long-term viability often hinges on the success of new projects. Optimistic investors view a substantial increase in new funds as good news because it reduces the firm's short-term default risk and allows management to undertake new, potentially more profitable, projects. However, given the firm's distressed status, there is a high cost associated with raising external capital, and pessimistic investors do not expect new projects to generate a sufficient return to cover this cost. In summary, there is a large degree of uncertainty regarding whether new projects will pay off, and the long-term viability of distressed firms often depends on the outcome.

Additionally, distressed companies tend to be small volatile companies, which results in their being more costly to arbitrage (Shleifer and Vishny, 1997; Stambaugh et al., 2015). Adverse short-term price movements can force arbitrageurs to provide additional capital while simultaneously causing investors to lose confidence and consider withdrawing invested funds. On average, distressed firms also have lower institutional ownership, which has been associated with the availability of borrowable shares, and short-sale constraints are more likely to be a factor when non-lending investors hold a greater percentage of shares (Nagel, 2005).

Boehme et al. (2006) emphasizes that if either of the two conditions is not present, short-sale constraints or dispersion of opinions, overpricing will not occur. For instance, if investors hold a

wide range of valuation opinions and there are no constraints on short-selling, then if the market price were to rise above its equilibrium level an increase in shorting activity would force its price back down. Similarly, in the presence of severe short-selling constraints but no divergence of opinion, all investors will value the company equally, as there is a lack of extreme optimists or pessimists, and its equilibrium price will be equal to this common valuation.

Given that investors in distressed firms that raise large amounts of external capital are likely to have greater dispersion in their valuations and face greater short-sale constraints, I expect overvaluation will be more prevalent within this subgroup of distressed stocks. The most optimistic investors are willing to pay a price above the average valuation held by market participants, and short-selling limitations prevent mispricing from being exploited by arbitrageurs. This leads to the main hypothesis.

Hypothesis 1. The underperformance of distressed stocks relative to healthy stocks (i.e. the distress anomaly) is concentrated among firms with high external financing activity in the prior year.

Overly optimistic valuations can exist in the presence of short-selling constraints coupled with differences of opinion; however, over time the uncertainty regarding the fair value of firms will gradually be reduced as value relevant information reaches the market. Although information is provided to investors through a variety of events throughout the year (e.g., press releases, analysts' forecasts, etc.), I focus on quarterly earnings announcements, as they provide investors with an official update on how the firm is performing and typically involve a conference call in which management discusses both the prior and upcoming quarters. On average, it is expected that the most optimistic investors will be disappointed by the actual results. This leads to the second hypothesis.

Hypothesis 2. A significant portion of the underperformance of distressed stocks with high external financing activity occurs around quarterly earnings announcements.

Within the group of highly distressed, high external financing firms, there is likely to be some additional variation in the degree of dispersion in investor's valuations produced by external financ-

ing events as well as differences in the severity of short-selling constraints. For instance, external financing activity will likely generate a wider range of opinions among younger firms, because their limited history adds to the challenge in establishing an accurate valuation. Likewise, low analyst coverage is also expected to allow for a greater dispersion of opinions, as professional analysts' estimates provide a point of reference in establishing an appropriate valuation. In terms of short-selling limitations, stocks with lower institutional ownership are more likely to face constraints that are binding, and stocks with higher idiosyncratic volatility will be more costly to arbitrage because of the inability of arbitrageurs to fully hedge against adverse price movements. This leads to the final hypothesis.

Hypothesis 3. The underperformance of distressed stocks among firms with high external financing growth is more severe for firms that are more difficult to value and more costly to sell short.

2.3 External Financing, Financial Distress, and the Distress Anomaly

This section details the construction of the external financing and distress variables and also reviews existing evidence on the distress anomaly. The full sample consists of all firms with non-missing data used to construct the distress and external financing variables as well as available monthly returns. Returns and stock prices are from the Center for Research in Security Prices (CRSP), and accounting data is from the Compustat Annual and Quarterly Fundamental Files. The full sample includes 1,108,901 firm-month observations during the sample period from 1981 to 2014, which coincides with the start date used in Campbell et al. (2008), as it has been documented that failures were relatively infrequent before the 1980s.[22]

2.3.1 *External Financing*

To explore the effect of external financing on firm performance and the distress anomaly, I construct a measure following Bradshaw et al. (2006) using information from the statement of cash

[22]Additionally, Eisdorfer et al. (2013) note the availability of quarterly Compustat data is more limited in earlier years.

flows from the Compustat Annual files. Specifically, I define net external financing, XFIN, as the sum of net equity related financing, EFIN, and net debt related financing, DFIN,

$$XFIN = EFIN + DFIN \tag{2.1}$$

where EFIN is computed as total funds received from the sale of common and preferred stock (SSTK) less funds paid towards the purchase of common and preferred stock (PRSTKC) less cash dividends (DV), and DFIN is computed as funds raised from the issuance of long-term debt (DLTIS) less funds paid toward long-term debt reduction (DLTR) plus changes in current debt (DLCCH). I require the availability of all cash flow variables with the exception of changes in current debt, which is set to zero if missing. I scale XFIN, EFIN, and DFIN by average total assets (AT) so that the financing variables take into account the relative size of each firm. Additionally, the three financing variables are winsorized at the 1^{st} and 99^{th} percentiles in order to reduce the effects of outliers.

2.3.2 *Financial Distress*

Throughout the vast literature on financial distress there are a number of commonly used ways to quantify distress. Two approaches that have been popular, especially in early studies, are the models of Altman (1968) and Ohlson (1980), which use accounting variables to predict bankruptcy. Additionally, the Moody's KMV model, which relies on the structural default model of Merton (1974), has received considerable use from both academics and practitioners. In this paper, I use the distress measure from CHS (2008) in the main analysis, which is constructed by estimating the 12-month-ahead probability of failure using a logit model.

Aside from utilizing more recent data the CHS (2008) measure offers several advantages. First, the model utilizes both accounting and market data and is shown to have better predictive power than competing models. Further, failure is defined more broadly to include not only firms that file for Chapter 7 or Chapter 11 bankruptcy but also those that receive a D credit rating from a leading credit rating agency or delist from their stock exchange for financial reasons. This is advantageous as many years contain relatively few bankruptcies, and many financially troubled firms never reach bankruptcy. Finally, asset pricing studies generally find greater return spreads between healthy and distressed firms when using the *CHS* variable, likely because it captures the risk of failure more

precisely. To construct this measure I combine monthly market data from CRSP with quarterly accounting data from Compustat and utilize the results from the CHS (2008) logit model. To help ensure the availability of accounting information, I lag all Compustat data by 4 months. The distress measure is computed as follows:

$$\begin{aligned} CHS_{it} = & -9.16 - 20.26\, NIMTAAVG_{it} + 1.42\, TLMTA_{it} - 7.13\, EXRETAVG_{it} \\ & + 1.41\, SIGMA_{it} - 0.045\, RSIZE_{it} - 2.13\, CASHMTA_{it} + 0.075\, MB_{it} \\ & - 0.058\, PRICE_{it} \end{aligned} \tag{2.2}$$

where NIMTA is net income (NIQ) divided by the market value of assets, TLMTA is the book value of liabilities (LTQ) divided by the market value of assets, EXRET is the log of the excess return on the firm's stock relative to the S&P 500 Index, SIGMA is the standard deviation of daily returns over the past three months, RSIZE is the ratio of the log of the firm's market capitalization (PRC x SHROUT / 1000) relative to that of the S&P 500 index, CASHMTA is the firm's cash and short-term investments (CHEQ) scaled by the market value of assets, MB is the market-to-book ratio[23], and PRICE is the log of the firm's price per share (PRC) truncated from above at \$15. NIMTAAVG and EXRETAVG represent weighted moving averages of NIMTA and EXRET. I construct these following CHS (2008) as

$$NIMTAAVG_{t-1,t-12} = \frac{1-\phi^3}{1-\phi^{12}}(NIMTA_{t-1,t-3} + \ldots + \phi^9 NIMTA_{t-10,t-12}) \tag{2.3}$$

$$EXRETAVG_{t-1,t-12} = \frac{1-\phi}{1-\phi^{12}}(EXRET_{t-1} + \ldots + \phi^{11} EXRET_{t-12}) \tag{2.4}$$

where $\phi = 2^{-\frac{1}{3}}$.[24] All inputs are winsorized at the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles of the pooled sample. To limit transaction costs and the effects of bid-ask bounce, I eliminate all stocks with prices below \$1 at the time of portfolio formation and only include the common stocks of non-financial firms (i.e., exclude SIC codes 6000 to 6999) that trade on NYSE, NASDAQ, or AMEX. Because distressed stocks face an increased likelihood of being delisted, delisting returns are incorporated into a stock's final monthly return whenever available. Failing to do this would likely impart an upward bias on

[23]Book value is measured quarterly as in Hou et al. (2015). In particular, book equity is shareholders' equity plus balance-sheet deferred taxes and investment tax credit (TXDITCQ), if available, minus the book value of preferred stock. Depending on availability, I use stockholders' equity (SEQQ), or common equity (CEQQ) plus the carrying value of preferred stock (PSTKQ), or total assets (ATQ) less total liabilities (LTQ) in that order as shareholders' equity. Preferred stock is measured as the redemption value (PSTKRQ) if available, or the carrying value of preferred stock, or zero if both are missing.

[24]I refer the interested reader to CHS (2008) for further details on the distress variable's construction.

the returns to distressed stocks, both in general and relative to healthy stocks.

2.3.3 *Distress Anomaly Overview*

The finding in Dichev (1998) that high bankruptcy risk firms earn significantly lower returns than similar healthy firms has led to a substantial body of research which has sought to explain this seemingly anomalous result (e.g., Campbell et al., 2008; Chava and Purnanandam, 2010; Garlappi and Yan, 2011; Conrad et al., 2014; Friewald et al., 2014; Hackbarth et al., 2015). In Table 2.1, Panel A explores the strength of the distress anomaly within the current sample period by sorting all firms into equal-sized deciles based on their estimated level of distress at the end of the previous month. A portfolio that is long stocks in the least distressed decile (i.e. healthy stocks) and short stocks in the most distressed decile (i.e. distressed stocks) is also constructed to test the difference in performance. Presented are the average excess-returns for each of the value-weighted decile portfolios and the long-short portfolio as well as alphas with respect to the Capital Asset Pricing Model (CAPM), Fama-French 3-factor model, and Carhart 4-factor model.[25]

The seven decile portfolios with the lowest failure risk (D1 to D7) exhibit fairly limited variation in average returns, which is perhaps unsurprising as their differences in failure probability are also very small. However, there is a substantial drop off when moving to the eighth, ninth, and tenth deciles, as these portfolios earn average monthly excess returns of 0.43%, 0.12% and -0.20%, respectively. The average return difference between the portfolio of the healthiest firms (D1) and the most distressed firms (D10) is 0.93% and statistically significant. Additionally, the CAPM, Fama-French 3-factor model, and Carhart 4-factor model fail to explain the returns to the long-short portfolio resulting in average monthly abnormal returns of 1.42%, 1.77%, and 0.87%, respectively. These results are similar to those reported in the existing literature and confirm the existence of the distress anomaly in the current sample period.

Panel B reports the factor loadings from the Carhart 4-factor model regressions, which despite failing to explain the low returns to distressed stocks, perform the best of the three models. Focusing on the long-short (D1–D10) portfolio, it is observed that the factor loadings are significantly negative on the model's market (MKT), size (SMB), and value factors (HML). This lowers the expected

[25]There is evidence that more recently developed asset pricing models explain a greater percentage of the return spread between healthy and distressed firms. Such models are considered in later tests; however, the focus in this table is on confirming existing evidence of the distress anomaly within the current sample.

return of the portfolio; thus, effectively increasing its abnormal return and explains why the alpha relative to the Fama-French 3-factor model is much larger. The addition of the momentum factor (UMD) appears to capture much of the outperformance of healthy stocks relative to distressed stocks, as its inclusion reduces the long-short portfolio's abnormal return by more than half (1.77% to 0.87%); however, it is still highly significant ($t = 3.12$). In fact, the UMD factor loadings decrease monotonically from the decile portfolio of healthiest stocks (D1) to most distressed stocks (D10). The decline in momentum loadings as distress increases is expected, as healthier stocks tend to have experienced higher past returns than distressed stocks by construction.

Average firm level characteristics are presented in Panel C. Characteristic values are found by first computing the cross-sectional means and medians across all firms within each portfolio and then computing the time series averages of these values. The patterns revealed in the characteristics suggest that distressed firms tend to have smaller market capitalizations, lower market-to-book ratios, and lower past returns, which is consistent with the patterns in the factor loadings.

The *CHS* failure probability increases monotonically across the portfolios by construction, since this is the sorting variable used to construct the portfolios. Interestingly, the average values of net external financing are also strictly increasing when moving from the lowest to highest distress decile. Firms in the portfolio of healthiest stocks have an average external financing ratio of -2.57%. This suggests these firms use more money towards paying dividends, repurchasing stock, and paying off debt than they raise by borrowing new funds and issuing stock, as healthy companies are generally able to rely on strong earnings to support growth. In contrast, distressed firms rely more heavily on external capital with the average firm raising outside funds net of any payouts equal to 9.34% of average assets. This suggests the external financing effect could potentially impact a large number of distressed stocks given their tendency to rely on external capital.

Figure 2.1 graphically highlights the severity of the underperformance of distressed stocks over the sample period. This figure presents the cumulative monthly returns to investments in: (1) the decile portfolio of healthiest stocks; (2) the decile portfolio of most distressed stocks; (3) the market portfolio; and (4) the risk-free asset. Also reported on the right-hand side of the figure are ending balances given an initial investment of $1 in each portfolio. The portfolio of healthy stocks tracks the market quite closely but results in a higher final balance ($56.40 vs. $36.63). This is not particularly surprising since healthy firms tend to be larger and less volatile than other companies

and often follow the general movements of the market. In contrast, the distressed portfolio performs far worse than the overall market and results in an even lower cumulative return than an investment in the risk-free asset ($0.23 vs. $4.48). Its extreme volatility and poor average performance both contribute to this anomalous finding.

Table 2.2 reports correlations for the main variables of interest over the full sample period. In addition to the distress and external financing variables, the table includes the log of firm size (market cap), log book-to-market, and the cumulative return from month *t-12* to *t-2* (Mom). The correlations are computed using only the observations from the end of each fiscal year, since all variables except *CHS* and *Mom* are updated annually.

The first column shows that net external financing is more highly correlated with equity financing than debt financing, although both correlations are large by construction. Consistent with evidence from the distress portfolio sorts, I find that external financing is also positively correlated with the *CHS* failure probability as distressed firms tend to raise more external capital relative to their existing asset bases on average; however, the correlation coefficient is modest at 0.108. The table also indicates that the external financing variable tends to be larger for small firms and low book-to-market firms but exhibits a very weak relation with past returns.

2.4 Empirical Analysis

This section tests the hypothesis that the distress anomaly will be concentrated among firms with high prior year external financing activity. The extreme balance sheet growth of these firms and uncertainty associated with new projects is predicted to create a large dispersion of beliefs among investors regarding their fair values. In the presence of short-selling constraints, which are more severe for distressed firms, only the most optimistic investors will take positions in their stocks leading to overvaluation. In contrast, distressed firms with limited external financing growth, whose operations are more stable, are predicted to be fairly valued and earn returns commensurate with their level of risk.

2.4.1 *Descriptive Statistics*

In order to study the relation between recent external financing activity and the distress anomaly, I sort all firms into portfolios based on their values of the distress and external financing measures. Each month I first assign all stocks to distress quintile portfolios based on their computed *CHS* value. Subsequently the stocks within each portfolio are divided into quintiles again based on each firm's level of *XFIN* to form 25 double-sorted portfolios.[26]

Table 2.3 displays the average firm-level characteristics for each portfolio. Panels A and B show again that distressed firms tend to have smaller market capitalizations and lower market-to-book ratios. One notable exception to this general pattern, however, is the high distress, high external financing portfolio whose firms have an average market-to-book ratio of 2.50. Thus, while most distressed stocks are considered value stocks based on their depressed valuations, the firms in this portfolio have valuations consistent with investors expecting significant growth despite their current distressed status. Interestingly, all five of the portfolios in the top quintile of recent external financing growth (XFIN5) have relatively high average market-to-book ratios, ranging from 2.28 to 2.50; however, no concrete inferences can by drawn from these simple statistics as higher valuations can reflect higher growth potential, overvaluation, or some combination of the two.

Panels C, D, and E report the average values of *EFIN*, *DFIN*, and *XFIN*. The high distress, high external financing portfolio stands out as these firms raised substantial amounts of capital within the past year relative to their existing asset bases. On average, their net external financing ratio is equal to 42.95%, and they raise funds through a combination of debt and equity.[27] It is also observed that most healthy firms have made net payments to investors as three of the five portfolios in the least distressed quintile (D1) have negative average values of *XFIN*. Additionally, Panel F shows that the sorting procedure works well in minimizing differences in failure probability. The average *CHS* distress measure is similar across different external financing portfolios in the same distress quintile; therefore, differences in failure probability are unlikely to account for large differences in the strength of the distress anomaly for different *XFIN* levels.

[26] Independent sorts are used as a robustness test with the performance results presented in Appendix Table A2.1. With independent sorting, the high distress, high external financing portfolio contains slightly more than double the average number of firms in the high distress, low external financing portfolio.

[27] *EFIN* and *DFIN* are winsorized after being added together to generate *XFIN*. This helps to ensure that any extreme refinancing transactions (e.g. issuing large amounts of stock to payoff debt) do not impact net external financing but does not always preserve the equality between *XFIN* and its components.

The final two panels report summary statistics for idiosyncratic volatility (IVOL) and institutional ownership, which are proxies for the degree of short-sale constraints. Panel G presents the average firm IVOL, computed monthly as the standard deviation of daily return residuals relative to the Carhart 4-factor model (annualized). Prior research has highlighted the role of IVOL in limiting arbitrage. Mispricing among a stock with no IVOL can be exploited without much risk, as arbitrageurs are able to fully hedge against its price movements by taking offsetting positions in other financial securities; however, maintaining a short position becomes increasingly risky as IVOL increases. As a result, prior research shows that an arbitrageur's optimal position in a security is decreasing in the level of IVOL (Pontiff, 2006; Stambaugh et al., 2015). Thus, the table suggests that distressed stocks present far greater arbitrage risk, as the mean IVOL of stocks in the five distressed portfolios ranges from 70.28% to 72.28% compared to a range of 24.74% to 30.18% among healthy firms.

Panel H presents average values of institutional ownership, which is measured as the percentage of shares owned by institutional investors using information from Thomson Reuters' 13-F filings data. Institutional ownership is an additional proxy for short-selling constraints because in order to short a stock arbitrageurs must be able to locate shares to borrow, which is typically done through institutional owners (D'Avolio, 2002; Nagel, 2005). The reported values provide further evidence that distressed firms face greater short-sale limitations, as average institutional ownership decreases substantially with the level of distress. It is also worth noting that because all distressed stock portfolios exhibit similar values for both IVOL and institutional ownership, differences in arbitrage risk are unlikely to explain differences in their performance; rather, the data suggests the potential for mispricing is generally greater among all distressed stock portfolios.

2.4.2 *Double-Sorted Portfolio Returns*

I now evaluate the performance of the twenty-five portfolios formed by double-sorting firms on their levels of distress, *CHS*, and external financing, *XFIN*, in addition to the returns to zero net-investment portfolios that are long healthy firms and short distressed firms within each external financing quintile. This allows for an evaluation of how the strength of the distress anomaly varies with prior external financing activity, and as stated in Hypothesis 1, I expect the underperformance of distressed stocks will be concentrated among firms in the high external financing quintile. In

addition to adjusting for risk using the Carhart model, I also consider the 5-factor model that includes the Pastor and Stambaugh liquidity factor, Fama-French 5-factor model (with and without an additional factor for momentum), a model with the quality minus junk factor of Asness et al. (2014), and the Hou, Xue, and Zhang q-factor model.[28]

In Table 2.4, Panel A displays the excess returns and Hou, Xue, and Zhang (2015) q-factor model alphas with value-weighted portfolios. The performance relative to the q-factor model is emphasized, because this model performs best in the sense that it leaves the smallest average absolute alphas among the five long-short portfolios; however, the performance relative to the remaining factor models is considered subsequently.

