UNIVERSITY OF CALIFORNIA

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Systemic Risks, Financial Intermediaries, and Asset Markets

A dissertation submitted in partial satisfaction of the

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in Management

by

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ABSTRACT OF THE DISSERTATION

Systemic Risks, Financial Intermediaries, and Asset Markets

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Professor Francis Longstaff, Co-Chair

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The credit crisis of 2007-2009 has sparked an enormous interest in the role that financial intermediaries play in our economy. Recent literature examines how financial intermediaries affect not only macro-economic variables but also asset markets such as the stock and the bond markets. The underlying theme in this recent literature is that the function of financial intermediaries in our asset markets is not yet completely understood and requires further study. This dissertation is based on three chapters that examine the interaction between systemic risks, financial intermediaries, and asset markets

The first chapter is titled 'Counterparty Credit Risk and the Credit Default Swap Market'.

This chapter is a version of a forthcoming paper in the Journal of Financial Economics by the same title. This paper is coauthored with Navneet Arora and Francis Longstaff. Counterparty credit risk has become one of the highest-profile risks facing participants in financial markets. Despite this, relatively little is known about how counterparty credit risk is actually priced. In this chapter I examine this issue empirically. I find that counterparty credit risk is priced in the CDS market. The magnitude of the effect, however, is vanishingly small and is consistent with a market structure in which participants require collateralization of swap liabilities by counterparties.

The second chapter is titled 'Size Anomalies in U.S. Bank Stock Returns: A Fiscal Explanation'. This chapter is a version of a UCLA Anderson working paper. This paper is coauthored with Hanno Lustig. I show that the largest commercial bank stocks, measured by book value, have significantly lower risk-adjusted returns than small- and medium-sized bank stocks, even though large banks are significantly more levered. I find a size factor in the component of bank returns that is orthogonal to the standard risk factors. This size factor, which has the right covariance with bank returns to explain the average risk-adjusted returns, measures size-dependent exposure in banks to bank-specific tail risk. The variation in exposure can be attributed to differences in the financial disaster recovery rates between small and large banks. A general equilibrium model with rare bank disasters can match these alphas in a sample without disasters provided that the difference in disaster recovery rates between the largest and smallest banks is 35 cents per dollar of dividends.

In the final chapter of this dissertation I document a new stylized fact regarding aggregate bank credit growth and the excess returns of bank stocks. I find that a 1% increase in bank credit growth rate implies that excess returns on bank stocks over the next one year are lower by nearly 3%. Unlike most other forecasting relationships, credit growth tracks bank stock returns over the business cycle and explains nearly 14% of the variation in bank stock returns over a 1-year horizon. I show that this predictive variation in returns reflects the representative agent's rational response to a small time-varying probability of a tail event that impacts banks and bank-dependent firms. Consistent with this hypothesis I show that the predictive power, as measured by the absolute magnitude of the coefficient on credit growth and the adjusted-R^2 at the the 1-year horizon, depends systematically on variables that regulate exposure to tail risk. Historically, the probability of a tail event increases in a recession, therefore this mechanism also explains the observed correlation between variation in aggregate bank credit level and business conditions.

The dissertation of Priyank Gandhi is approved.

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2012

To my parents, Mr. Prakash Chand Gandhi and Mrs. Laj Gandhi

To my wife, Ritu

To my son, Devansh

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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Chapter 1 of this dissertation is a version of a published paper in the Journal of Financial Economics titled Counterparty Credit Risk and the Credit Default Swap Market. This paper is co-authored with Navneet Arora and Francis Longstaff. The paper is available via the Journal of Financial Economics, Volume 103, Issue 2, February 2012, Pages 280 - 293. The authors are grateful for the comments of Darrell Duffie, Chris Jones, Peter Knez, Peter Meindl, Derek Schaeffer, Victor Wong, and seminar participants at the 2010 NYU Moody's Conference, the 2010 Moody's Risk Practitioner Conference in San Francisco, the 2010 SIAM conference on Financial Mathematics and Engineering, and the 2010 USC/UCLA Financial Research Conference. The authors are particularly grateful for the comments and advice of the editor Bill Schwert and an anonymous referee.

Chapter 2 of this dissertation is a version of a UCLA Anderson Working Paper titled Size Anomalies in Bank Stock Returns: A Fiscal Explanation. This paper is co-authored with Hanno Lustig. The paper is available electronically at http://www.nber.org/papers/w16553. The authors thank Viral Acharya, Martin Bodenstein, Markus Brunnermeier, John Campbell, John Cochrane, Ron Feldman, Cesare Fracassi, Etienne Gagnon, Mark Garmaise, Mark Grinblatt, Jennifer Huang, John Krainer, Arvind Krishnamurthy, David Laibson, Jonathan Parker, Lasse Pedersen, Andrea Raffo, Richard Roll, Jan Schneider, Martin Schneider, Clemens Sialm, Rob Vishny, and Skander Vandenheuvel for detailed and helpful comments, as well as seminar participants at UT Austin, Chicago Booth, NYU Stern, Harvard Economics, the Federal Reserve Board of Governors, the Federal Reserve Bank of San Francisco, and the Society for Economic Dynamics 2010 Annual Meeting in Montreal, and the 2010 Stanford Institute for Theoretical Economics.

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1 Chapter 1: Counterparty Credit Risk and the Credit Default Swap Market

1.1 Introduction

During the past several years, counterparty credit risk has emerged as one of the most important factors driving financial markets and contributing to the global credit crisis. Concerns about counterparty credit risk were significantly heightened in early 2008 by the collapse of Bear Stearns, but then skyrocketed later in the year when Lehman Brothers declared Chapter 11 bankruptcy and defaulted on its debt and swap obligations[1]. Fears of systemic defaults were so extreme in the aftermath of the Lehman bankruptcy that Euro-denominated CDS contracts on the U.S. Treasury were quoted at spreads as high as 100 basis points.

Despite the significance of counterparty credit risk in the financial markets, however, there has been relatively little empirical research about how it affects the prices of contracts and derivatives in which counterparties may default. This is particularly true for the $57.3 trillion notional credit default swap (CDS) market in which defaultable counterparties sell credit protection (essentially insurance) to other counterparties[2]. The CDS markets have been the focus of much attention recently because it was AIG's massive losses on credit default swap positions that led to the Treasury's $182.5 billion bailout of AIG. Furthermore, concerns about the extent of counterparty credit risk in the CDS market underlie recent proposals to create a central clearinghouse for CDS transactions[3].

[1]Lehman Brothers filed for Chapter 11 bankruptcy on September 15, 2008. During the same month, American International Group (AIG), Merrill Lynch, Fannie Mae, and Freddie Mac also failed or were placed under conservatorship by the U.S. government.

[2]The size of the CDS market as of June 30, 2008 comes from estimates reported by the Bank for International Settlements.

[3]For example, see the speech by Federal Reserve Board Chairman Ben S. Bernanke at the Council on

This paper uses a unique proprietary data set to examine how counterparty credit risk affects the pricing of CDS contracts. Specifically, this data set includes contemporaneous CDS transaction prices and quotations provided by 14 large CDS dealers for selling protection on the same set of underlying reference firms. Thus, we can use this cross-sectional data to measure directly how a CDS dealer's counterparty credit risk affects the prices at which the dealer can sell credit protection. A key aspect of the data set is that it includes most of 2008, a period during which fears of counterparty defaults in the CDS market reached historical highs. Thus, this data set provides an ideal sample for studying the effects of counterparty credit risk on prices in derivatives markets.

Four key results emerge from the empirical analysis. First, we find that there is a significant relation between