Focusing first on the long-short portfolio returns unadjusted for risk (left-hand side), I find that distressed stocks actually outperform healthy stocks within the bottom two external financing quintiles, as the average monthly returns are -0.08% and -0.36% among the XFIN1 and XFIN2 firms. This is surprising given the severe underperformance of distressed firms overall during the sample period. Within the XFIN3 quintile the long-short portfolio earns an average return of 0.30% per month but is not significantly different from zero ($t = 0.69$). The distress-based long-short portfolio returns become statistically significant among the XFIN4 stocks with an average monthly return of 0.91% ($t = 2.27$) but are substantially larger among stocks in the top external financing quintile, XFIN5, at 1.97% per month ($t = 4.66$). This suggests the vast majority of the distress anomaly profits are generated by firms with high levels of external financing within the past year consistent with Hypothesis 1.

The excess returns to the five high distress (D5) portfolios also exhibit large differences in performance. The portfolios of distressed stocks in the two lowest external financing quintiles, XFIN1 and XFIN2, perform quite well, earning average excess returns of 0.82% and 0.93% per month, respectively. These are also the only two distressed portfolios that distribute more funds to investors than they receive on average. In contrast, distressed firms in the top quintile of external financing (XFIN5) do much worse than the risk-free rate averaging an astonishingly low excess return of -1.26% per month. With large dispersion in investor beliefs, the degree of overvaluation is expected to be substantial when short-sale constraints cause arbitrageurs to have limited partic-

[28]Results relative to the CAPM and Fama-French 3-factor model are also considered but not reported. For both models, the average estimated alphas are considerably larger in magnitude compared to the models presented.

ipation. Such overvaluation is subsequently reflected in future underperformance consistent with the findings here.

While the distress-based long-short portfolio earns much higher returns among high *XFIN* stocks, I test whether differences in risk factor exposures can explain these findings. The right-hand side of the panel presents portfolio alphas relative to the q-factor model, which leaves the smallest average pricing errors of the models considered and includes factors related to the market, size, investment, and profitability. In unreported results, I find the investment factor loadings are more negative for high XFIN stocks, thereby explaining some of the underperformance associated with firms with high external financing. Additionally, portfolios of healthy firms tend to have much larger loadings on the profitability factor but much smaller loadings on the market and size factors, so these risk adjustments partially offset one another. In each *XFIN* quintile, however, the long-short portfolio alpha is lower than its average return.

Within the bottom four external financing quintiles the long-short portfolio alphas are not significant at the five percent level with values ranging from -0.55 to 0.32. This suggests the q-factor model is relatively successful in explaining the return spreads between healthy and distressed stocks including the return spread in the XFIN4 quintile. In contrast, the model fails to explain most of the long-short portfolio's return in the XFIN5 quintile, as the average monthly alpha is large at 1.22% and highly significant (t = 3.62). This highlights that the distress anomaly is concentrated in the group of firms with high external financing activity.[29]

It is also worth noting that the returns to the portfolios of healthy firms are well explained by the q-factor model. All of the portfolios within the D1 quintile have alphas that are near zero and insignificant, and any abnormal returns to the long-short portfolios are derived almost exclusively from shorting distressed firms. For instance, focusing on the XFIN5 portfolios where the distress anomaly is concentrated, the portfolio of healthy firms has an insignificant alpha of -0.00% (t = -0.01) while the portfolio of distressed firms has a highly significant negative alpha of -1.22% (t = -4.26) per month. This supports the prediction that the distress anomaly profits are derived from overvaluation of distressed stocks in the short leg.

Panel B presents the results using equal-weighted portfolio returns. Overall, the same general

[29]In unreported results, I find the effects of momentum are well captured by the q-factor model's profitability factor, as suggested in Hou, Xue, and Zhang (2015). The alphas are nearly identical when adding the momentum factor, UMD, to their model. For example, the high external financing long-short portfolio alpha is 1.18%.

pattern is observed, as the distress anomaly profits are far more substantial within the high external financing quintile where the long-short portfolio average return is 1.72% per month. Conversely, within the bottom two XFIN quintiles the average monthly return is negative, and within the XFIN3 quintile it is small and near zero. This indicates that distress, by itself, does not lead to low future returns among the majority of stocks.

Figure 2.2 graphically illustrates the extreme differences in the performance of distressed stocks depending upon their level of prior year external financing activity. Plotted are the cumulative gains of a \$1 investment made in: (1) the portfolio of high distress, low XFIN stocks; (2) the portfolio of high distress, high XFIN stocks; (3) the market portfolio; and (4) the risk-free asset. The portfolio of distressed stocks in the lowest external financing quintile performs similarly to the overall stock market, resulting in a final balance of \$26.49. Additionally, the portfolio of distressed stocks in the XFIN2 quintile (not shown) performs even better over the sample period producing an ending balance of \$39.25. In contrast, a \$1 investment in the portfolio of distressed firms with high external financing results in a final balance of two-tenths of one cent – a cumulative loss of 99.8%. The extreme losses experienced by this subgroup of firms drives the overall low returns to distressed stocks.

The results indicate that external financing has a large impact on the future performance of distressed stocks; however, instead of investor overoptimism, it is possible that other known risk factors are able to explain these findings. To explore this possibility in Table 2.5, Panel A reports the performance of the five distress-based long-short portfolios relative to other well-known factor models.[30]

When adjusting for risk using the Carhart 4-factor model the long-short portfolio alphas within the bottom three XFIN quintiles are insignificant and close to zero. These portfolios present less of a challenge for most factor models, as the unadjusted excess returns are also small and insignificant. Turning to the XFIN4 and XFIN5 portfolios it is observed that the Carhart model fares considerably worse than the q-factor model in explaining the strength of the distress anomaly, as the long-short portfolio alpha is now also significant within the XFIN4 quintile (0.74, $t = 2.54$) and is much larger

[30] I would like to thank the respective authors for making their factors available. I obtain data on the MKT, SMB, HML, and UMD factors from Ken French's data library, as well as for the RMW and CMA factors used in the Fama-French five-factor model. Data on the risk-free rate as proxied by the one-month T-bill return is also found here. The liquidity factor is obtained from Lubos Pastor's website, and the quality minus junk factor is obtained from the AQR data library. Lu Zhang provided data for the q-factor model factors through email correspondence.

within the XFIN5 quintile (1.74, $t = 5.86$). Thus, the Carhart model is unable to account for the underperformance of the high distress, high external financing stocks. When adding the Pastor and Stambaugh liquidity factor as an additional control the results are largely unchanged; consequently, differences in liquidity risk are unlikely to explain the findings.

Next, I report portfolio alphas relative to the Fama-French 5-factor model, which like the q-factor model has the advantage of controlling for both profitability and investment. Both of these factors could help explain the abnormal returns, as healthy firms are considerably more profitable than distressed firms, and the investment factor may capture some of the effects associated with external financing. The results, however, suggest these factors do little to explain the underperformance of the high distress, high external financing portfolio, as the long-short portfolio generates a significant monthly alpha of 1.92% ($t = 5.17$) within the highest external financing quintile. Fama and French (2015) report that although they do not include a momentum factor in their 5-factor model, when the left-hand-side portfolios have a strong momentum tilt, like the portfolios formed on distress do, including a momentum factor is crucial. Consequently, I also measure the performance of the long-short portfolios relative to their model augmented with an additional factor for momentum, UMD. This model does better at capturing the returns to the long-short portfolios, but it does not come close to fully eliminating the large alpha among high external financing stocks which is still 1.39% ($t = 4.63$). The alphas for the other four long-short portfolios are all insignificant at the five percent level with estimated abnormal returns ranging from -0.49% to 0.44%.

Finally, I also measure abnormal returns relative to a model consisting of the market factor in addition to the quality-minus-junk (QMJ) factor utilized in Asness et al. (2014). In their study, Asness et al. show that investors pay a higher price for high quality stocks but not by a very large margin, which results in high quality stocks earning a superior risk-adjusted return. However, the results indicate that this model tends to underpredict the returns to distressed stocks within the XFIN1 and XFIN2 quintiles, as both long-short portfolios yield a significantly negative abnormal return. The model is also unable to explain the low returns to the high distress, high external financing portfolio, and the long-short portfolio within the XFIN5 quintile earn a significantly positive abnormal return (1.11, $t = 3.19$). As always, there remains a possibility that an unidentified source of risk can explain the underperformance of the highly distressed stocks with high prior external financing activity. However, the severe failures of current asset pricing models is consistent

with the hypothesis that extreme external financing growth causes optimistic investors to overpay for the possibility that a distressed firm will make a comeback, and the remaining analysis provides tests to support this explanation.

To ensure the results are robust and not specific to a particular subsample, Panel B first divides the full sample into periods of expansion and recession based on the business cycle dates according to NBER. Within the bottom four external financing quintiles, the healthy minus distressed long-short portfolio only earns a significant return in the XFIN4 quintile during periods of expansion (0.98, $t = 2.41$) and the return is insignificant for all four portfolios during recessions. Conversely, within the XFIN5 quintile of high external financing firms, the long-short portfolio yields large average monthly returns in both subsamples, earning 1.86% during periods of expansion and 2.65% during periods of recession. Despite being considerably larger, the average return during recessions is not statistically significant, as the standard error is much higher because of the smaller sample size. The full sample period contains 354 expansionary months compared to only 54 months that are part of economic recessions. These results suggest variation in performance over the business cycle is unlikely to explain the findings, since similar patterns are found within both sub-periods. Additionally, for systematic risk related to the business cycle to explain the findings, the high distress, high external financing portfolio would need to earn higher returns during recessions, thereby, providing investors with a greater payoff when the marginal utility of wealth is higher.

Also reported are the average returns to the long-short portfolios during the 1980s, 1990s, and from the year 2000 to the end of the sample period. The evidence suggests the underperformance of the high distress, high external financing portfolio persisted throughout the sample period and was particularly strong during the 1980s and 1990s, as the long-short portfolio of XFIN5 stocks earned significant average monthly returns of 2.30% and 2.45%, respectively. From the year 2000 forward this portfolio still earned large albeit lower returns, but the result is only marginally significant (1.45, $t = 1.79$). The reduced significance in the final subperiod can largely be attributed to the increased volatility and higher returns earned by distressed stocks immediately following the 2008 financial crisis, as documented by Eisdorfer and Misirli (2016).[31] This is also consistent with there

[31] In their study, Eisdorfer and Misirli report that subsequent to the top 10 bear markets in their sample the decile portfolio of most distressed stocks outperformed the decile portfolio of healthiest stocks by an average of 10.23% per month. Similar "crashes" are shown to occur for momentum strategies in Daniel and Moskowitz (2015) during which loser stocks rebound.

being limited overoptimism in the aftermath of the crisis.

Panel C presents the results when extending the portfolio holding period, which addresses the concern that the results are sensitive to rebalancing frequency. I consider holding periods of 6, 12, and 18 months where the portfolio weights are allowed to drift with returns to prevent the need for any rebalancing adjustments. For each rebalancing frequency, none of the long-short portfolios within the bottom four external financing quintiles earn a significant average monthly return, whereas the portfolio of high external financing firms does in all cases. As expected, the return to the long-short portfolio within XFIN5 becomes smaller when the rebalancing frequency is extended, as stocks are then held in the portfolio based on increasingly stale information, but the return is still large and highly significant even when rebalancing as infrequently as once every eighteen months.

2.4.3 *Fama-MacBeth Regressions with Distress and External Financing*

To further explore the interaction between financial distress and external financing activity, I also conduct cross-sectional Fama-MacBeth (1973) regressions. This approach allows for an evaluation of the *CHS-XFIN* interaction strength while directly controlling for other standard return predictors. In addition, I am able to measure the marginal impact of distress on future returns and evaluate whether it has any predictive power not captured by its interaction with external financing. The results from these regressions are presented in Table 2.6, and the main specification displayed in the fifth row takes the form:

$$\begin{aligned} Ret_{i,t+1} = \beta_0 + \beta_1 log(Size_{i,t}) + \beta_2 log(B/M_{i,t}) + \beta_3 Mom_{i,t} + \beta_4 CHS_{i,t} + \beta_5 XFIN_{i,t} \\ + \beta_6 CHS \cdot XFIN_{i,t} + e_{i,t+1} \end{aligned} \tag{2.5}$$

where the dependent variable is the monthly stock return in excess of the risk-free rate and the independent variables include the log market capitalization (Size), log book-to-market (B/M), cumulative return from month *t-12* to *t-2* (Mom), distress failure probability (CHS), external financing (XFIN), and an interaction term between the distress and external financing variables.[32] I multiply all coefficients by 100 for readability and report t-statistics based on Fama-MacBeth standard errors in parentheses.

[32] In the interest of space, only the most common controls are included. The results are similar with the addition of further controls for common predictors such as profitability and accruals with the results available upon request.

The coefficients presented in the table reflect time series averages of the cross-sectional regression estimates over the full sample period from 1981 to 2014. The first specification does not yet include the distress or external financing variables but confirms that the sign for each of the controls is consistent with prior literature. As expected, firm size has a negative though insignificant effect on returns while book-to-market and momentum are positively associated with future returns. The second regression adds the *CHS* failure probability, which enters with a significantly negative coefficient (-1.23, t = -2.85), consistent with prior research that finds distressed stocks earn anomalously low returns. In the third regression the external financing variable, *XFIN*, is added and found to have a significantly negative coefficient (-1.87, t = -9.12), as is found in Bradshaw et al. (2006). Specification four then separates *XFIN* into its two components, *EFIN* and *DFIN*, and indicates that both equity and debt financing play a role in contributing to lower future returns.

The fifth row presents the main specification, which includes both the distress and external financing variables as well a term to measure their interaction. As before, the *CHS* failure probability has a negative coefficient; however, it is much smaller in magnitude and no longer statistically significant (-0.73, t = -1.59), as the inclusion of the external financing terms appears to subsume much of its explanatory power. Interestingly, both *XFIN* and its interaction with the *CHS* distress variable are negative and highly significant. This is consistent with the findings from the portfolio sorts and suggests that not only do firms that raise large amounts of external financing experience lower future returns, but the relation between external financing and future returns is also stronger for firms experiencing severe financial distress as predicted given their greater short sale constraints.

Finally, the sixth regression specification includes *EFIN* and *DFIN* and interacts each separately with the *CHS* distress measure. Both *EFIN* and *DFIN* enter with negative coefficients and are highly significant. The interactions terms are both negative as well; however, only the *DFIN* interaction with *CHS* is statistically significant at conventional levels. The results presented here are generally consistent with the evidence in Park (2015), which documents lower returns to distressed firms that issue common stock, but suggest debt financing has a stronger interaction with the *CHS* distress variable. Importantly, the signs on each of the external financing components and their interaction terms are negative as predicted while the *CHS* coefficient falls even further (-0.63, t = -1.37), which suggests that, in contrast to the results in prior research, financial distress only has a large impact on future returns when coupled with large external financing growth that increases

the dispersion of opinions about firms' values.

2.4.4 *Abnormal Earnings Announcement Returns*

The decisions of distressed firms to raise external capital can create overvaluation, and because of short-sale limitations selling pressure will be generated primarily when current stockholders choose to sell their shares. This causes stock prices to remain elevated until the degree of uncertainty is reduced and optimistic investors revise their beliefs. On average these investors will tend to be disappointed upon observing the true realization of firm performance. In particular, reductions in differences of opinion and overvaluation should be concentrated in information rich periods such as around earnings announcement dates given that new information does not flow linearly to the market. Thus, Hypothesis 2 predicts that a significant portion of the underperformance of highly distressed firms with high external financing activity will occur around earnings announcements.

Table 2.7 reports the performance of the twenty-five double-sorted portfolios around earnings announcements dates to test if a significant amount of the underperformance associated with high distress, high external financing stocks is, in fact, concentrated in these high information periods. To measure investor reactions to earnings news over time, I reform portfolios based on the *CHS* and *XFIN* measures at the end of each June and hold them for one year. Following the literature, cumulative returns are measured from day *t-1* to *t+1* each quarter, where day *t=0* represents the earnings announcement date. Next, to transform this measure to an abnormal return, I subtract either the corresponding cumulative return on the market portfolio over the same three-day period (market-adjusted), or the average earnings announcement return for firms in the same size and book-to-market quintiles within that quarter (benchmark-adjusted). The benchmark adjusted returns help to ensure the results are not driven by previously documented book-to-market announcement effects (Griffin and Lemmon, 2002). The quarterly announcement returns for the year are then averaged and multiplied by four to produce an annualized figure.

Panel A presents the results with value-weighted portfolio announcement returns. The difference between the market-adjusted returns earned by healthy firms (D1) and distressed firms (D5) exhibits a similar pattern to the average returns presented in Table 2.4. In particular, the announcement returns to distressed firms within the bottom two external financing quintiles are larger than those earned by healthy firms, although the differences are not statistically significant. In some instances,

the mere ability to announce earnings may be viewed as a positive signal for distressed companies. In contrast, within the top external financing quintile, XFIN5, the portfolio of distressed stocks earns the lowest abnormal announcement returns (-2.84, t = -3.46), and the difference between the least and most distressed portfolios is large and significant (4.56, t = 3.61). The results for the benchmark-adjusted returns exhibit a similar pattern. These return differences are economically large as predicted by Hypothesis 2, especially considering that the earnings announcement windows reflect a total of only 12 trading days across the four quarters, and investors are likely to obtain much additional information about firm performance from other events throughout the year.

Panel B displays the results when equal-weighting the abnormal returns for each portfolio, and the overall results are similar. Within the XFIN5 quintile, the portfolio containing the most distressed stocks experiences less negative market-adjusted returns than in Panel A, but its underperformance is still large and significant (-2.24, t = -2.96), as is the difference between the least and most distressed portfolios (2.72, t = 3.55). The results in this section are consistent with the predictions of Hypothesis 2 and confirm that the negative returns to the high distress, high external financing portfolio are more pronounced around earnings announcements when overly optimistic investors are typically disappointed by the lack of improved profitability.

2.4.5 *Limits to Arbitrage and Uncertainty*

Large influxes of external capital create uncertainty and significant dispersion in investor valuations, particularly among distressed firms whose long-term survival depends highly on the success of new capital projects. This can create overvaluation, as greater limits to arbitrage among distressed stocks allow optimists to bid up stock prices while short-sellers are prevented from taking a position against them. However, within each portfolio of firms there remains some variation in both the degree of uncertainty regarding firm valuations as well as short-sale limitations. Consequently, Hypothesis 3 predicts that stock overvaluation and subsequent underperformance will be most severe for firms that are particularly difficult to value and challenging to sell short.

Table 2.8 tests this hypothesis by considering several proxies for short-sale constraints (Panels A and B) and uncertainty (Panels C and D) that have been explored in the literature (Nagel, 2005; Boehme et al., 2006; Campbell et al., 2008; Berkman et al., 2009; Stambaugh et al., 2012). Each month I assign the stocks from each portfolio into two groups, low and high, based on the

median value of either idiosyncratic volatility (IVOL), residual institutional ownership (ResInst), residual analyst coverage (ResAn), or firm age. I focus only on the portfolios in the highest external financing quintile, XFIN5, where the underperformance is concentrated and report the excess return and q-factor model alpha of the long leg (D1), short leg (D5), and the difference (D1–D5).

Panel A reports the results for IVOL, which represents fluctuations in a stock's price that are unassociated with risk factors and is considered a proxy for arbitrage risk (Stambaugh et al., 2015). Consistent with IVOL deterring arbitrageurs from taking a position in overpriced stocks, I find the healthy minus distressed long-short portfolio earns a large and highly significant abnormal return among the high IVOL subgroup (1.56, $t = 3.82$), which is driven primarily by the underperformance of the short leg. In contrast, among low IVOL stocks a similar long-short portfolio produces a return that is much smaller and insignificant at conventional levels (0.76, $t = 1.52$). Within this group, short-sellers are expected to be more willing to bet against overvalued stocks, thereby limiting mispricing.

Panel B evaluates the impact of differences in ResInst, which is computed following Campbell et al. (2008) as the residual from a regression of the percentage of shares owned by institutional investors on relative size (RSIZE) and year indicator variables. Controlling for RSIZE allows the measure to capture differences in institutional ownership that are independent of size, as the two variables are highly correlated. D'Avolio (2002) documents that shares are typically lent by institutional investors; therefore, short-selling constraints are more likely to affect stocks with low institutional ownership. Further, Nagel (2005) suggests there is also an indirect channel that prevents overpricing from correcting, as non-institutional stockholders are less sophisticated and may be less likely to sell when a stock becomes overpriced. Consistent with these explanations, I find the underperformance of high distress, high external financing firms is more severe when ResInst is low.

Panel C explores the influence of residual analyst coverage (ResAn), and Panel D explores the effect of firm age. Following the literature, I measure ResAn as the residual of a regression of the log of one plus the number of analysts covering each firm on relative firm size and year indicators, and I compute Age as the number of years since a firm first entered the CRSP database. Both of these variables are expected to influence the degree of uncertainty and dispersion in investor opinions. Specifically, greater analyst coverage can limit the dispersion of opinions and extent of overopti-

mism, because sell-side analysts provide relatively sophisticated estimates of future performance that are available to the market. Likewise, older, more-established firms are expected to be easier to value given their longer operating histories. Consistent with the predictions of Hypothesis 3, I find the underperformance of the high distress, high external financing portfolio is more pronounced among stocks with lower residual analyst coverage and for younger firms. This adds support to the overarching explanation that the distress anomaly is driven by the overvaluation of firms with high external financing growth, which is increasing in the degree of dispersion in investor opinions and the limitations to short selling.

2.5 Robustness Tests

This section presents robustness tests to rule out alternate explanations for the external financing effect found among distressed stocks. Specifically, I explore the performance of the double-sorted portfolios during periods of high and low sentiment. Subsequently, I provide a closer look at how the relation between the external financing variable and future returns varies with the level of distress.[33]

2.5.1 *Impact of Investor Sentiment*

Stambaugh et al. (2012) document that many asset pricing anomalies are more pronounced following periods of high sentiment and are either weak or non-existent following periods of low sentiment. They present an explanation that is similar in that it focuses on mispricing caused by high sentiment (i.e. overoptimism) combined with impediments to short-selling; however, they focus on the impact of market-wide sentiment on asset prices more broadly. Although they do not discuss the source of overoptimism, their study suggests it may be responsible for many anomalies. The decision to raise external capital represents a firm-specific event capable of generating overvaluation, and its effects are likely to be amplified by market-wide sentiment. To explore the impact of sentiment on the distress and external financing double-sorted portfolios, I divide the sample into periods of high and low sentiment based on the prior month's value of the investor sentiment index developed in Baker and Wurgler (2006).

[33] Appendix Table A2.2 also reports the results from tests comparing the strength of the external financing effect on distressed stocks to the effect of other relevant characteristics such as book-to-market, skewness, and profitability.

In Table 2.9, Panel A displays the average monthly returns to portfolios that are long healthy firms (D1) and short distressed firms (D5) within each external financing quintile. Consistent with anomaly returns being more pronounced after periods when overall optimism is high, the long-short portfolio returns are higher within each of the external financing quintiles following periods of high investor sentiment. In both subsamples the distress anomaly appears strongest among XFIN5 firms, but following periods of low sentiment the long-short portfolio returns are much smaller (0.94, t = 1.56) than following periods of high sentiment (3.00, t = 5.17). Further, the high distress, high external financing portfolio earns an abysmal average excess return of -3.05% (t = 5.17) during periods of high sentiment, which supports the mispricing hypothesis as distressed firms are especially prone to overvaluation when both the dispersion of investor opinions is high, and the market is more optimistic in general.

It is possible that much of the difference in performance between the two subsamples can be attributed to certain risk factors having higher or lower returns when sentiment is high. The evidence in Panel B reflects this possibility, as the q-factor model alphas are very similar between the high and low sentiment subsamples. In each instance, only the abnormal return to the healthy minus distressed long-short portfolio consisting of XFIN5 firms is statistically significant, and the unexplained outperformance of healthy stocks relative to distressed stocks is similar in magnitude during times of low (1.16, $t = 2.72$) and high sentiment (1.24, $t = 2.55$). Overall, the results suggest that market sentiment can amplify the degree of overvaluation associated with high distress, high external financing stocks, but it also does not drive the results.

2.5.2 *The Level of Distress and the Strength of the External Financing Effect*

Next, I investigate how the impact of external financing varies with the level of distress by dividing the full sample into quintiles based on the *CHS* distress variable and conducting cross-sectional Fama and MacBeth (1973) regressions separately on each group of stocks. This approach allows for an in-depth look at how the relative importance of all return predictors, including external financing, change as the level of firm distress increases without needing to estimate multiple interaction terms. Another useful feature is the ability to conduct formal difference-in-means tests

for whether the impact of a predictor variable is equal for two groups.[34]

The primary focus is on how the *XFIN* coefficient changes across distress quintiles. As before, I predict its impact will be more negative among highly distressed firms, as their stocks are generally subject to greater short-sale constraints and new capital projects are associated with a wide range of possible outcomes and investor opinions. In each specification the dependent variable is the monthly return in excess of the risk-free rate, and the control variables include the log of firm size, log book-to-market, momentum, negative accruals, positive accruals, positive profitability, a dummy variable for negative profitability, and external financing.[35] The cross-sectional regressions take the form:

$$\begin{aligned} Ret_{i,t+1} = \beta_0 + \beta_1 log(Size_{i,t}) + \beta_2 log(B/M_{i,t}) + \beta_3 Mom_{i,t} + \beta_4 negAcc_{i,t} + \beta_5 posAcc_{i,t} \\ + \beta_6 posROE_{i,t} + \beta_7 negROE_{i,t} + \beta_8 XFIN_{i,t} + e_{i,t+1} \end{aligned} \tag{2.6}$$

The results from Table 2.10 indicate that the *XFIN* variable has a negative impact on next period returns and is statistically significant within all distress quintiles; however, its coefficient and t-statistic decrease monotonically when moving from the quintile of least distressed to most distressed firms. The coefficient on the *XFIN* variable also appears to decrease somewhat gradually across the first four distress quintiles, ranging from -0.91 to -1.54, before falling sharply to -2.46 in the most distressed quintile (D5). This suggests that external financing activity is associated with particularly low future returns among the most distressed stocks, as its estimated coefficient is more than two-and-a-half times greater among D5 firms than D1 firms.

The final row tests whether the coefficients of the cross-sectional regressions estimated using only D5 stocks differ significantly from the coefficients obtained when including all non-D5 stocks. Highlighting the strength of the external financing effect among distressed stocks, the difference in estimated coefficients is largest for the *XFIN* variable, as its impact is significantly more negative among D5 firms (-1.21, t = -4.06).

The log book-to-market and negative accruals variables are the only other predictors to exhibit significant differences in coefficients between distressed stocks and all other stocks (-0.28, t = -2.73

[34]This procedure is similar to that of Fama and French (2008) who divide their full sample into three groups (micro, small, and big) based on market cap and explore the predictive strength of the most well-documented anomaly variables within each group.

[35]These controls consist of all of the variables from the dissecting anomalies regressions of Fama and French (2008) with the exception of net stock issuance and asset growth per share which present natural collinearity issues when included with external financing.

and 0.62, $t = 2.59$; respectively), and the differences are much smaller in magnitude. Interestingly, the coefficient on log book-to-market is smaller for distressed firms than for all other firms. This is in contrast to the findings of Griffin and Lemmon (2002) who document that the book-to-market effect is more pronounced among distressed stocks. Although their study uses an earlier sample period, in unreported results, I find the coefficient on book-to-market is larger for the group of D5 firms compared to non-D5 firms when *XFIN* is dropped from the regressions, which is consistent with their findings and suggests the external financing variable captures the effect. The results from this section confirm that external financing activity is associated with severe underperformance among distressed stocks and has a much larger impact than other widely studied anomaly variables.

2.6 Conclusion

This study provides an explanation for the underperformance of distressed stocks and finds that the well-documented distress anomaly only exists among firms with high recent external financing activity. The decision by distressed firms to raise external capital can generate significant overpricing by producing a divergence of investor opinions. The most optimistic investors assign high valuations, as the additional funds provide firms with liquidity and allow them to undertake new projects that can facilitate a recovery, whereas more pessimistic investors assign low valuations, as external capital comes with a high cost and new projects may not payoff. In the presence of short-sale impediments, however, which I show are more severe for distressed companies, only the most optimistic investors influence a stock's price while arbitrageurs take no position in the stock. This results in a market price above the average valuation of all market participants that is increasing in the degree of dispersion in beliefs. As a result, I expect the distress anomaly will be driven by low returns to distressed firms with high external financing activity.

The empirical evidence is consistent with this explanation. By sorting firms into portfolios based on their levels of distress and net external financing, I find the distress anomaly, measured as the outperformance of healthy stocks relative to distressed stocks, only exists among firms in the highest external financing quintile. Further, this healthy minus distressed long-short portfolio derives its abnormal returns almost exclusively from the underperformance of the high distress, high external financing portfolio which is large, persistent, and cannot be explained by previously

identified risk factors. In contrast, existing factor models can explain the returns to the remaining eighty percent of distressed stocks. In fact, within the bottom two quintiles distressed stocks earn higher returns than healthy stocks, although the difference is not statistically significant.

The external financing explanation also implies that when new value-relevant information reaches the market, the overvaluation of highly distressed, high external financing firms will be reduced, as optimistic investors will be disappointed on average and revise their expectations downward. To test this empirically, I measure the performance of the double-sorted portfolios around earnings announcement dates when investors receive an update of firms' actual performance. The results support this view, as a significant portion of the underperformance of the high distress, high external financing portfolio is concentrated in these periods.

Finally, I also explore characteristics that make firms more challenging to value or subject to greater short-sale constraints, both of which are expected to increase the external financing effect. Consistent with this, I document more negative abnormal returns when firms also have higher idiosyncratic volatility, lower institutional ownership, lower analyst coverage, and fewer years since becoming publicly traded. This adds support to the central explanation, as the distribution of investor opinions is expected to be wider for firms that are more challenging to value, and short-sale impediments prevent professional arbitrageurs from exploiting potential mispricing.

Table 2.1: Performance of Portfolios Sorted on CHS Distress-Risk

This table presents the results from sorting stocks into deciles (least distressed, D1, to most distressed, D10) based on the CHS (2008) measure of financial distress at the end of each month. This variable is constructed using monthly market data and quarterly accounting data. Panel A displays value-weighted portfolio returns in excess of the risk-free rate, as well as alphas relative to the CAPM, Fama-French 3-factor model, and Carhart 4-factor model. Returns and alphas are reported in percent per month with the corresponding t-statistics below in parentheses. Panel B reports the loadings on the factors from the Carhart 4-factor model regressions with t-statistics displayed below in parentheses. Panel C reports mean and median firm characteristics for the stocks in each portfolio. Size is the market value of equity (in millions of dollars). Market-to-book is the ratio of the market value of equity to the book value of equity. Momentum (reported in percent) is the cumulative return from month *t-12* to *t-2*, *CHS* is the monthly failure probability (reported in percent) based on the CHS measure of distress, and *XFIN* is the annual net cash flow received from external financing activities as a percentage of average total assets. Characteristic values are calculated by first computing the cross-sectional means and medians across all stocks within each portfolio, and then reporting their time series averages. The sample period is 1981 to 2014.

Decile Portfolios		D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D1–D10
Panel A: Portfolio Alphas												
Excess return		0.73	0.63	0.65	0.69	0.60	0.75	0.56	0.43	0.12	-0.20	0.93
		(3.29)	(3.08)	(3.22)	(3.11)	(2.44)	(2.64)	(1.71)	(1.10)	(0.28)	(-0.38)	(2.10)
CAPM alpha		0.18	0.10	0.13	0.12	-0.02	0.05	-0.24	-0.50	-0.86	-1.24	1.42
		(1.71)	(1.28)	(1.63)	(1.35)	(-0.20)	(0.36)	(-1.49)	(-2.38)	(-3.31)	(-3.47)	(3.49)
FF3F alpha		0.28	0.13	0.12	0.10	-0.02	-0.00	-0.27	-0.55	-0.97	-1.50	1.77
		(2.61)	(1.79)	(1.53)	(1.13)	(-0.22)	(-0.02)	(-1.77)	(-2.91)	(-4.16)	(-4.79)	(4.85)
Carhart alpha		0.10	0.01	0.10	0.16	0.13	0.23	0.04	-0.15	-0.47	-0.77	0.87
		(1.04)	(0.12)	(1.28)	(1.87)	(1.28)	(1.84)	(0.27)	(-0.94)	(-2.42)	(-3.10)	(3.12)
Panel B: Carhart Regression Coefficients												
MKT		0.90	0.90	0.87	0.93	0.95	1.07	1.15	1.29	1.35	1.37	-0.47
		(39.50)	(55.69)	(46.98)	(45.96)	(39.54)	(36.13)	(36.79)	(34.36)	(29.21)	(23.23)	(-7.09)
SMB		-0.06	-0.13	-0.15	-0.06	0.09	0.12	0.41	0.67	0.87	1.32	-1.39
		(-2.01)	(-5.61)	(-5.52)	(-1.97)	(2.61)	(2.94)	(9.16)	(12.54)	(13.32)	(15.82)	(-14.81)
HML		-0.11	-0.02	0.04	0.01	-0.06	0.01	-0.08	-0.08	-0.01	0.17	-0.28
		(-3.28)	(-0.78)	(1.28)	(0.42)	(-1.67)	(0.16)	(-1.63)	(-1.38)	(-0.14)	(1.88)	(-2.81)
UMD		0.21	0.15	0.02	-0.08	-0.19	-0.29	-0.38	-0.49	-0.61	-0.88	1.10
		(9.95)	(10.16)	(1.27)	(-4.02)	(-8.29)	(-10.24)	(-12.72)	(-13.87)	(-13.99)	(-15.91)	(17.63)
Panel C: Firm Characteristics												
Size	Mean	4,765.5	4,982.3	3,851.0	3,086.1	2,287.4	1,659.8	1,058.2	541.4	261.8	103.9	
	Median	3,332.9	4,098.6	2,715.6	1,904.8	1,292.3	919.6	492.1	245.0	115.3	42.8	
Market-to-Book	Mean	1.99	2.20	2.11	1.99	1.91	1.83	1.80	1.79	1.78	1.68	
	Median	2.01	2.26	2.16	2.03	1.95	1.86	1.84	1.81	1.80	1.72	
Momentum	Mean	31.9	30.3	26.8	24.2	21.2	17.8	14.1	9.0	0.2	-19.4	
	Median	30.9	29.9	26.4	23.8	20.6	17.8	13.8	9.0	-1.3	-22.6	
CHS (Failure $\hat{P}$)	Mean	0.016	0.022	0.027	0.032	0.038	0.047	0.060	0.083	0.134	0.419	
	Median	0.016	0.021	0.026	0.031	0.037	0.045	0.056	0.077	0.121	0.401	
XFIN	Mean	-2.57	-0.89	0.42	1.52	2.63	3.79	4.91	6.17	7.62	9.34	
	Median	-2.46	-0.57	0.58	1.64	2.42	3.53	4.72	5.84	7.29	9.21	

Table 2.2: Cross-Correlation Table for Distress and External Financing Variables

This table presents Pearson correlation coefficients for the primary variables of interest. XFIN is net external financing computed as the sum of EFIN and DFIN, where EFIN is net equity financing measured as funds raised from the sale of common and preferred stock less payments for the repurchase of common and preferred stock less dividends, and DFIN is net debt financing measured as funds raised from the issuance of long-term debt less payments used to reduce long-term debt plus changes in current debt. All external financing variables are deflated by average total assets and winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentiles. CHS_t is a firm's monthly failure probability as predicted by the CHS measure of financial distress. Log(Size) is the log of a firm's market value of equity in millions of dollars. Log(B/M) is the log of book equity divided by market equity. Mom is the cumulative stock return from month *t-12* to *t-2*. All correlations are significant at the one percent level.

Variables	XFIN_t	EFIN_t	DFIN_t	CHS_t	Log(Size)_t	Log(B/M)_t	Mom_t
XFIN_t	1.000						
EFIN_t	0.782	1.000					
DFIN_t	0.591	-0.020	1.000				
CHS_t	0.108	0.101	0.050	1.000			
Log(Size)_t	-0.089	-0.131	0.022	-0.319	1.000		
Log(B/M)_t	-0.193	-0.193	-0.067	0.120	-0.290	1.000	
Mom_t	0.011	0.049	-0.051	-0.243	0.109	-0.342	1.000

Table 2.3: Characteristics of Portfolios Sorted on Distress and External Financing

This table reports average firm characteristics for twenty-five double-sorted portfolios formed by sorting stocks first into distress quintiles (least distressed, D1, to most distressed, D5), and then into quintiles based on the level of external financing (low external financing, XFIN1, to high external financing, XFIN5). Financial distress is measured using the failure model of CHS (2008), and external financing is the net funds raised from external sources. Portfolios are formed based on the month-end values of the two variables of interest and are held for the subsequent month. The characteristics displayed include Size (market cap in millions of dollars), Market-to-Book ratio (market equity divided by book equity), Equity Financing (net funds raised through common and preferred stock transactions), Debt Financing (net funds raised through issuance and repayment of debt), External Financing (sum of equity and debt financing), CHS - Failure $\hat{P}$ (monthly failure probability based on CHS model), Idiosyncratic Volatility (annualized standard deviation of daily return residuals relative to Carhart 4-Factor Model) and Institutional Ownership (the percentage of shares outstanding owned by institutional investors). All external financing variables are deflated by average total assets. Characteristic values are calculated by first computing the cross-sectional mean across all stocks within each portfolio, and then reporting their time series averages. The sample period is 1981 to 2014. Panels C, D, E, and G are reported in percent, and the sample period is 1981 to 2014.

	D1 (low)	D2	D3	D4	D5 (high)	D1 (low)	D2	D3	D4	D5 (high)
	Panel A: Size					Panel B: Market-to-Book				
XFIN1 (low)	7,701.8	4,316.5	2,140.7	764.1	194.1	2.39	2.25	1.92	1.66	1.46
XFIN2	6,713.5	4,666.7	2,523.1	946.0	191.2	1.99	1.85	1.61	1.50	1.40
XFIN3	3,816.4	3,603.6	1,800.3	746.3	174.2	1.82	1.82	1.70	1.68	1.58
XFIN4	2,769.6	2,609.4	2,072.7	943.2	196.8	1.94	2.00	1.85	1.79	1.70
XFIN5 (high)	3,351.2	2,137.8	1,326.8	598.8	157.8	2.31	2.33	2.28	2.37	2.50
	Panel C: Equity Financing (EFIN)					Panel D: Debt Financing (DFIN)				
XFIN1 (low)	-9.55	-6.44	-4.26	-2.55	-1.06	-3.62	-4.89	-5.97	-7.25	-8.59
XFIN2	-4.42	-2.95	-1.71	-0.79	-0.09	-1.20	-1.33	-1.41	-1.51	-1.50
XFIN3	-2.14	-1.28	-0.47	0.09	0.63	-0.36	0.06	0.38	0.76	1.27
XFIN4	-0.31	0.06	0.49	1.29	2.66	0.42	2.13	3.62	5.02	6.81
XFIN5 (high)	7.41	9.45	12.20	17.03	24.83	5.79	10.30	12.97	14.81	16.10

	D1 (low)	D2	D3	D4	D5 (high)	D1 (low)	D2	D3	D4	D5 (high)
	Panel E: External Financing (XFIN)					Panel F: CHS (Failure $\hat{P}$)				
XFIN1 (low)	-13.85	-11.82	-10.64	-10.19	-10.05	0.02	0.03	0.04	0.07	0.26
XFIN2	-5.66	-4.31	-3.15	-2.32	-1.62	0.02	0.03	0.04	0.07	0.26
XFIN3	-2.51	-1.23	-0.11	0.83	1.88	0.02	0.03	0.04	0.07	0.27
XFIN4	0.10	2.17	4.08	6.28	9.45	0.02	0.03	0.04	0.07	0.29
XFIN5 (high)	13.35	20.16	26.01	33.26	42.95	0.02	0.03	0.04	0.07	0.30
	Panel G: Idiosyncratic Volatility (IVOL)					Panel H: Institutional Ownership				
XFIN1 (low)	24.74	28.61	34.53	44.99	70.44	0.491	0.470	0.419	0.348	0.260
XFIN2	24.23	26.62	32.93	45.15	71.38	0.478	0.476	0.424	0.351	0.260
XFIN3	26.58	30.40	36.39	47.07	72.18	0.461	0.453	0.405	0.347	0.265
XFIN4	30.18	31.02	34.05	43.92	70.28	0.453	0.467	0.427	0.368	0.261
XFIN5 (high)	29.18	31.69	36.81	46.86	72.28	0.513	0.488	0.434	0.349	0.238

Table 2.4: Performance of Portfolios Sorted on Distress and External Financing

This table displays the performance of portfolios formed by sorting all stocks into distress quintiles (least distressed, D1, to most distressed, D5), and then subsequently into quintiles based on the level of external financing (low external financing, XFIN1, to high external financing, XFIN5). Financial distress is measured using the failure model of CHS (2008), and external financing is the net funds raised from external sources relative to average total assets. Portfolios are formed based on the month-end values of the two variables of interest and are held for the subsequent month. This table displays the average monthly excess returns and HXZ q-factor model alphas for the 25 portfolios as well as for portfolios that are long healthy stocks and short distressed stocks (D1–D5) within the same XFIN quintile. Panel A reports the results using value-weighted portfolio returns while Panel B repeats the analysis using equal-weighted portfolios. All returns and alphas are in percent per month with the corresponding t-statistics in parentheses. The sample period is 1981 to 2014.

	D1	D2	D3	D4	D5	D1–D5	D1	D2	D3	D4	D5	D1–D5
Panel A: Value-Weighted Portfolio Returns and Alphas												
	Excess Return						HXZ Q-Factor Alpha					
XFIN1 (low)	0.74	0.96	0.89	1.11	0.82	-0.08	-0.10	0.40	0.48	0.60	0.01	-0.11
	(3.52)	(4.51)	(3.04)	(3.25)	(1.87)	(-0.21)	(-0.90)	(3.49)	(2.78)	(3.10)	(0.05)	(-0.37)
XFIN2	0.57	0.63	1.09	0.90	0.93	-0.36	-0.08	0.00	0.55	0.38	0.47	-0.55
	(2.75)	(2.96)	(4.46)	(2.72)	(2.13)	(-1.01)	(-0.76)	(0.01)	(4.21)	(1.98)	(1.83)	(-1.89)
XFIN3	0.74	0.52	0.51	0.72	0.43	0.30	-0.00	-0.23	0.08	0.62	0.43	-0.43
	(3.34)	(2.31)	(1.89)	(1.85)	(0.85)	(0.69)	(-0.03)	(-1.94)	(0.55)	(2.87)	(1.42)	(-1.26)
XFIN4	0.74	0.77	0.59	0.37	-0.16	0.91	-0.03	0.11	0.20	0.10	-0.34	0.32
	(3.00)	(3.22)	(2.18)	(1.01)	(-0.34)	(2.27)	(-0.19)	(0.77)	(1.28)	(0.51)	(-1.19)	(0.95)
XFIN5 (high)	0.71	0.43	0.07	-0.33	-1.26	1.97	-0.00	-0.23	-0.52	-0.54	-1.22	1.22
	(2.61)	(1.62)	(0.23)	(-0.83)	(-2.41)	(4.66)	(-0.01)	(-1.81)	(-3.64)	(-2.74)	(-4.26)	(3.62)
Panel B: Equal-Weighted Portfolio Returns and Alphas												
	Excess Return						HXZ Q-Factor Alpha					
XFIN1 (low)	1.01	1.14	1.22	1.23	1.03	-0.02	0.22	0.36	0.48	0.63	0.63	-0.40
	(4.92)	(5.13)	(4.81)	(4.13)	(2.69)	(-0.07)	(3.00)	(4.28)	(5.14)	(5.13)	(3.12)	(-1.94)
XFIN2	0.87	1.06	1.07	1.11	1.06	-0.19	0.13	0.31	0.43	0.55	0.88	-0.76
	(4.36)	(4.96)	(4.46)	(3.72)	(2.61)	(-0.64)	(1.80)	(4.03)	(5.09)	(4.65)	(4.18)	(-3.46)
XFIN3	0.98	0.96	0.94	0.94	0.82	0.17	0.22	0.24	0.34	0.56	0.70	-0.48
	(4.60)	(4.02)	(3.51)	(2.93)	(1.98)	(0.58)	(2.92)	(3.13)	(4.02)	(4.51)	(3.40)	(-2.23)
XFIN4	1.02	0.94	0.76	0.63	0.11	0.91	0.27	0.20	0.19	0.20	-0.12	0.39
	(4.15)	(3.81)	(2.88)	(2.01)	(0.27)	(3.29)	(2.91)	(2.37)	(2.00)	(1.75)	(-0.62)	(1.78)
XFIN5 (high)	0.87	0.67	0.38	-0.03	-0.85	1.72	0.03	-0.04	-0.22	-0.44	-0.72	0.74
	(3.33)	(2.43)	(1.29)	(-0.09)	(-1.88)	(5.15)	(0.29)	(-0.40)	(-2.12)	(-3.31)	(-3.07)	(2.85)

Table 2.5: Robustness of Portfolios Sorted on Distress and External Financing

This table reports the performance of zero net-investment portfolios that are long stocks in the least distressed quintile of firms, D1, and short stocks in the most distressed quintile, D5, within each external financing quintile. Panel A displays the monthly alphas of these portfolios relative to the Carhart model, Carhart model plus the Pastor and Stambaugh liquidity factor, LIQ, Fama-French 5-Factor Model, Fama-French 5-Factor Model plus the momentum factor, UMD, and the market factor plus quality minus junk factor from Asness et al. (2014). The raw returns to the long-short portfolios are displayed for subsamples in Panel B. The sample is partitioned into periods of expansion and recession with recessions defined according to the NBER as well as subperiods (1981 – 1989, 1990 – 1999, and 2000 – 2014). Panel C presents results excess returns using longer portfolio holding periods. When rebalancing semi-annually portfolios are reformed at the end of every June and December, and when rebalancing annually portfolios are only reformed at the end of June. All returns are in percent per month with corresponding t-statistics below in parentheses.

	D1 – D5				
	XFIN1	XFIN2	XFIN3	XFIN4	XFIN5
Panel A: Alternate Factor Models					
Carhart	0.15	-0.20	0.17	0.74	1.74
	(0.55)	(-0.73)	(0.53)	(2.54)	(5.86)
Carhart + LIQ	0.20	-0.18	0.22	0.85	1.80
	(0.72)	(-0.65)	(0.67)	(2.88)	(6.00)
FF5F	0.41	-0.23	0.16	0.93	1.92
	(1.28)	(-0.75)	(0.43)	(2.59)	(5.17)
FF5F + UMD	0.01	-0.49	-0.35	0.44	1.39
	(0.03)	(-1.76)	(-1.10)	(1.47)	(4.63)
MKT + QMJ	-0.94	-1.08	-0.63	0.13	1.11
	(-2.83)	(-3.67)	(-1.77)	(0.37)	(3.19)
Panel B: Sub-samples					
Expansion	-0.07	-0.47	0.31	0.98	1.86
	(-0.18)	(-1.26)	(0.72)	(2.41)	(4.59)
Recession	-0.15	0.33	0.27	0.41	2.65
	(-0.10)	(0.27)	(0.15)	(0.29)	(1.50)
1980s	0.97	-0.04	0.36	1.25	2.30
	(2.07)	(-0.07)	(0.74)	(2.75)	(4.41)
1990s	0.05	-0.27	0.33	1.35	2.45
	(0.07)	(-0.45)	(0.47)	(2.15)	(4.01)
2000s	-0.81	-0.62	0.25	0.41	1.45
	(-1.22)	(-0.96)	(0.30)	(0.54)	(1.79)
Panel C: Longer Holding Periods					
6 months	-0.07	-0.20	0.60	0.75	1.78
	(-0.19)	(-0.58)	(1.52)	(1.94)	(4.13)
12 months	0.14	-0.55	0.63	0.10	1.50
	(0.39)	(-1.39)	(1.72)	(0.27)	(3.36)
18 months	0.15	-0.44	-0.11	0.23	1.17
	(0.44)	(-1.31)	(-0.29)	(0.62)	(2.98)

Table 2.6: Fama-MacBeth Regressions with Distress, External Financing Interaction Term

This table presents the results from cross-sectional Fama-MacBeth (1973) regressions that are conducted each month during the sample period. The dependent variable is a firm's stock return in excess of the risk-free rate, and the independent variables include Size (log market cap in millions), B/M (log of book equity divided by market equity), Mom (the cumulative stock return from month *t-12* to *t-2*), CHS (failure likelihood), XFIN (net funds from external financing), EFIN (net funds from equity financing), and DFIN (net funds from debt financing). I also interact the CHS failure probability with each of the three financing variables. All external financing variables are deflated by average total assets. Int is the average regression intercept, and R^2 is the average monthly R^2. Coefficients are the time-series averages of the monthly regression estimates, and t-statistics are based on the time-series standard deviations of the monthly estimates. The sample period is 1981 to 2014.

	Dependent Variable: Ret_{t+1}											
	Int	Log Size	Log B/M	Mom	CHS	XFIN	CHS x XFIN	EFIN	DFIN	CHS x EFIN	CHS x DFIN	R^2
Coefficient	0.87	-0.01	0.38	0.70								0.02
t-statistic	(2.37)	(-0.22)	(5.09)	(4.09)								
Coefficient	1.08	-0.03	0.37	0.65	-1.23							0.03
t-statistic	(3.47)	(-0.84)	(5.09)	(4.51)	(-2.85)							
Coefficient	0.99	-0.03	0.28	0.64		-1.87						0.03
t-statistic	(2.78)	(-0.71)	(4.06)	(3.83)		(-9.12)						
Coefficient	0.99	-0.03	0.28	0.64				-1.83	-2.14			0.03
t-statistic	(2.79)	(-0.68)	(4.23)	(3.81)				(-5.84)	(-9.52)			
Coefficient	1.12	-0.04	0.26	0.60	-0.73	-1.49	-2.69					0.03
t-statistic	(3.68)	(-1.15)	(3.94)	(4.29)	(-1.59)	(-6.82)	(-2.03)					
Coefficient	1.10	-0.04	0.27	0.60	-0.63			-1.45	-1.45	-3.89	-6.31	0.04
t-statistic	(3.67)	(-1.10)	(4.10)	(4.32)	(-1.37)			(-4.20)	(-6.13)	(-1.60)	(-2.98)	

Table 2.7: Three-Day Cumulative Abnormal Returns Around Earnings Announcements

This table displays the annualized abnormal returns around earnings announcements for portfolios formed by sorting all stocks into distress quintiles (least distressed, D1, to most distressed, D5), and then subsequently into quintiles based on the level of external financing (low external financing, XFIN1, to high external financing, XFIN5). The cumulative return for each stock is calculated from day *t-1* to *t+1* where $t = 0$ represents the day of the earnings announcement. The market-adjusted return is computed by subtracting the return on the market portfolio over the same period. The benchmark-adjusted return subtracts the average earnings announcement return for firms in the same size and book-to-market quintiles. Portfolios are reformed at the end of each June and held for one year. The figures are annualized by taking the average three-day abnormal return and multiplying by four. The sample period is 1981 to 2014.

	D1	D2	D3	D4	D5	D1–D5	D1	D2	D3	D4	D5	D1–D5
Panel A: Value-Weighted Announcement Returns												
	Market-Adjusted Return						Benchmark-Adjusted Return					
XFIN1 (low)	0.02	0.58	1.15	0.75	1.29	-1.27	-0.74	-0.14	0.54	0.00	0.87	-1.62
	(0.05)	(1.60)	(2.22)	(1.32)	(1.31)	(-1.16)	(-1.62)	(-0.31)	(0.99)	(0.00)	(0.88)	(-1.36)
XFIN2	0.54	0.77	0.50	-0.24	0.80	-0.26	-0.12	0.24	-0.01	-0.84	-0.17	0.05
	(1.28)	(2.59)	(0.95)	(-0.47)	(0.84)	(-0.27)	(-0.32)	(0.70)	(-0.02)	(-1.71)	(-0.19)	(0.06)
XFIN3	0.37	0.39	0.68	-0.46	-2.25	2.62	-0.33	-0.27	-0.22	-1.02	-2.84	2.51
	(1.06)	(0.73)	(0.94)	(-0.52)	(-1.83)	(2.12)	(-0.76)	(-0.48)	(-0.30)	(-1.17)	(-2.19)	(1.84)
XFIN4	1.20	1.20	0.72	0.04	-0.09	1.21	0.45	0.77	0.11	-1.00	-0.47	0.92
	(2.38)	(2.12)	(1.64)	(0.05)	(-0.01)	(0.81)	(0.75)	(1.30)	(0.24)	(-1.09)	(-0.38)	(0.59)
XFIN5 (high)	1.72	0.95	-0.39	0.03	-2.84	4.56	0.93	0.46	-0.80	-0.44	-3.12	4.05
	(2.24)	(1.59)	(-0.65)	(0.05)	(-3.46)	(3.61)	(1.18)	(0.73)	(-1.35)	(-0.69)	(-3.72)	(2.96)
Panel B: Equal-Weighted Announcement Returns												
	Market-Adjusted Return						Benchmark-Adjusted Return					
XFIN1 (low)	1.05	1.10	1.28	1.66	3.26	-2.21	0.40	0.25	0.51	0.32	1.40	-1.00
	(3.52)	(3.58)	(3.77)	(4.44)	(4.94)	(-3.96)	(1.75)	(0.89)	(1.62)	(0.98)	(2.80)	(-1.91)
XFIN2	1.01	1.03	0.91	1.02	3.34	-2.34	0.25	0.38	-0.02	-0.25	1.49	-1.23
	(3.74)	(3.71)	(3.41)	(2.56)	(4.01)	(-3.19)	(1.40)	(1.83)	(-0.09)	(-0.74)	(2.65)	(-2.09)
XFIN3	0.67	1.54	0.57	1.04	1.84	-1.17	0.02	0.85	-0.14	0.07	0.20	-0.18
	(2.42)	(4.20)	(1.70)	(2.58)	(3.22)	(-2.02)	(0.10)	(2.68)	(-0.59)	(0.23)	(0.43)	(-0.32)
XFIN4	1.60	0.36	-0.06	0.05	1.42	0.18	0.86	-0.10	-0.74	-0.81	0.13	0.73
	(5.68)	(1.13)	(-0.23)	(0.15)	(2.15)	(0.26)	(3.07)	(-0.36)	(-3.24)	(-2.45)	(0.25)	(1.18)
XFIN5 (high)	0.49	-0.02	-0.60	-1.20	-2.24	2.72	0.12	-0.32	-0.82	-1.48	-2.61	2.73
	(1.22)	(-0.05)	(-2.59)	(-2.96)	(-2.96)	(3.55)	(0.40)	(-0.91)	(-3.42)	(-4.31)	(-4.28)	(4.17)

Table 2.8: Limits to Arbitrage and Uncertainty

This table evaluates the strength of the distress anomaly among high XFIN firms (top quintile) that are expected to be more difficult to arbitrage or harder to value. Stocks are first sorted into distress quintiles (least distressed, D1, to most distressed, D5) and external financing quintiles (low external financing, XFIN1, to high external financing, XFIN5). We retain only the five portfolios within the XFIN5 quintile, and each portfolio is then divided evenly into two groups by idiosyncratic volatility, residual analyst coverage, residual institutional ownership, or firm age. Idiosyncratic volatility is computed as the standard deviation of residuals from Carhart model regressions estimated on all trading days in the prior month for each firm, residual institutional ownership is the residual from regressions of the percentage of shares owned by institutional investors on a firm's relative size and year indicator variables, residual analyst coverage is computed in the same manner except the dependent variable is the log of one plus the number of analysts covering the firm, and firm age is the number of months since the firm entered the CRSP database. Reported are excess returns and q-factor model alphas from regressions of the form, $R_{i,t} = \alpha_i + aMKT_t + bME_t + cI/A_t + dROE_t + \epsilon_{i,t}$, where $R_{i,t}$ is the excess return in month t to either the long leg (D1), the short leg (D5), or the difference (D1 – D5). The sample period is 1981 to 2014, and all returns and alphas are in percent per month with corresponding t-statistics below in parentheses.

	Excess Return			HXZ Q-Factor Alpha		
	D1	D5	D1–D5	D1	D5	D1–D5
			Panel A: Idiosyncratic Volatility (IVOL)			
Low IVOL	0.67	-0.48	1.15	-0.05	-0.78	0.76
	(2.47)	(-0.81)	(2.22)	(-0.33)	(-1.64)	(1.52)
High IVOL	1.04	-1.31	2.36	0.38	-1.18	1.56
	(2.75)	(-2.43)	(5.25)	(1.46)	(-3.94)	(3.82)
			Panel B: Residual Institutional Ownership			
Low ResInst	0.65	-1.28	1.93	0.04	-1.19	1.23
	(2.21)	(-2.23)	(3.90)	(0.20)	(-3.20)	(2.90)
High ResInst	0.99	-0.76	1.75	0.20	-0.65	0.84
	(3.27)	(-1.27)	(3.41)	(1.11)	(-1.58)	(1.80)
			Panel C: Residual Analyst Coverage			
Low ResAn	0.77	-1.74	2.51	0.10	-1.66	1.76
	(2.88)	(-3.22)	(5.46)	(0.59)	(-4.78)	(4.34)
High ResAn	0.80	-1.02	1.82	0.04	-1.04	1.09
	(2.70)	(-1.86)	(4.03)	(0.25)	(-3.10)	(2.81)
			Panel D: Firm Age			
Low Age (Young)	0.88	-1.48	2.36	0.23	-1.28	1.51
	(2.76)	(-2.70)	(5.37)	(1.21)	(-4.19)	(4.06)
High Age (Old)	0.69	-0.78	1.48	-0.02	-0.91	0.89
	(2.56)	(-1.33)	(2.85)	(-0.12)	(-2.08)	(1.86)

Table 2.9: Distress Anomaly Abnormal Returns During Periods of Low and High Investor Sentiment

This table evaluates the impact of investor sentiment on the return performance of a zero net-investment portfolio that is long healthy stocks and short distressed stocks among firms with different levels of prior year external financing growth. Stocks are sorted first into distress quintiles, and then subsequently into quintiles based on the level of external financing (low external financing, XFIN1, to high external financing, XFIN5). The long leg consists of stocks within the healthiest quintile of firms (D1) and the short leg includes stocks from the most distressed quintile of firms (D5). The sample period is divided evenly into halves (Low and High) based on the prior month's level of investor sentiment. Reported are excess returns and q-factor model alphas from regressions of the form, $R_{i,t} = \alpha_i + aMKT_t + bME_t + cI/A_t + dROE_t + \epsilon_{i,t}$, where $R_{i,t}$ is the excess return in month t to either the long leg, the short leg, or the difference. The sample period is 1981 to 2014, and all returns and alphas are in percent per month with corresponding t-statistics below in parentheses.

	Low Sentiment			High Sentiment		
	Long Leg (D1)	Short Leg (D5)	L–S (D1–D5)	Long Leg (D1)	Short Leg (D5)	L–S (D1–D5)
Panel A: Excess Returns						
XFIN1 (low)	0.99	1.53	-0.53	0.49	0.11	0.38
	(3.59)	(2.29)	(-0.92)	(1.53)	(0.19)	(0.73)
XFIN2	0.90	1.98	-1.08	0.24	-0.13	0.37
	(3.28)	(3.34)	(-2.25)	(0.77)	(-0.21)	(0.69)
XFIN3	1.21	1.91	-0.70	0.25	-1.06	1.32
	(4.14)	(2.72)	(-1.18)	(0.78)	(-1.46)	(2.06)
XFIN4	1.17	1.24	-0.07	0.31	-1.58	1.89
	(3.53)	(1.90)	(-0.13)	(0.85)	(-2.27)	(3.34)
XFIN5 (high)	1.45	0.51	0.94	-0.05	-3.05	3.00
	(4.07)	(0.71)	(1.56)	(-0.11)	(-4.09)	(5.17)
Panel B: HXZ Q-Factor Model Alphas						
XFIN1 (low)	-0.13	-0.12	-0.01	-0.09	0.15	-0.24
	(-0.95)	(-0.31)	(-0.02)	(-0.48)	(0.36)	(-0.50)
XFIN2	-0.08	0.50	-0.58	-0.09	0.47	-0.56
	(-0.60)	(1.46)	(-1.57)	(-0.55)	(1.22)	(-1.25)
XFIN3	0.09	0.40	-0.31	-0.12	0.45	-0.57
	(0.58)	(1.19)	(-0.81)	(-0.62)	(0.95)	(-1.05)
XFIN4	0.10	-0.14	0.24	-0.14	-0.50	0.35
	(0.48)	(-0.36)	(0.51)	(-0.77)	(-1.21)	(0.75)
XFIN5 (high)	0.37	-0.79	1.16	-0.41	-1.65	1.24
	(1.94)	(-2.24)	(2.72)	(-1.87)	(-3.89)	(2.55)

Table 2.10: Cross-Sectional Regressions By Distress Quintile

This table shows the results from monthly cross-sectional Fama-MacBeth regressions that are conducted separately for each distress quintile (least distressed, D1, to most distressed, D5). The dependent variable is a firm's stock return in excess of the risk-free rate, and the independent variables include Size (log market cap in millions), B/M (log book equity divided by market equity), Mom (the cumulative stock return from month *t-12* to *t-2*, negAcc (the change in operating working capital per split adjusted share if the value is negative and zero otherwise), posAcc (the change in operating working capital per split adjusted share if the value is positive and zero otherwise), posROE (return on equity if the value is positive and zero otherwise), negROE (a dummy variable which equals one if return on equity is negative and zero otherwise), and XFIN (net proceeds from external financing activities scaled by average assets). Int is the average regression intercept, and R^2 is the average monthly R^2. Coefficients are the time-series averages of the monthly regression estimates (or difference between average estimates), and t-statistics are based on the time-series standard deviations of the monthly estimates (or differences between monthly estimates).

	Int	Log Size	Log B/M	Mom	neg Acc	pos Acc	pos ROE	neg ROE	XFIN	R^2
D1 Firms (Low Distress)										
Coefficient	1.43	-0.13	-0.07	0.50	-0.48	-0.37	-0.14	-0.43	-0.91	0.05
t-statistic	(4.97)	(-3.96)	(-0.76)	(3.55)	(-1.28)	(-0.83)	(-0.29)	(-2.01)	(-2.88)	
D2 Firms										
Coefficient	1.60	-0.13	0.13	0.60	0.12	-0.47	0.58	-0.05	-0.94	0.06
t-statistic	(5.00)	(-3.42)	(1.32)	(4.04)	(0.36)	(-1.24)	(1.30)	(-0.29)	(-3.54)	
D3 Firms										
Coefficient	1.07	-0.03	0.26	0.71	-0.05	-0.71	0.01	0.02	-1.37	0.05
t-statistic	(3.61)	(-0.66)	(2.73)	(5.01)	(-0.14)	(-2.26)	(0.02)	(0.15)	(-5.53)	
D4 Firms										
Coefficient	0.85	-0.00	0.43	0.48	-0.32	0.19	0.12	0.15	-1.54	0.05
t-statistic	(2.77)	(-0.07)	(4.92)	(3.10)	(-1.21)	(0.62)	(0.23)	(1.27)	(-6.20)	
D5 Firms (High Distress)										
Coefficient	1.41	-0.14	0.21	0.42	0.58	-1.01	-0.46	-0.13	-2.46	0.03
t-statistic	(3.50)	(-1.89)	(2.13)	(1.90)	(2.83)	(-2.87)	(-0.60)	(-0.89)	(-8.70)	
All but D5										
Coefficient	1.16	-0.05	0.50	0.69	-0.04	-0.36	0.69	0.05	-1.25	0.04
t-statistic	(4.09)	(-1.50)	(4.62)	(5.37)	(-0.22)	(-1.69)	(2.15)	(0.59)	(-6.70)	
D5 - All but D5										
Coefficient	0.25	-0.09	-0.28	-0.27	0.62	-0.65	-1.15	-0.18	-1.21	
t-statistic	(0.85)	(-1.39)	(-2.73)	(-1.57)	(2.59)	(-1.62)	(-1.42)	(-1.26)	(-4.06)	

Figure 2.1: Performance of Healthy and Distressed Stocks, 1981 – 2014

This figure displays the cumulative returns to four different portfolios over the sample period of 1981 to 2014. The four portfolios include: (1) the decile portfolio with the lowest default risk "healthy stocks"; (2) the decile portfolio with the highest default risk "distressed stocks"; (3) the market portfolio consisting of all CRSP firms incorporated in the U.S.; and (4) a risk-free asset, which is proxied by the one-month Treasury Bill. The right margin of the table displays the final dollar values of each portfolio at the end of the sample period, given a $1 investment at the start of January 1981. Cumulative returns to stock portfolios are computed using monthly value-weighted returns.

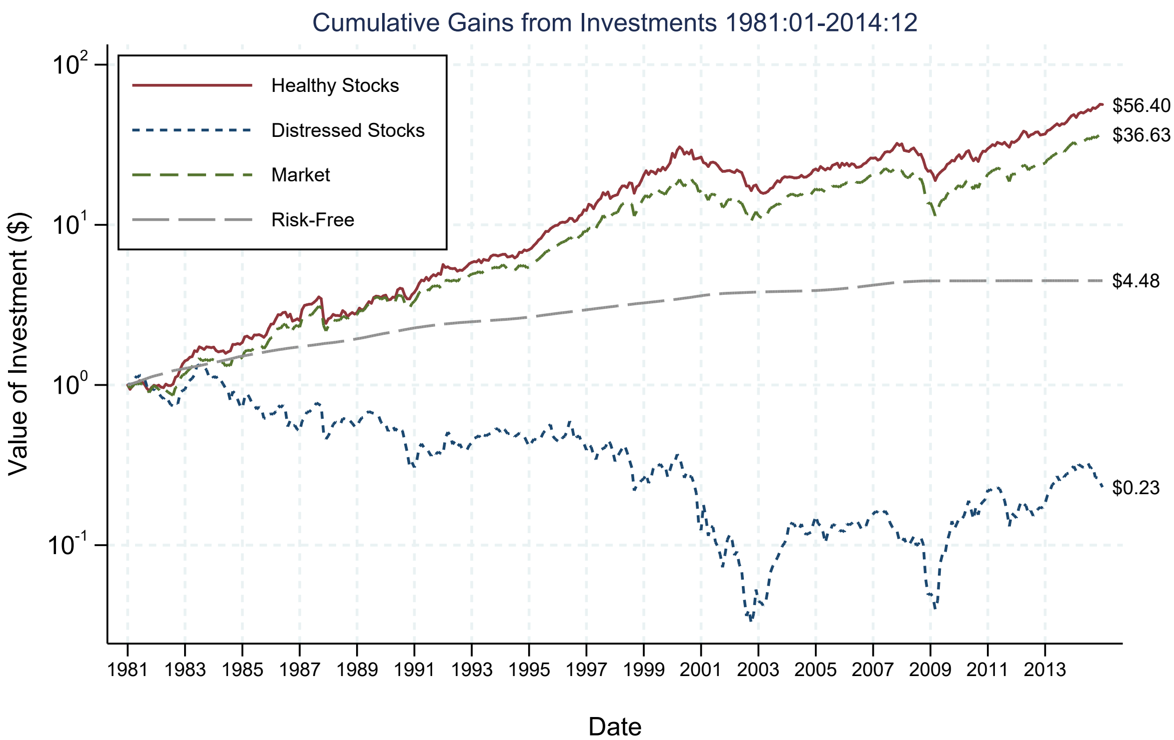
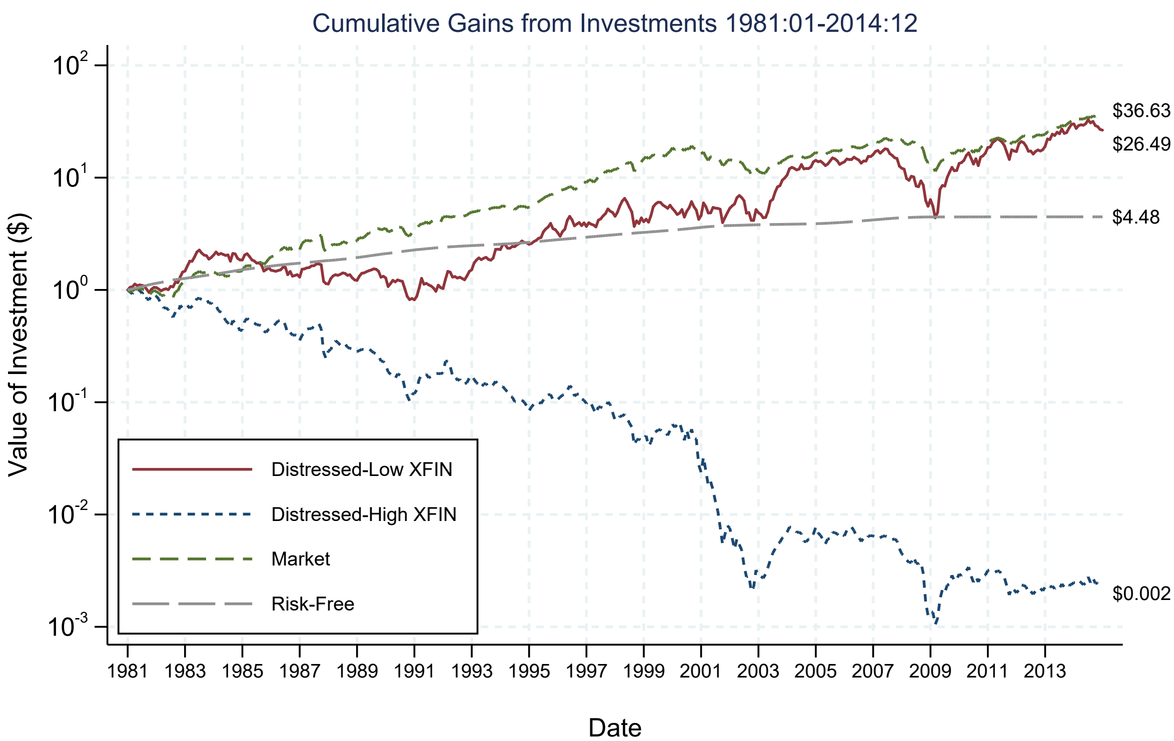


Figure 2.2: Performance of High and Low External Financing Distressed Stocks
This figure displays the cumulative returns to four different portfolios over the sample period of 1981 to 2014. The four portfolios include: (1) the portfolio of firms in the highest quintile of default risk and lowest quintile of external financing "Distressed-Low XFIN"; (2) the portfolio of firms in the highest quintile of default risk and highest quintile of external financing "Distressed-High XFIN"; (3) the market portfolio consisting of all CRSP firms incorporated in the U.S.; and (4) a risk-free asset, which is proxied by the one-month Treasury Bill. The right margin of the table displays the final dollar values of each portfolio at the end of the sample period, given a $1 investment at the start of January 1981. Cumulative returns to stock portfolios are computed using monthly value-weighted returns.



Appendix

Table A2.1: Performance of Portfolios Formed By Independent Sorts

This table displays the performance of portfolios formed by sorting all stocks into distress quintiles (least distressed, D1, to most distressed, D5), and independently into quintiles based on the level of external financing (low external financing, XFIN1, to high external financing, XFIN5). Financial distress is measured using the failure model of CHS (2008), and external financing is the net funds raised from external sources relative to average total assets. Portfolios are formed based on the month-end values of the two variables of interest and are held for the subsequent month. This table displays the average monthly excess returns and HXZ q-factor model alphas for the 25 portfolios as well as for portfolios that are long healthy stocks and short distressed stocks (D1–D5) within the same XFIN quintile. Portfolio returns are value-weighted, and returns and alphas are in percent per month with the corresponding t-statistics in parentheses. The sample period is 1981 to 2014.

	Portfolio Returns and Alphas											
	D1	D2	D3	D4	D5	D1–D5	D1	D2	D3	D4	D5	D1–D5
	Excess Return						HXZ Q-Factor Alpha					
XFIN1 (low)	0.68	0.89	0.81	0.95	0.86	-0.17	-0.10	0.36	0.43	0.71	0.20	-0.30
	(3.38)	(4.14)	(2.73)	(2.84)	(1.81)	(-0.41)	(-1.05)	(3.19)	(2.39)	(3.21)	(0.61)	(-0.86)
XFIN2	0.62	0.66	1.18	0.95	1.28	-0.66	-0.07	-0.05	0.68	0.35	0.65	-0.72
	(2.97)	(3.19)	(4.89)	(2.84)	(2.89)	(-1.74)	(-0.71)	(-0.55)	(4.98)	(1.81)	(2.25)	(-2.17)
XFIN3	0.77	0.62	0.57	0.85	0.82	-0.05	0.05	-0.13	0.05	0.49	0.36	-0.31
	(3.23)	(2.71)	(2.07)	(2.37)	(1.77)	(-0.14)	(0.37)	(-1.05)	(0.31)	(2.54)	(1.32)	(-1.01)
XFIN4	0.82	0.59	0.59	0.47	-0.13	0.95	0.08	-0.10	0.22	0.27	-0.24	0.33
	(3.00)	(2.39)	(2.24)	(1.28)	(-0.26)	(2.34)	(0.53)	(-0.71)	(1.46)	(1.39)	(-0.83)	(0.94)
XFIN5 (high)	0.75	0.47	-0.02	-0.22	-0.84	1.59	0.06	-0.16	-0.60	-0.43	-0.82	0.88
	(2.63)	(1.71)	(-0.05)	(-0.56)	(-1.67)	(3.87)	(0.34)	(-1.09)	(-4.25)	(-2.33)	(-3.15)	(2.65)

Table A2.2: Distressed Firms Sorted on External Financing and Other Return Determinants

This table displays q-factor model alphas of portfolios formed by independently sorting firms from the highest distress quintile into portfolios based on their values of external financing and either book-to-market, skewness as proxied by the maximum daily return within the prior month (MAX), or profitability (YB) measured as equity income divided by the book value of equity. In each sort firms are assigned to one of three tercile portfolios. The left-hand side displays results when firms can be reassigned to a new portfolio each month while the right-hand side only rebalances the portfolios at the end of June and December. Portfolios are equal-weighted with alphas reported in percent per month with corresponding t-statistics in parentheses. The sample period is 1981 to 2014.

	Monthly Rebalancing				Semi-Annual Rebalancing			
Panel A: External Financing and Book-to-Market								
	BM1 (L)	BM2	BM3 (H)	H–L	BM1 (L)	BM2	BM3 (H)	H–L
XFIN1 (Low)	0.55	0.50	1.02	0.47	0.46	0.60	1.00	0.54
	(2.03)	(2.37)	(4.12)	(1.65)	(1.67)	(2.84)	(4.17)	(2.00)
XFIN2	0.41	0.71	0.61	0.20	0.57	0.63	0.67	0.09
	(1.60)	(3.33)	(2.62)	(0.74)	(2.22)	(2.90)	(2.71)	(0.34)
XFIN3 (High)	-0.59	-0.43	-0.38	0.21	-0.56	-0.18	-0.27	0.29
	(-2.47)	(-1.73)	(-1.36)	(0.73)	(-2.26)	(-0.71)	(-0.97)	(1.00)
Low – High	1.14	0.93	1.40		1.02	0.78	1.27	
	(5.00)	(4.00)	(5.37)		(4.03)	(3.18)	(4.93)	
Panel B: External Financing and Skewness								
	Max1 (L)	Max2	Max3 (H)	L–H	Max1 (L)	Max2	Max3 (H)	L–H
XFIN1 (Low)	0.93	0.96	0.30	0.63	0.78	0.67	0.75	0.03
	(4.25)	(4.12)	(1.15)	(2.48)	(3.72)	(2.69)	(2.93)	(0.12)
XFIN2	1.14	0.64	0.06	1.08	0.69	0.98	0.32	0.38
	(5.43)	(2.85)	(0.23)	(4.51)	(3.28)	(4.20)	(1.23)	(1.58)
XFIN3 (High)	0.13	-0.17	-1.40	1.53	-0.25	-0.24	-0.68	0.43
	(0.56)	(-0.73)	(-4.94)	(5.97)	(-1.02)	(-0.99)	(-2.55)	(1.66)
Low – High	0.80	1.13	1.70		1.03	0.91	1.43	
	(3.99)	(4.85)	(6.12)		(4.67)	(3.94)	(4.91)	
Panel C: External Financing and Profitability								
	YB1 (L)	YB2	YB3 (H)	H–L	YB1 (L)	YB2	YB3 (H)	H–L
XFIN1 (Low)	0.63	0.90	0.63	-0.00	0.43	0.80	0.79	0.36
	(2.24)	(3.80)	(2.91)	(-0.00)	(1.55)	(3.34)	(3.74)	(1.40)
XFIN2	0.78	0.55	0.43	-0.35	0.93	0.57	0.43	-0.50
	(2.96)	(2.45)	(2.04)	(-1.32)	(3.28)	(2.58)	(2.00)	(-1.75)
XFIN3 (High)	-0.60	-0.47	-0.28	0.32	-0.39	-0.23	-0.40	-0.01
	(-2.20)	(-1.87)	(-1.12)	(1.12)	(-1.52)	(-0.94)	(-1.58)	(-0.04)
Low – High	1.22	1.37	0.90		0.82	1.03	1.19	
	(4.54)	(5.72)	(4.01)		(2.92)	(4.13)	(5.30)	

Chapter 3

Financial Distress, Corporate Takeovers, and Stock Returns

3.1 Introduction

Financial theory suggests that distressed firms should earn higher returns to compensate investors for bearing greater risk; however, the existing literature finds they earn puzzlingly low stock returns (Dichev, 1998; Campbell et al., 2008; Chava and Purnanandam, 2010; Garlappi and Yan, 2011; Friewald et al., 2014; Conrad et al., 2014). The inability of asset pricing models to explain the underperformance associated with low failure risk firms has resulted in a "distress anomaly". I attempt to shed light on this puzzle by examining the relation between financial distress, takeover probability, and future returns.

Many distressed firms possess a greater likelihood of being acquired in a takeover due to their smaller market capitalizations, relatively low valuations, and the opportunity for acquirers to improve the profitability of existing operations. However, firm characteristics result in considerable variation in the likelihood of receiving a takeover bid, as some firms are more attractive targets than others, and this variation can have a significant impact on future performance. I evaluate two hypotheses that predict a strong relation between takeover exposure and future distressed firm performance but offer competing predictions.

The first hypothesis is based on a *risk-based explanation*, as the possibility of corporate takeover reduces the risk that a firm reaches bankruptcy. Not only does a high probability of being rescued via acquisition result in a firm being less risky than its financial statements suggest, the target firm's shareholders also typically enjoy the benefit of receiving a large bid premium if a takeover occurs.[36] Due to the reduction in risk resulting from takeover exposure, the risk-based hypothesis predicts that distressed firms will earn lower returns if their probability of being acquired is high.

Alternatively, the *managerial alignment hypothesis* focuses on the role of takeover exposure as a governance mechanism, which reduces misalignment between the interests of managers and shareholders. Specifically, the managers of distressed firms have an incentive to take less risk than desired by shareholders, including foregoing positive expected NPV projects, in order to minimize the risk of failure. When a firm reaches bankruptcy, the CEO is unlikely to obtain another executive position or remain in charge of the current company in a reorganization (Eckbo et al., 2016); therefore, managers' risk aversion and career concerns can create substantial agency conflicts. A

[36] Andrade et al. (2001) report a median bid premium of 37.9% during their sample spanning from 1973 to 1998.

high probability of takeover mitigates this issue by lessening failure risk and creating an active market for corporate control, which incentivizes managers to make value maximizing decisions. In contrast, among firms with a low probability of becoming a takeover target, managers can opt to "play it safe" by avoiding investment in risky projects. Thus, the managerial alignment hypothesis predicts distressed firms will underperform when the probability of takeover is low.

I explore the interaction between takeover probability and distressed firm performance by estimating each firm's probability of becoming a takeover target in the following year. Evidence from portfolio tests supports the managerial alignment hypothesis, as the distress anomaly is concentrated in the group of low takeover exposure firms. A portfolio that goes long healthy firms and short distressed firms earns large and significant abnormal returns within this subgroup of stocks, whereas similar long-short portfolios generate small and insignificant returns among moderate and high takeover probability firms. This result suggests the distress anomaly only exists among a subset of stocks. Cross-sectional Fama-MacBeth (1973) regressions yield similar findings as a distress-takeover interaction term indicates a high probability of takeover is associated with significantly higher future returns among distressed stocks consistent with the disciplining effect of potential takeover.

The managerial alignment hypothesis suggests that distressed firm managers have an incentive to engage in value-destroying decisions that reduce firm risk when takeover exposure is limited. I investigate whether this is manifested in future operating performance and find evidence of reduced risk taking behavior that results in poor overall performance. Specifically, distressed firms with a low likelihood of being acquired invest less, reduce leverage, and experience lower future cash flows and profitability. This is consistent with distressed firm managers placing greater importance on personal career concerns than the maximization of firm value.

In a related study, Gormley and Matsa (2016) examine managers' incentives to play it safe and provide evidence that after managers are insulated by the adoption of state-level antitakeover laws, they undertake value-destroying diversifying acquisitions that involve acquiring companies that are likely to reduce their firm's risk.[37] The acquisitions are shown to be associated with significantly lower announcement returns and are more prevalent among CEOs under age 55, who they claim

[37] Gormley and Matsa (2016) focus on the adoption of business combination laws, which were passed in more than 30 states between 1985 and 1991. Given that these event dates are concentrated before the start of my sample period, I focus on firm level differences in the likelihood of being acquired.

have more to gain from reducing risk as the result of having more years remaining in their careers. In this study, I explore an additional source of career concerns related to the risk of firm failure.

To my knowledge this is the first study to examine the relationship between takeover likelihood and the distress anomaly at the firm level. Eisdorfer et al. (2014) explore the distress anomaly in an international setting using data from 34 countries and provide evidence on the potential drivers of the returns to distressed stocks. One of the factors they consider is the strength of country-level takeover legislation, and their results are in agreement with a risk-based explanation as they find the distress anomaly is stronger in countries with more takeover-friendly laws. However, they provide evidence that other country-level differences contribute to their findings, and while they provide a thorough country-level analysis there are several advantages to exploring a firm-specific takeover measure among U.S. firms.

First, the distress anomaly has been documented in numerous studies using primarily U.S. stocks, and there is evidence that the effect has remained significant over an extended period of time. While international evidence suggests the distress anomaly is also present in several other countries, it appears to be less pronounced in some countries and nonexistent in others. By focusing on the U.S. sample, I am able to avoid having to control for additional sources of heterogeneity related to country-level differences while benefiting from the use of a firm-specific measure of takeover exposure that exhibits considerable variation.

Additionally, there is greater data availability and accounting data are more reliable for domestic firms; therefore, I am able to use the Campbell, Hilscher, and Szilagyi (2008, hereafter CHS) measure of distress. This measure is developed using a logistic regression model to predict failure, and it includes both accounting and market variables as predictors. CHS (2008) and Eisdorfer et al. (2014) also find the distress anomaly appears weaker when using alternate proxies for distress, such as the distance-to-default measure, consistent with evidence that the *CHS* variable measures financial distress more precisely.

Although this is the first study to examine the effect of firm-level takeover exposure on the distress anomaly, prior literature has highlighted that distressed firms are generally more likely to become takeover targets. For instance, Wruck (1990) finds that roughly 7% of companies that undergo a legal bankruptcy in the U.S. are acquired by other firms. An even greater number of companies are likely to complete merger deals prior to reaching bankruptcy in order to avoid the

high associated costs. However, I show that while distressed companies are more likely to become takeover targets on average, some firms possess characteristics that make them unattractive to potential acquirers, which reduces the disciplinary role of takeovers (Scharfstein, 1988). As a result, agency conflicts are expected to be severe and appear to hinder future performance.

The rest of this paper is organized as follows. Section 3.2 outlines the hypotheses for the impact of takeover exposure on distressed firm performance. Section 3.3 introduces the distress and takeover models and also provides summary statistics. Section 3.4 tests the hypotheses and presents the main empirical results. Section 3.5 provides a series of robustness tests. Section 3.6 concludes.

3.2 Hypotheses

Alternative and competing predictions exist for the impact of takeover exposure on distressed firm performance. This section discusses these hypotheses, which suggest the distress anomaly will either be concentrated among firms with high takeover exposure, low takeover exposure, or that takeover exposure will have no significant effect on distressed firm performance.

3.2.1 ***Risk-Based Hypothesis***

Failure models assess the degree of distress risk by estimating the probability a firm will fail within a specified time horizon. The majority of these models use predictors based on financial statement information which is then occasionally supplemented with stock market data, and although a variety of distress measure exist, there is general agreement that firms experiencing negative profits and recent stock price declines have a higher likelihood of failing. Corporate takeovers, however, can prevent a firm from ever reaching bankruptcy. Thus, while a firm may be experiencing significant operating losses and have limited long-run viability, if its characteristics make it attractive to potential acquirers its true failure risk will be substantially lower than it appears.

The *risk-based hypothesis* predicts the distress anomaly will be concentrated among firms with high takeover exposure. While traditional measures of distress risk suggest these firms have a high chance of failure based on their poor operating performance, a high probability of being acquired reduces this risk, thereby making these companies relatively safe. Additionally, the subgroup of

firms that are successfully acquired are likely to experience large positive stock returns given the size of the typical bid premium. Consequently, the risk-based explanation suggests distressed firms with high takeover probability should earn lower returns, whereas distressed firms with a low probability of being rescued via takeover should earn higher returns as compensation for the greater chance of experiencing bankruptcy. This explanation is consistent with the evidence presented in Eisdorfer et al. (2014) who explore the impact of takeover friendly legislation in an international sample and provide evidence that the distress anomaly is stronger in countries with more friendly takeover laws. I explore whether a similar effect can explain the underperformance of distressed stocks in the U.S. using firm-level differences in takeover likelihood.

3.2.2 *Managerial Alignment Hypothesis*

A substantial body of work explores the disciplinary role of corporate takeovers on managerial behavior. Because agency conflicts can allow managers to engage in empire building activities that generate private benefits for themselves (Baumol, 1959; Marris, 1964; Williamson, 1964), exert less effort than desired by shareholders in order to enjoy the "quiet life" (Hölmstrom, 1979; Grossman and Hart, 1983; Bertrand and Mullainathan, 2003), or take value destroying actions that reduce firm risk (Jensen and Meckling, 1976; Gormley and Matsa, 2016), the possibility of a corporate takeover places pressure on management to work in the best interest of shareholders or risk losing control. In the case of highly distressed firms this disciplining mechanism is of particular value, because managers have an incentive to "play it safe" in order to protect their position, and failures often have large negative consequences for the CEO. For instance, Eckbo et al. (2016) explore a sample of firms filing for Chapter 11 bankruptcy and find that approximately two-thirds of incumbent CEOs leave the executive labor market during the bankruptcy event period and suffer substantial wealth losses as a result, thereby creating an incentive for managers to avoid risky projects. In contrast, shareholders benefit when the firm undertakes any positive NPV project, including risky ones that may result in a higher chance of failure.[38] Consequently, the possibility of a corporate takeover should mitigate this agency conflict and create greater alignment between managers' and shareholders' interests.

[38] It is worth noting that the value of shareholders' option to default is also increasing in the volatility of the firm as noted by Eisdorfer et al. (2013).

The *managerial alignment hypothesis* therefore predicts the underperformance of distressed company stocks will be concentrated among low takeover exposure firms. In particular, distressed firm managers who are insulated from the possibility of takeover are more likely to forego profitable opportunities due to career concerns and risk aversion related to uncertain project outcomes. If investors do not fully account for the impact of agency conflicts, such value destroying decisions are expected to be associated with long-run stock price underperformance resulting in a "distress anomaly" among low takeover exposure firms. Conversely, when takeover probability is high, managers are incentivized to act in shareholders' best interest in order to maintain control. Therefore, this hypothesis predicts high takeover exposure distressed firms will earn returns commensurate with their level of risk.

3.2.3 *No Relation Hypothesis*

A third possibility is that if the probability of receiving a takeover bid is properly accounted for by investors and reflects a source of unsystematic risk that is unrelated to future firm performance, then takeover likelihood should have no relation to the distress anomaly. The returns to the portfolio of distressed firms with the highest likelihood of being acquired are still expected to fluctuate with the amount of realized takeovers; however, abnormal returns should be zero on average. Therefore, the *no relation hypothesis* predicts the strength of the distress anomaly will be similar across all levels of takeover likelihood. Given the documented underperformance of distressed firms over time, this hypothesis merely rules out takeover exposure as an explanation for the distress anomaly as it cannot account for prior findings.

3.3 Data and Summary Statistics

3.3.1 *Financial Distress Variable*

I use the Campbell et al. (2008) measure of financial distress (i.e., CHS) to estimate the failure probability for each firm. The *CHS* failure model has the advantage of incorporating both market and accounting data and is shown to have better predictive power than competing models.[39]

[39]The distress measures from Altman (1968) and Ohlson (1980) are frequently used in earlier studies on financial distress; however, Franzen et al. (2007) provide evidence that purely accounting-based models of distress have become less accurate in more recent periods. Additionally, the Moody's KMV model which relies on the structural default model of Merton (1974) has received considerable use from both academics and practitioners but has been found to

Following Campbell et al. (2008), I combine monthly market data from CRSP with quarterly accounting data from Compustat, where accounting information is lagged to ensure it is publicly available. The *CHS* distress variable used to estimate the probability of failure with a twelve month forecast horizon is then computed as follows:

$$\begin{aligned} CHS_{it} = &-9.16 - 20.26\, NIMTAAVG_{it} + 1.42\, TLMTA_{it} - 7.13\, EXRETAVG_{it} \\ &+ 1.41\, SIGMA_{it} - 0.045\, RSIZE_{it} - 2.13\, CASHMTA_{it} + 0.075\, MB_{it} \\ &- 0.058\, PRICE_{it} \end{aligned} \tag{3.1}$$

where NIMTA is net income divided by the market value of assets, TLMTA is the book value of liabilities divided by the market value of assets, EXRET is the log of the excess return on the firm's stock relative to the S&P 500 Index, SIGMA is the standard deviation of daily returns over the past three months, RSIZE is the ratio of the log of the firm's market capitalization divided by that of the S&P 500 index, CASHMTA is the firm's cash and short-term investments scaled by the market value of assets, MB is the market-to-book ratio, and PRICE is the log of the firm's price per share truncated from above at \$15. NIMTAAVG and EXRETAVG represent weighted moving averages of NIMTA and EXRET. I construct them following CHS (2008) as shown below,

$$NIMTAAVG_{t-1,t-12} = \frac{1-\phi^3}{1-\phi^{12}}(NIMTA_{t-1,t-3} + \ldots + \phi^9 NIMTA_{t-10,t-12}) \tag{3.2}$$

$$EXRETAVG_{t-1,t-12} = \frac{1-\phi}{1-\phi^{12}}(EXRET_{t-1} + \ldots + \phi^{11} EXRET_{t-12}) \tag{3.3}$$

where $\phi = 2^{-\frac{1}{3}}$. All inputs are winsorized at the 5^{th} and 95^{th} percentiles of the pooled sample. To limit transaction costs and the effects of bid-ask bounce, I eliminate all stocks with prices below \$1 at the time of portfolio formation.[40] Given the focus on firms experiencing financial difficulties, it is also important to incorporate delisting returns. I use the CRSP reported delisting return whenever available if a firm's final monthly return is missing, and I compound the returns if one is present.

I then combine the stock market and accounting data with takeover information from Thomson One Banker. The takeover data becomes available in 1980, and I use the first ten years to generate out-of-sample takeover probability forecasts in order to avoid look-ahead bias. The following period spanning 1990 to 2013 is then used throughout the remaining analysis to test the impact of takeover

contribute minimal explanatory power beyond that captured by the *CHS* measure.

[40]See CHS (2008) for a detailed description of distress variable construction.

likelihood on distressed firm performance. The sample includes all common equity securities (share code 10 or 11) with non-missing data listed on NYSE, AMEX, and NASDAQ except for utility (SIC codes 4900 to 4999) and financial firms (SIC codes 6000 to 6999), which are highly regulated entities and also exhibit differences in operating structure.

To evaluate the strength of the distress anomaly in the current sample, I sort stocks into five portfolios each month based on their computed *CHS* distress value. Table 3.1 reports both descriptive statistics and performance measures for each of the distress quintile portfolios. The characteristics displayed include size, market-to-book, past return from month *t-12* to *t-2*, the standard deviation of daily stock returns over the past three months (Sigma), leverage, return on assets (net profit), and the percentage of firms with positive income. For each characteristic, I first compute the cross-sectional mean and median of all firms in each portfolio and then report the time series average of these values. Several of the characteristics exhibit a monotonic relation with the level of financial distress. For instance, distressed firms appear to have smaller market capitalizations (size), lower market-to-book ratios, lower past returns, higher return standard deviations, higher book leverages, and lower profitability ratios.

The table also reports the performance of each distress portfolio and a zero net-investment portfolio that is long stocks in the least distressed quintile (D1) and short stocks in the most distressed quintile (D5). I report average monthly excess returns relative to the risk-free rate as well as alphas relative to the CAPM, Fama-French 3-factor model, and Carhart 4-factor model.[41] The first four distress quintile portfolios earn average excess returns ranging from 51 to 69 basis points per month; however, the portfolio of highly distressed firms, despite consisting of firms that are much riskier by standard measures, only averages an excess return of 18 basis points per month. Thus, when adjusting for risk using the CAPM and Fama-French 3-factor model, the underperformance of the high distress portfolio (D5) becomes even more pronounced. The D5 portfolio has large loadings on the market, size, and value factors, which causes its abnormal returns to be significantly negative, and the long-short portfolio earns a significantly positive abnormal return of 1.16% ($t = 2.86$) relative to the CAPM and 1.34% ($t = 3.67$) relative to the Fama-French 3-factor model. The addition of the momentum factor, UMD, in the 4-factor model explains much of the underperformance associated with distressed stocks; however, the alpha remains economically

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

large and statistically significant (0.57%, $t = 2.17$), which confirms the existence of the distress anomaly documented in prior studies.

3.3.2 *Takeover Probability*

To estimate the likelihood that a given firm will become a takeover target within the following year, I obtain historical data on all mergers and acquisitions of publicly traded firms from Thomson One Banker. Following the takeover literature, I exclude bids classified as acquisitions of partial stakes, minority squeeze-outs, buybacks, and recapitalizations in order to only capture takeover events that are expected to have a substantial impact on firm value. I define a dummy variable, TO, which takes the value of one if a firm is a takeover target in year t and zero otherwise.

I estimate takeover probability using a model that includes the independent variables from Billett and Xue (2007). Their model has the advantage of including the primary takeover predictor variables that have been documented in the mergers and acquisitions literature while posing minimal data availability limitations.[42] The logit model used to obtain a predicted value of being acquired within the next year is as follows:

$$logit(TO_{it}) = ln\left(\frac{TO_{it}}{1 - TO_{it}}\right) = \beta' X_{it-1} \tag{3.4}$$

where X_{it} is a vector containing a constant and firm specific characteristics. The explanatory variables are computed using each firm's most recent fiscal year-end accounting data. These include ROAIA, SIZEEQ, LEVBIA, MKBK, SALEGR, NPPE, ITODUM, and year indicator variables, where ROAIA is operating income before depreciation scaled by total assets less the industry median ratio, SIZEEQ is the log of the market value of equity adjusted to 2012 dollars using the consumer price index, LEVBIA is the ratio of debt to total assets less the industry median leverage ratio, MKBK is the ratio of market equity to book equity, SALEGR is the log of the ratio of current sales to prior year sales, NPPE is net property, plant, and equipment scaled by total assets, and ITODUM is a variable that takes the value of one if there was a takeover attempt within the firm's industry in the prior year and zero otherwise. Industry adjustments are made by subtracting the

[42] Approximately 10 percent of firm-month observations are eliminated because of a missing *CHS* distress variable; however, the takeover probability can be estimated for all of the remaining firms. The main sample contains 805,555 firm-month observations over the period 1990 to 2013.

median value of all firms with the same two-digit SIC code, and ITODUM is based on takeovers with the same four-digit SIC code. Annual accounting variables are winsorized at the 1$^{\text{st}}$ and 99$^{\text{th}}$ percentile to reduce the effect of outliers.

I estimate the likelihood that each firm will receive a takeover bid within the following twelve months using an expanding-window estimation. The takeover model is first estimated using historical data from the period 1980 to 1989 to predict the likelihood of being acquired in 1990. The model is then re-estimated each year using all available data to generate the subsequent forecast. Table 3.2 presents the logit model estimation results for the full sample period. Overall, the estimated coefficients are consistent with findings in the prior literature. Large firms and firms with high market-to-book ratios are significantly less likely to become takeover targets. This result is intuitive as fewer firms have the resources necessary to acquire a large company, and evidence in Hertzel and Li (2010) suggests market-to-book ratios may reflect both a growth option component as well as a mispricing component, thereby creating an incentive to acquire firms with depressed market values that trade at a bargain price. The results also indicate that firms with higher book leverage are also more likely to become takeover targets. This result, while less intuitive, is consistent with evidence documented in Cremers et al. (2009). Further, firms with high amounts of fixed assets, as measured by NPPE, are less likely to be acquired, and firms within an industry that experienced at least one takeover bid within the prior year are more likely to be acquired. Although the coefficients are unreported, year controls are also included to control for the high concentration of takeover events in particular time periods.

Overall, the model is highly significant with a p-value of less than 0.0001, and the pseudo R^2 is comparable to that reported in the prior literature.[43] While it is challenging to predict whether a specific firm will receive a takeover bid in a given year, the model does a good job of separating firms with a relatively high or low likelihood of being acquired as illustrated by Figure 3.1. When sorting firms into takeover likelihood quintile portfolios, the percentage of realized takeovers occurring within each portfolio increases monotonically with the predicted probability and ranges from 13.97% for the lowest takeover probability portfolio to 25.35% for the highest. Thus, reliable differences in takeover exposure appear to exist among firms when evaluated at the portfolio level.

[43]For reference, Cremers et al. (2009) report a pseudo R^2 of 1.76% in their base model predicting takeover attempts.

3.3.3 *Double-Sorted Portfolio Characteristics*

To explore the interaction between financial distress and takeover exposure, I sort all firms into portfolios based on these two measures. In particular, stocks are independently sorted into five quintiles based on their level of distress, *CHS*, and into terciles based on their estimated takeover probability, *TO*. Table 3.3 displays the average characteristic values for firm size, market-to-book ratio, cumulative returns from month *t-12* to *t-2*, the number of stocks in each portfolio, *CHS* distress, and estimated takeover probability. All reported figures are obtained by first computing the cross-sectional average of all firms in the portfolio and then computing the time series average of these values.

Panel A reveals that the average size of firms varies greatly across both the level of distress and takeover likelihood. Within each takeover tercile, the average market capitalization decreases with the level of distress, and within each distress quintile firm size increases as takeover probability declines. This result is expected based on the negative size coefficients in the distress and takeover models as well as basic economic intuition. Panel B displays average market-to-book ratios, which highlights an interesting pattern. While the portfolios of distressed firms with high takeover exposure (TO1) and moderate takeover exposure (TO2) exhibit the lowest average market-to-book ratios, reflecting the tendency of distressed firms to have depressed valuations, the portfolio with low takeover exposure (TO3) has an average market-to-book ratio that is among the highest at 2.42. These high valuations imply that either investors expect substantial growth from these firms despite their distressed status and recent struggles, that investors have overvalued these firms' stocks, or a combination of these two factors.

Panel C indicates that healthy firms tend to be winner stocks while distressed firms tend to be loser stocks. This relation occurs largely by construction, as Equation 3.1 shows that a moving average of excess returns is a key predictor of future failure events. As a result, it is important to control for momentum when assessing the differences in performance between healthy firms and distressed firms. Panel D also reveals that the high distress, high takeover exposure portfolio contains the greatest number of firms, as distressed stocks are generally more likely to become takeover targets.

Additionally, panels E and F highlight that the sorting procedure is effective at minimizing

differences in distress risk across portfolios within the same distress quintile as well as differences in takeover probability across portfolios within the same takeover tercile. This implies that differences in failure risk are unlikely to account for any observed differences in the strength of the distress anomaly across takeover exposure levels. The following section explores the performance of the double-sorted portfolios while focusing on the interaction between the level of financial distress and a firm's likelihood to receive a takeover bid.

3.4 Results

This section tests the hypotheses and evaluates whether differences in takeover exposure help to explain the distress anomaly. The managerial alignment hypothesis predicts distressed firm underperformance will be concentrated in low takeover exposure firms as the result of agency conflicts, whereas the risk-based hypothesis predicts distressed firm underperformance will be concentrated in high takeover exposure firms as a high probability of being acquired reduces the risk that a firm will reach bankruptcy.

3.4.1 *Asset Pricing Tests*

Table 3.4 reports the performance of the fifteen double-sorted portfolios using time series asset pricing regressions. Panel A displays average monthly returns in excess of the risk-free rate as well as portfolio alphas relative to the CAPM, Fama-French 3-factor model, and Carhart 4-factor model.[44] Also reported are the returns to zero net-investment portfolios that are long high-takeover firms and short low-takeover firms within the same distress quintile and portfolios that are long healthy firms and short distressed firms within the same takeover likelihood tercile. Particular attention is given to the latter group of long-short portfolios displayed in the final column (D1 – D5), as they reflect the strength of the distress anomaly among firms with either high, medium, or low probability of receiving a takeover bid.

The portfolio excess returns (upper-left) first reveal that within each distress quintile, high takeover exposure firms earn a higher average return than low takeover exposure firms. The difference is not statistically significant in the bottom two quintiles, D1 and D2; however, it becomes

[44]The four factors included as independent variables include the market, size, and book-to-market factors of Fama and French (1993) plus the Carhart (1997) momentum factor.

significant within the top three distress quintiles (D3, D4, and D5). Further, the long-short portfolio return is most significant, both economically and statistically, in the high distress quintile (D5). A portfolio that is long distressed firms with the highest probability to be acquired and short those least likely to be acquired yields an average return of 1.23% per month (t = 3.15). This result is consistent with the finding in Avramov et al. (2013) that many asset pricing anomalies are concentrated in high credit risk firms.

The performance of the distress-based long-short portfolios is of primary interest, since the focus is on explaining the distress puzzle. I find a portfolio that is long healthy firms and short distressed firms within the highest takeover likelihood tercile earns an insignificant average monthly return of 0.28% (t = 0.57). This is inconsistent with the predictions of the risk-based hypothesis, which suggests the distress anomaly should be more pronounced among high takeover exposure firms. Likewise, a long-short portfolio constructed using firms within the middle takeover probability tercile earns a return that is insignificant and economically small (0.31%, t = 0.58). In contrast, within the lowest takeover exposure tercile, I find the distress anomaly is strong, as the long-short portfolio produces a significant average return of 1.21% per month (t = 2.21). Additionally, the short leg consisting of high distress, high takeover probability firms underperforms the risk-free rate by an average of 54 basis points per month. This evidence is consistent with the managerial alignment hypothesis in which managers fail to act in the best interests of shareholders when shielded from the threat of takeovers resulting in poor future performance.

Next, I examine the performance of the long-short distress portfolios relative to asset pricing factor models to evaluate whether known risk factors can explain the observed results. Similar overall patterns in performance across takeover terciles are observed; however, the alphas relative to the CAPM and Fama-French 3-factor models are much larger than the excess returns. Within the high, moderate, and low takeover terciles the CAPM alphas are 0.83%, 0.97%, and 1.86% while the 3-factor model alphas are even larger at 1.06%, 1.15%, and 2.00%, respectively. The larger risk-adjusted returns are consistent with the results from Table 1, as each of the long-short portfolios loads negatively on the market, SMB, and HML factors.

The strong pattern in past returns across the distress portfolios makes it important to control for the effects of momentum; otherwise, a large portion of the long-short portfolio abnormal returns may be attributed to its well-documented effects. Consequently, I place greater emphasis on the

abnormal returns relative to the 4-factor model. Similar to the findings for excess returns, the distress-based long-short portfolios earn small insignificant alphas among both high and moderate takeover exposure firms. Despite the overall strength of the distress anomaly, this result suggests it is basically non-existent in the majority of distressed stocks.

Within the group of low takeover likelihood firms, however, the long-short portfolio generates a large and highly significant 4-factor alpha of 1.35% per month (t = 3.77). Thus, the distress anomaly appears to be driven by high failure risk firms that are unlikely to receive a takeover bid. Additionally, the majority of the long-short portfolio's abnormal return is derived from the short leg, which earns a 4-factor alpha of -1.30% per month (t = -4.09). In contrast, the portfolio returns of healthy firms in the low takeover exposure group are well explained by the 4-factor model (0.05%, t = 0.42). Overall, these findings are consistent with greater career concerns and risk aversion of distressed firms' managers creating unmitigated agency conflicts when the threat of takeover is low.

Panel B reports the factor loadings from the Carhart 4-factor model. This panel confirms that the distress-based long-short portfolios (D1 – D5) load heavily on several of the standard asset pricing factors. For instance, within each takeover group the healthy minus distressed long-short portfolio has a significant negative loading on the market and size (SMB) factors and a significant positive loading on the momentum (UMD) factor. This covariance in returns is expected given the tendency for distressed firms to be small, volatile companies that have experienced substantial losses during the prior year. Given the known relation between these factors and stock returns, it is important to control for their effects in order to test for an independent distress effect.

3.4.2 *Distress, Takeover Likelihood, and Future Operating Performance*

The results from the portfolio tests provide evidence consistent with the managerial alignment hypothesis, which predicts distressed firm managers will act in their own self-interest and play it safe when their firm is unlikely to face a takeover attempt. Table 3.5 further explores this hypothesis by examining distress, takeover probability, and their relation to future operating performance. I conduct panel regressions where the dependent variable is one-year-ahead return on assets (ROA), gross profitability (GP), cash flows (CF), capital expenditures (CAPX), cash holdings (Cash), or book leverage (LEV). All dependent variables are scaled by total assets to account for differences in firm size, and all regressions control for the log of firm size, book-to-market, and age as well as

firm and year fixed effects. If a low likelihood of being acquired alters management's decisions of whether to engage in risky projects, this should be reflected in observable outcomes.

The primary variable of interest in the performance prediction regressions is the distress-takeover interaction term, as this indicates whether the possibility of takeover has a greater disciplinary effect on distressed firm managers who face greater career concerns and have reason to be more risk averse due to the possibility of failure. The first three regressions explore different measures of profitability as the dependent variable: return on assets, gross profitability, and cash flows to assets. As expected, firms tend to experience lower future profits following periods of distress as indicated by the significantly negative coefficient on *CHS*. Additionally, firms with a high probability of being acquired tend to experience marginally higher return on assets (Column 1) and significantly higher cash flows (Column 3), which is consistent with the threat of takeover incentivizing managers to maximize firm profits in general. Interestingly, the interaction term is significantly positive in all three regressions. This adds support to the managerial alignment hypothesis and suggests distressed firms that are insulated from the threat of takeover experience particularly poor future net profits, gross profits, and cash flows.

Column 4 tests the relation between the distress and takeover measures and future capital expenditures. The positive coefficient on the distress-takeover interaction term suggests distressed firms with high takeover exposure invest significantly more in the following year compared to low takeover exposure distressed firms. This result is consistent with the idea that managers have an incentive to play it safe when distress is high and the likelihood of being acquired is low by foregoing investment in risky projects. Column 5 indicates that firms with a high probability of being acquired tend to have lower future cash holdings, although the takeover effect does not differ significantly with the level of distress, and the interaction term in Column 6 indicates that future book leverage is lower for distressed firms when the probability of takeover is low. Overall, these results support the managerial alignment hypothesis by providing evidence that distressed firms take on less risk when takeover likelihood is low to the detriment of shareholders.

3.4.3 *Fama-MacBeth regressions with distress and takeover likelihood*

To further explore the relation between takeover likelihood and the performance of distressed stocks, I conduct Fama and MacBeth (1973) regressions. This approach offers the advantage of

being able to simultaneously control for many characteristics known to be associated with the cross-section of stock returns. Additionally, the interaction between the distress and takeover likelihood measures can be explicitly modeled and tested while controlling for other return predictors. The results of these cross-sectional regressions are reported in Table 3.6, and the main specification shown in columns 4 and 5 takes the form:

$$\begin{aligned} Ret_{i,t+1} = \beta_0 + \beta_1 log(Size_{i,t}) + \beta_2 log(B/M_{i,t}) + \beta_3 PastReturn_{i,t} + \beta_4 Rev_{i,t} + \beta_5 CHS_{i,t} \\ + \beta_6 TO_{i,t} + \beta_7 CHS \cdot TO_{i,t} + e_{i,t+1} \end{aligned} \tag{3.5}$$

where the dependent variable is the monthly stock return in excess of the risk-free rate and the independent variables include log market capitalization (Size), log book-to-market (B/M), cumulative return from month *t-12* to *t-2* (Past Return), past one-month return (Rev), distress (CHS), takeover probability (TO), and an interaction term between the distress and takeover variables. I multiply all coefficients by 100 for readability and report t-statistics based on Newey-West corrected standard errors (with twelve lags) to address potential autocorrelation issues.

The first regression specification reveals that all control variables enter with the expected signs. The coefficient on size is negative but insignificant indicating a weaker size effect following its documentation by Banz (1981). I also find positive coefficients on book-to-market and past return (momentum).[45] Additionally, I find that stocks with high prior month returns tend to perform worse in the following month, as the coefficient on *Rev* is negative and significant. This is consistent with the evidence of short-term reversals found in Jegadeesh (1990). Specification 2 adds the *CHS* distress variable, which enters with a negative coefficient (-1.198, t = -2.24) while specification 3 indicates that a firm's takeover probability is positively associated with future returns (0.452, t = 5.08).

Specification 4 simultaneously controls for both financial distress and takeover exposure and also includes a term for their interaction. I find the general effects of takeovers and distress survive, and their interaction is positive and marginally significant (1.099, t = 1.70). Specification 5 repeats the analysis but uses data from the quarterly Compustat files to update each firm's takeover probability more frequently. Specifically, I construct the takeover predictors using the most recently available data from quarterly financial statements together with the coefficients from equation 3.4 to estimate

[45]The insignificant coefficient on past return is largely attributable to the higher volatility of momentum in recent years including the momentum crash in 2009 documented by Daniel and Moskowitz (2015).

takeover probability. This measure has a correlation of 0.90 with the takeover probability estimated using annual data but is likely to capture changes in a firm's attractiveness to potential acquirers in a more timely manner. I find the results are largely unchanged; however, the interaction term is now significant at the five percent level as the coefficient's standard error is reduced (1.092, t = 2.02). The results are consistent with the managerial alignment hypothesis that distressed firms underperform significantly when there is limited potential for a takeover.

3.5 Robustness Tests

This section tests the robustness of the results from Section 3.4. In particular, I explore the performance of the double-sorted portfolios over the business cycle, during different subperiods, and with varying portfolio rebalancing frequencies. Further, I evaluate the performance of the double-sorted portfolios when using the quarterly takeover measure.

3.5.1 *Subsamples*

In Table 3.7, Panel A tests whether differences in performance over the business cycle can explain the findings. The excess returns and 4-factor model alphas to the distress-based long-short portfolios (D1–D5) are reported separately for periods of expansion and recession as defined by the NBER, and the results indicate that the distress anomaly is much stronger when the likelihood of becoming a takeover target is low during both expansions and recessions. The 4-factor alphas are insignificant during both expansions and recessions among high and moderate takeover likelihood firms but are large and significant among low takeover likelihood firms.

If differences in systematic risk related to the business cycle were to explain the underperformance of the low takeover exposure distressed firms, this portfolio should perform relatively well during recessions and relatively poorly during expansions, thereby offering investors hedging benefits to compensate for the lower average returns. The results presented here suggest this is not the case as the high distress, low takeover likelihood portfolio performs significantly worse than similar low distress firms in both periods, and the long-short portfolio returns are larger during recessions. These results support the managerial alignment hypothesis, as the distress anomaly is concentrated in firms with a low probability of being acquired and distressed firm managers' incentives to play

it safe should be greater during recessions when risk aversion and career concerns are likely to be amplified.[46]

Panel B evaluates whether the results hold over time or are driven by the earlier or later part of the sample period, as the performance of the long-short portfolios is reported separately before and after the year 2000. Not only does this allow for the examination of portfolio performance over time, but these two subperiods are characterized by very different market conditions. While the 1990s were a time of relatively strong growth and investor optimism, the period following the turn of the century has included several large downturns with both the burst of the tech-bubble in the early 2000s and the financial crisis of 2008.

The excess returns suggest that while the distress anomaly is consistently stronger among low takeover exposure firms, distressed firms in general have not performed as poorly after the year 2000. The sizable differences across subperiods is largely attributed to the severe "crash" of distress-based strategies experienced in 2009.[47] The 4-factor alphas, however, indicate that after adjusting for risk, distress firms with low takeover exposure have underperformed significantly in both subperiods. The abnormal returns to the long-short portfolios were -0.03%, 0.03% and 1.62% during the 1990s and 0.30%, 0.42%, and 0.95% during the 2000s within the high, medium, and low takeover likelihood groups, respectively. If a risk-based explanation that takes into account the time-varying marginal utility of wealth were to explain the results, it is expected that the high-distress, low-takeover exposure firms would do very well in certain periods when marginal utility is high despite earning low returns on average; however, Panels A and B find consistent underperformance across all subperiods, which is consistent with the managerial alignment hypothesis.

Throughout the main analysis stocks are assigned to portfolios based on the most up-to-date, publicly available information at the start of each month. While most distressed firms tend to stay distressed for multiple months and the takeover measure is only updated annually, it is possible the results only hold with frequent portfolio rebalancing. In particular, distressed firms that recover could have strong future performance but experience most of their gains after exiting the highest distress quintile. Panel C addresses this issue by considering different portfolio holding periods. In

[46] The lower t-statistic during recessionary periods result primarily from there being fewer recessionary periods resulting in a larger standard error; however, the alpha is still large and significant at conventional levels.

[47] Eisdorfer and Misirli (2016) document that distressed stocks actually earned substantially higher returns than healthy stocks subsequent to the most severe market downturns.

particular, I test the results when reassigning firms to one of the fifteen portfolios on a quarterly, semi-annual, or annual frequency. The return patterns are generally similar to those presented in Table 3.4 with monthly portfolio assignment. In each instance the outperformance of healthy firms relative to distressed firms is greatest within the low takeover probability tercile, although the return spread does gradually decline as the rebalancing frequency decreases. However, the 4-factor alphas to the long-short portfolio of low takeover firms are significant at each rebalancing frequency with values of 1.10%, 0.95%, and 0.93% with quarterly, semi-annual, and annual rebalancing, respectively. Overall, portfolio holding periods do not seem to greatly alter the main results.

3.5.2 *Quarterly Takeover Measure*

In the takeover model estimated in Table 3.2 following Billett and Xue (2007), all of the predictor variables are constructed using accounting information from 10-K filings. In this section, I consider the impact of using publicly available accounting data from quarterly filings to update firm takeover probabilities every three months. This allows the takeover measure to more readily reflect changes in a firm's financial condition that can make it a more or less desirable takeover target.

Table 3.8 presents the results for the double-sorted portfolios while using the same takeover model but with quarterly accounting data. The results are generally similar to those presented in Table 3.4. The excess returns (upper-left) and 4-factor alphas (lower-right) both indicate the distress anomaly is concentrated among firms that face a minimal likelihood of becoming a takeover target. The CAPM and 3-factor model alphas also indicate that the distress anomaly is stronger among low takeover exposure firms but the alphas are again significant among all takeover groups, which appears to be the result of a strong momentum loading. Previous work has primarily focused on the existence of the distress anomaly across all firms, but the evidence here suggests the under-performance is limited to firms that are more insulated from potential takeovers. Consequently, this long-standing puzzle may not be a reflection of distress risk itself, but rather a manifestation of severe agency conflicts among the distressed firms that are least likely to be acquired.

3.6 Conclusions

Distressed companies are often attractive takeover targets as a result of their smaller size, relatively low valuations, and the opportunity for an acquirer to better utilize the firms' assets. This study investigates how the likelihood of being acquired affects the performance of distressed company stocks and tests competing explanations that offer competing testable hypotheses. Specifically, while a risk-based explanation predicts that a high probability of being acquired reduces the true failure risk of distressed firms, which could lower investors' required returns; a managerial alignment hypothesis predicts that when distressed companies face a low probability of being acquired, self-interested managers have an incentive to "play it safe" as the result of risk aversion and career concerns leading to poor future performance and low stock returns.

I find evidence consistent with the managerial alignment hypothesis, as the underperformance of distressed stocks is concentrated in firms with the lowest probability of receiving a takeover bid. Within this subgroup of firms, a zero net-investment portfolio that is long healthy firms and short distressed firms earns significant abnormal returns that are economically large and unexplained by common risk factors, business cycle effects, or particular subperiods. In contrast, a distress-based long-short portfolio earns small and insignificant abnormal returns among firms with moderate or high takeover exposure, which contradicts the risk-based hypothesis and suggests the distress anomaly is driven by a minority of firms.

To test the relation between takeovers and the distress anomaly, I use the *CHS* measure of financial distress as well as a measure of takeover likelihood estimated using historical takeover data. Cross-sectional Fama-MacBeth regressions yield similar results to the portfolio tests and suggest financial distress is associated with significantly lower returns among firms with a low probability of receiving a takeover bid. Additionally, predictive regressions that explore operating performance outcomes add support to the managerial alignment hypothesis, as distressed firms that are unlikely to be acquired invest less, decrease their leverage, and experience lower future profitability. While playing it safe may benefit the manager by reducing the near-term probability of going bankrupt, it appears to be at the expense of shareholders who seek an optimal return on their investment. Although existing governance data is limited for distressed firms, future research should look to explore whether additional governance mechanisms that reduce agency conflicts are

effective at enhancing the performance of distressed, low takeover exposure firms.

Table 3.1: Characteristics of Portfolios Sorted on CHS Distress-Risk

This table provides descriptive statistics for quintile portfolios formed by sorting stocks into five portfolios (least distressed, D1, to most distressed, D5) based on the CHS (2008) measure of financial distress. The CHS variable is constructed using monthly market data and quarterly accounting data. For each characteristic, I first calculate the cross-sectional mean and median of all stocks in each portfolio. I then report the time series averages of these means and medians. Size is the market value of equity (in millions of dollars). Market-to-book is the ratio of the market value of equity to the book value of equity. Past return (reported in percent) is the cumulative return from month *t-12* to *t-2*. Sigma (reported in percent) is the annualized standard deviation of daily stock returns over the past 3 months. Leverage (reported in percent) is the ratio of total liabilities to total assets. Net Profit (reported in percent) is the ratio of the prior year's net income to total assets. The percentage of firms with positive net income is reported subsequently. This table also reports portfolio average monthly excess returns (relative to the risk-free rate) as well as factor model alphas. Returns and alphas are reported in percent per month with the corresponding t-statistics below in parentheses. The sample period is 1990 to 2013.

		D1	D2	D3	D4	D5	D1–D5
Size	Mean	6,234.3	4,435.7	2,395.3	1,015.3	218.2	
	Median	752.8	745.9	428.6	186.0	54.6	
Market-to-Book	Mean	2.32	2.25	1.98	1.79	1.69	
	Median	2.14	2.00	1.66	1.40	1.18	
Past return	Mean	32.8	26.8	21.8	14.7	-7.9	
	Median	21.2	14.4	7.3	-1.9	-22.7	
Sigma	Mean	37.8	42.2	49.0	60.8	87.8	
	Median	35.0	39.0	46.0	58.1	85.3	
Leverage	Mean	33.5	44.1	48.2	50.8	54.5	
	Median	32.0	45.4	49.9	52.4	56.1	
Net Profit	Mean	8.58	5.73	2.20	-3.13	-15.98	
	Median	8.45	6.05	3.87	1.45	-6.03	
% Positive income	Mean	93.7	88.7	78.7	61.7	31.5	
	Median	100.0	100.0	100.0	87.2	1.4	
Excess return		0.69	0.69	0.68	0.51	0.18	0.52
		(2.93)	(2.77)	(2.10)	(1.15)	(0.29)	(1.06)
CAPM alpha		0.18	0.13	-0.03	-0.40	-0.98	1.16
		(1.93)	(1.85)	(-0.24)	(-1.90)	(-2.81)	(2.86)
3-factor alpha		0.23	0.14	-0.03	-0.44	-1.11	1.34
		(2.50)	(2.08)	(-0.23)	(-2.23)	(-3.61)	(3.67)
4-factor alpha		0.08	0.17	0.16	-0.13	-0.49	0.57
		(0.99)	(2.56)	(1.58)	(-0.75)	(-2.13)	(2.18)

Table 3.2: Takeover Likelihood Estimation

This table presents the results from a logistic regression used to estimate the likelihood that a firm will receive a takeover bid within the following year. The dependent variable is an indicator variable that equals one if the firm is a takeover target in year *t* and zero otherwise, and all predictor variables are constructed at the end of year *t-1*. The independent variables used to predict which firms will receive a takeover bid are chosen following the model of Billett and Xue (2007). The predictors include industry adjusted operating income before depreciation scaled by total assets (ROAIA), the log of market equity inflated to 2012 dollars using the CPI (SIZEEQ), industry adjusted leverage where leverage is total liabilities scaled by total assets (LEVBIA), the ratio of market equity to book equity (MKBK), the log of sales divided by prior year sales (SALEGR), net plant, property and equipment divided by total assets (NPPE), and a dummy variable that equals one if a firm in the same industry (four-digit SIC code) was a takeover target in the past year (ITODUM). Industry adjustments are conducted by subtracting the median value for all firms in the same two-digit SIC code. All continuous predictor variables are also winsorized at the 1^{st} and 99^{th} percentiles to limit the effect of outliers. Year indicator variables are included to control for the clustering of mergers and acquisitions. Heteroskedasticity robust standard errors are used in obtaining the z-statistics, which are reported beneath the coefficient estimates in parentheses. The model estimation is reported for the period 1980 to 2013.

ROAIA	0.118
	(1.36)
SIZEEQ	-0.040
	(-6.24)
LEVBIA	0.536
	(8.01)
MKBK	-0.048
	(-8.48)
SALEGR	-0.024
	(-0.63)
NPPE	-0.174
	(-2.98)
ITODUM	0.279
	(9.90)
Year controls	Yes
Percentage of targets	5.10
Log likelihood	-23,800.17
Pseudo R^2	0.0190

Table 3.3: Characteristics of Portfolios Sorted on Distress Risk and Takeover Likelihood
Each month I independently sort stocks into five distress quintiles (least distressed, D1, to most distressed, D5) based on the CHS (2008) measure of financial distress and three takeover terciles (most likely to receive a takeover bid, TO1, to least likely, TO3) based on the probability of becoming a takeover target within the next year. The CHS distress variable is constructed using monthly market data and quarterly accounting data. Takeover probability, TO, is estimated using annual accounting data following the takeover model of Billett and Xue (2007). The characteristics reported include size (market equity in millions of dollars), market-to-book ratio (market equity divided by book equity), past return (cumulative return from month *t-12* to *t-2* in percent), number of stocks (average number of firms per month), CHS (financial distress measure), and takeover probability (the estimated probability of receiving a takeover bid in percent). Each month I compute the mean characteristic values for the stocks in each portfolio, and I report the time series averages of these values for the full sample period of 1990 to 2013.

	TO1 (high)	TO2	TO3 (low)	TO1 (high)	TO2	TO3 (low)
	Panel A: Size			Panel B: Market-to-Book		
D1 (healthy)	3,362.3	6,623.3	7,612.1	2.09	2.35	2.45
D2	3,072.9	4,155.6	5,379.7	1.97	2.21	2.51
D3	1,947.3	2,174.3	2,913.9	1.72	1.90	2.35
D4	692.7	1,183.4	1,240.5	1.50	1.65	2.30
D5 (distressed)	186.8	241.1	275.0	1.35	1.48	2.42
	Panel C: Past return			Panel D: Number of Stocks		
D1 (healthy)	35.2	31.7	32.5	143	197	219
D2	27.6	26.1	27.4	172	184	204
D3	21.1	21.7	23.2	190	186	184
D4	13.0	13.8	16.8	204	187	168
D5 (distressed)	-7.9	-9.3	-8.1	224	178	158
	Panel E: CHS			Panel F: Takeover Probability		
D1 (healthy)	0.02	0.02	0.02	6.19	5.14	3.96
D2	0.03	0.03	0.03	6.28	5.13	3.99
D3	0.04	0.04	0.04	6.38	5.15	4.03
D4	0.08	0.08	0.08	6.53	5.16	3.99
D5 (distressed)	0.31	0.30	0.31	6.74	5.18	3.81

Table 3.4: Performance of Distress Risk and Takeover Probability Sorted Portfolios

I independently sort stocks into distress quintiles (least distressed, D1, to most distressed, D5) and takeover terciles (high probability of becoming a takeover target, TO1, to low probability of becoming a takeover target, TO3). The distress risk measure is based on CHS (2008) using monthly market data and quarterly accounting data, and takeover likelihood is estimated using a logit model with the takeover predictors of Billett and Xue (2007). Portfolios are reformed monthly based on the prior month's ending values of the two variables of interest. Panel A displays the value-weighted average monthly excess returns, CAPM alphas, Fama-French 3-Factor model alphas, and Carhart 4-factor model alphas for the 15 portfolios as well as for long-short portfolios. All returns and alphas are in percent per month with the corresponding t-statistics in parentheses. Panel B reports each portfolio's 4-factor model factor loadings with corresponding t-statistics below. The sample period is 1990 to 2013.

Panel A: Portfolio Returns and Alphas												
	D1	D2	D3	D4	D5	D1–D5	D1	D2	D3	D4	D5	D1–D5
	Excess Return						CAPM Alpha					
TO1 (high)	0.97	0.80	0.84	1.02	0.69	0.28	0.47	0.25	0.19	0.13	-0.36	0.83
	(3.70)	(3.01)	(2.69)	(2.27)	(1.19)	(0.57)	(3.01)	(1.94)	(1.30)	(0.54)	(-0.95)	(1.92)
TO2	0.75	0.78	0.77	0.40	0.43	0.31	0.26	0.17	0.05	-0.46	-0.71	0.97
	(3.17)	(2.73)	(2.19)	(0.91)	(0.68)	(0.58)	(2.27)	(1.40)	(0.29)	(-1.87)	(-1.72)	(2.08)
TO3 (low)	0.68	0.59	0.38	0.27	-0.54	1.21	0.14	0.03	-0.39	-0.70	-1.73	1.86
	(2.58)	(2.24)	(1.02)	(0.53)	(-0.81)	(2.21)	(1.06)	(0.25)	(-2.11)	(-2.45)	(-4.08)	(3.89)
TO1 – TO3	0.30	0.20	0.46	0.76	1.23		0.34	0.22	0.58	0.84	1.37	
	(1.65)	(1.17)	(2.07)	(2.42)	(3.15)		(1.85)	(1.28)	(2.65)	(2.65)	(3.50)	
	Fama-French 3-Factor Alpha						Carhart 4-Factor Model Alpha					
TO1 (high)	0.47	0.19	0.09	-0.02	-0.59	1.06	0.32	0.19	0.29	0.39	0.04	0.28
	(2.99)	(1.51)	(0.62)	(-0.07)	(-1.67)	(2.53)	(2.10)	(1.42)	(2.32)	(1.97)	(0.13)	(0.84)
TO2	0.27	0.17	0.08	-0.54	-0.89	1.15	0.17	0.26	0.30	-0.16	-0.15	0.32
	(2.30)	(1.38)	(0.49)	(-2.28)	(-2.38)	(2.71)	(1.46)	(2.17)	(1.92)	(-0.80)	(-0.54)	(0.98)
TO3 (low)	0.24	0.07	-0.35	-0.63	-1.77	2.00	0.05	0.10	-0.15	-0.36	-1.30	1.35
	(1.90)	(0.59)	(-2.00)	(-2.62)	(-5.04)	(4.82)	(0.42)	(0.92)	(-0.92)	(-1.58)	(-4.09)	(3.77)
TO1 – TO3	0.24	0.13	0.43	0.62	1.18		0.27	0.08	0.44	0.74	1.34	
	(1.33)	(0.75)	(2.26)	(2.16)	(3.28)		(1.52)	(0.47)	(2.24)	(2.59)	(3.72)	

Panel B: 4-Factor Model Factor Loadings

	D1	D2	D3	D4	D5	D1–D5	D1	D2	D3	D4	D5	D1–D5
	Market Factor Loading						SMB Factor Loading					
TO1 (high)	0.86	0.92	1.03	1.26	1.40	-0.54	0.08	-0.00	0.03	0.48	0.84	-0.75
	(23.45)	(29.21)	(34.61)	(26.70)	(20.12)	(-6.74)	(1.75)	(-0.07)	(0.88)	(7.81)	(9.19)	(-7.18)
TO2	0.85	0.96	1.03	1.20	1.41	-0.56	-0.09	-0.04	0.18	0.43	1.11	-1.20
	(31.15)	(33.13)	(27.20)	(24.25)	(20.65)	(-7.13)	(-2.60)	(-1.09)	(3.61)	(6.62)	(12.41)	(-11.68)
TO3 (low)	0.93	0.89	1.10	1.28	1.49	-0.56	-0.12	-0.01	0.28	0.69	1.26	-1.38
	(35.96)	(32.55)	(27.86)	(23.38)	(19.39)	(-6.44)	(-3.61)	(-0.39)	(5.33)	(9.64)	(12.51)	(-12.24)
TO1 – TO3	-0.07	0.03	-0.07	-0.02	-0.09		0.21	0.01	-0.24	-0.21	-0.42	
	(-1.74)	(0.70)	(-1.45)	(-0.26)	(-1.05)		(3.63)	(0.20)	(-3.90)	(-2.29)	(-3.72)	
	HML Factor Loading						UMD Factor Loading					
TO1 (high)	0.03	0.17	0.22	0.16	0.21	-0.18	0.18	0.01	-0.24	-0.48	-0.74	0.92
	(0.68)	(3.86)	(5.26)	(2.44)	(2.18)	(-1.59)	(5.81)	(0.38)	(-9.38)	(-11.89)	(-12.60)	(13.60)
TO2	0.05	-0.02	-0.22	-0.00	-0.04	0.09	0.12	-0.11	-0.26	-0.45	-0.87	0.99
	(1.21)	(-0.42)	(-4.06)	(-0.03)	(-0.47)	(0.83)	(5.24)	(-4.42)	(-8.00)	(-10.70)	(-14.95)	(14.80)
TO3 (low)	-0.18	-0.11	-0.25	-0.47	-0.38	0.20	0.22	-0.04	-0.23	-0.33	-0.55	0.77
	(-4.93)	(-2.99)	(-4.58)	(-6.17)	(-3.56)	(1.69)	(10.19)	(-1.93)	(-6.99)	(-7.02)	(-8.44)	(10.59)
TO1 – TO3	0.21	0.28	0.47	0.63	0.59		-0.04	0.06	-0.00	-0.15	-0.19	
	(3.51)	(4.87)	(7.16)	(6.54)	(4.90)		(-1.19)	(1.56)	(-0.08)	(-2.57)	(-2.62)	

Table 3.5: Distress, Takeover Exposure, and Future Operating Performance

This table reports estimates from panel regressions that explore the ability of distress and takeover probability to predict future firm performance. The dependent variables are return on assets (Column 1), gross profits to total assets (Column 2), cash flow to total assets (Column 3), capital expenditures to total assets (Column 4), cash holdings to total assets (Column 5), and total liabilities to total assets (Column 6) in year *t+1*. The independent variables include CHS distress, takeover probability (estimated probability of receiving a takeover bid in the following 12 months), an interaction term between distress and takeover probability, the log of firm market capitalization (Size), log book-to-market, and log firm age (years since firm entered Compustat database). All estimated regressions include both firm and year fixed effects and robust standard errors are reported in parentheses. The sample period is 1990 to 2013.

	Dependent Variable					
	ROA (1)	GP (2)	CF (3)	CAPX (4)	Cash (5)	LEV (6)
CHS	-0.314	-0.142	-0.383	-0.099	-0.031	0.091
	(-5.55)	(-3.66)	(-8.14)	(-7.85)	(-1.23)	(2.23)
Takeover Probability	0.004	0.002	0.005	-0.010	-0.015	0.050
	(1.94)	(0.64)	(2.31)	(-12.20)	(-10.29)	(21.68)
CHS x Takeover Prob.	0.079	0.048	0.129	0.022	0.004	0.024
	(4.49)	(3.85)	(8.74)	(5.48)	(0.50)	(1.79)
Log(Size)	-0.007	-0.039	0.013	-0.004	-0.015	-0.037
	(-3.23)	(-14.57)	(6.75)	(-4.97)	(-10.71)	(-17.66)
Log(B/M)	-0.088	-0.088	-0.030	-0.032	-0.026	-0.044
	(-29.05)	(-27.49)	(-10.79)	(-27.99)	(-13.41)	(-15.57)
Log(Age)	0.005	0.032	0.009	-0.008	-0.003	0.034
	(1.44)	(7.04)	(2.64)	(-4.78)	(-0.89)	(8.47)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3.6: Fama-MacBeth Regressions on Distress Risk and Takeover Likelihood
This table displays the results from monthly cross-sectional Fama and MacBeth (1973) regressions. The dependent variable is the stock return in excess of the monthly risk-free rate. The independent variables include the log of market capitalization, log book-to-market, the cumulative return from month *t-12* to *t-2* (Past Return), the return in month *t-1* (Rev), the CHS measure of distress risk, and the firm's likelihood of being a takeover target within the next year. An interaction between the CHS distress measure and the takeover probability is included in the final two columns. Columns 1 through 4 use annual accounting data to construct each firm's takeover probability, while column 5 utilizes quarterly accounting data. I multiply all coefficients by 100, and report t-statistics based on Newey-West corrected standard errors (with twelve lags) below in parentheses. The sample period is 1990 to 2013.

	(1)	(2)	(3)	(4)	(5)
Log(Size)	-0.052	-0.081	-0.052	-0.086	-0.083
	(-0.93)	(-1.70)	(-0.96)	(-1.83)	(-1.79)
Log(B/M)	0.390	0.365	0.287	0.251	0.266
	(1.98)	(1.87)	(1.54)	(1.37)	(1.46)
Past Return	0.364	0.342	0.341	0.309	0.332
	(1.47)	(1.72)	(1.37)	(1.53)	(1.66)
Rev(1 Mo)	-2.477	-2.712	-2.570	-2.811	-2.839
	(-7.08)	(-7.64)	(-7.36)	(-8.05)	(-8.13)
CHS		-1.198		-4.591	-4.727
		(-2.24)		(-2.24)	(-2.65)
Takeover Probability			0.452	0.371	0.367
			(5.08)	(4.77)	(4.59)
CHS x Takeover Prob.				1.099	1.092
				(1.70)	(2.02)
Constant	1.328	1.582	-0.003	0.515	0.531
	(2.27)	(3.06)	(-0.01)	(1.08)	(1.17)
Takeover Measure	Ann	Ann	Ann	Ann	Qtr

Table 3.7: Robustness of Distress Anomaly Across Takeover Exposure Levels

This table reports the performance of zero net-investment portfolios that are long stocks in the least distressed, D1, and short stocks in the most distressed quintile, D5, within each takeover likelihood tercile. The portfolios are formed by independently sorting stocks into distress quintiles based on the CHS measure of financial distress and takeover terciles based on the estimated probability that a firm receives a takeover bid within the following 12 months. Panel A reports the performance of the long-short portfolios separately for periods of expansion and recession where business cycle dates are defined according to the NBER's determination of periods of expansion and contraction. Panel B divides the sample into the 1990s (1990 – 1999) and 2000s (2000 – 2013). Panel C highlights implements different holding periods in which portfolios are rebalanced either quarterly, semi-annually, or annually. I report both excess returns (left-hand side) and Carhart 4-factor model alphas (right-hand side). Returns and alphas are reported in percent per month with the corresponding t-statistics in parentheses. The sample period is 1990 to 2013.

	TO1 (high)	TO2	TO3 (low)	TO1 (high)	TO2	TO3 (low)
	Excess return			4-Factor Model alpha		
Panel A: Business Cycle Periods						
Expansion	0.39	0.14	0.96	0.49	0.13	1.02
	(0.80)	(0.27)	(1.74)	(1.45)	(0.38)	(2.77)
Recession	-0.46	1.49	2.92	-0.33	1.54	2.62
	(-0.23)	(0.64)	(1.40)	(-0.28)	(1.36)	(1.98)
Panel B: Subperiods						
1990s	0.63	0.60	2.05	-0.03	0.03	1.62
	(1.10)	(0.99)	(3.37)	(-0.07)	(0.07)	(3.71)
2000s	-0.81	-0.62	0.25	0.30	0.42	0.95
	(-1.22)	(-0.96)	(0.30)	(0.64)	(0.90)	(1.88)
Panel C: Longer Horizon						
3 months	0.28	0.60	1.05	0.13	0.56	1.10
	(0.58)	(1.14)	(2.04)	(0.40)	(1.78)	(3.33)
6 months	0.44	0.46	0.95	0.36	0.50	0.95
	(0.97)	(0.91)	(1.86)	(1.11)	(1.54)	(2.89)
12 months	0.10	0.41	0.64	0.36	0.74	0.93
	(0.23)	(0.82)	(1.17)	(1.01)	(2.19)	(2.59)

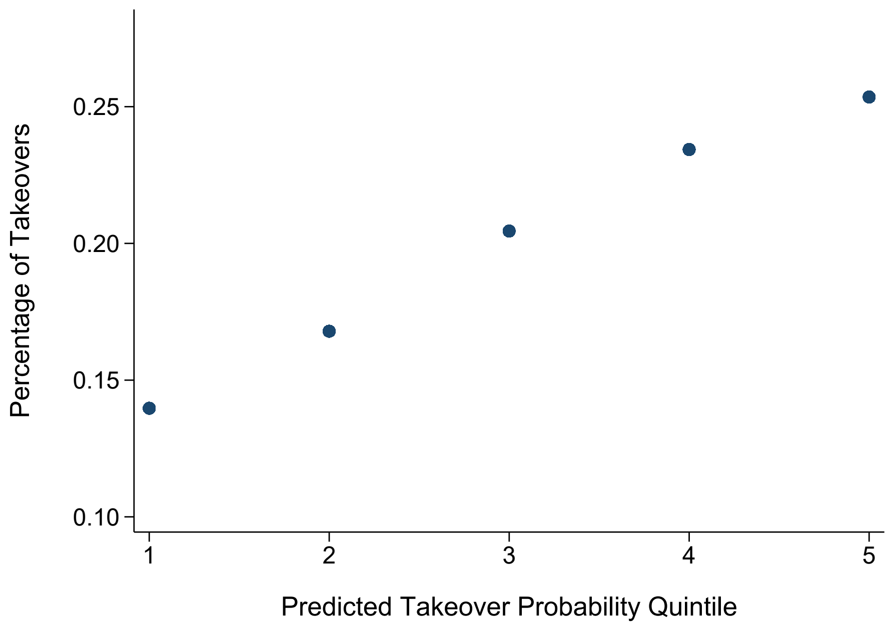
Table 3.8: Performance of Double-Sorted Portfolios with Quarterly Takeover Measure

I independently sort all stocks into distress quintiles (least distressed, D1, to most distressed, D5) and takeover terciles (high probability of becoming a takeover target, TO1, to low probability of becoming a takeover target, TO3). The distress risk measure is based on CHS (2008) using monthly market data and quarterly accounting data. Takeover probability is the probability that a firm will be a takeover target within the next year and is estimated using a logit model with the takeover predictors of Billett and Xue (2007). This table repeats prior analyses; however, quarterly accounting data is used to construct the takeover measure, so that the probabilities update every three months. The table displays the value-weighted average monthly excess returns, CAPM alphas, Fama-French 3-factor alphas, and Carhart 4-factor alphas for the 15 double-sorted portfolios as well as for long-short portfolios. All returns and alphas are in percent per month with the corresponding t-statistics in parentheses. The sample period is 1990 to 2013.

	Portfolio Returns and Alphas											
	D1	D2	D3	D4	D5	D1–D5	D1	D2	D3	D4	D5	D1–D5
	Excess Return						CAPM Alpha					
TO1 (high)	0.91	0.69	0.89	0.91	0.55	0.36	0.39	0.12	0.23	0.03	-0.54	0.93
	(3.45)	(2.50)	(2.77)	(2.03)	(0.91)	(0.75)	(2.70)	(0.91)	(1.45)	(0.11)	(-1.40)	(2.20)
TO2	0.77	0.80	0.66	0.40	0.31	0.46	0.29	0.20	-0.05	-0.51	-0.85	1.14
	(3.30)	(2.81)	(1.90)	(0.86)	(0.50)	(0.89)	(2.53)	(1.58)	(-0.32)	(-2.00)	(-2.22)	(2.64)
TO3 (low)	0.67	0.62	0.48	0.24	-0.49	1.15	0.14	0.06	-0.27	-0.72	-1.62	1.75
	(2.55)	(2.35)	(1.31)	(0.48)	(-0.75)	(2.10)	(1.03)	(0.50)	(-1.54)	(-2.50)	(-3.70)	(3.55)
TO1 – TO3	0.24	0.07	0.40	0.67	1.04		0.25	0.07	0.51	0.75	1.07	
	(1.31)	(0.36)	(1.78)	(2.06)	(2.55)		(1.34)	(0.37)	(2.25)	(2.27)	(2.62)	
	Fama-French 3-Factor Alpha						Carhart 4-Factor Model Alpha					
TO1 (high)	0.36	0.04	0.15	-0.13	-0.78	1.14	0.28	0.08	0.39	0.30	-0.09	0.37
	(2.48)	(0.31)	(0.93)	(-0.55)	(-2.15)	(2.80)	(1.91)	(0.59)	(2.86)	(1.59)	(-0.32)	(1.15)
TO2	0.27	0.22	-0.03	-0.61	-0.99	1.26	0.19	0.32	0.20	-0.22	-0.31	0.49
	(2.44)	(1.75)	(-0.19)	(-2.49)	(-2.89)	(3.26)	(1.67)	(2.68)	(1.33)	(-1.06)	(-1.20)	(1.69)
TO3 (low)	0.24	0.08	-0.24	-0.61	-1.66	1.90	0.03	0.08	-0.10	-0.38	-1.27	1.30
	(1.86)	(0.73)	(-1.47)	(-2.58)	(-4.58)	(4.41)	(0.26)	(0.73)	(-0.60)	(-1.67)	(-3.69)	(3.36)
TO1 – TO3	0.12	-0.04	0.39	0.48	0.88		0.25	-0.01	0.48	0.68	1.18	
	(0.68)	(-0.23)	(1.89)	(1.67)	(2.33)		(1.38)	(-0.03)	(2.35)	(2.40)	(3.16)	

Figure 3.1: Takeover Frequency By Predicted Takeover Probability Quintile

This figure displays the frequency with which firms receive takeover bids based on their predicted takeover probability. Each year, I sort firms into five takeover portfolios based on their probability of becoming a takeover target within the next 12 months, where takeover probability is estimated using annual accounting data following the model of Billett and Xue (2007). I then plot the percentage of total takeover bids received by firms within each takeover probability quintile portfolio. The sample period is 1990 to 2013.



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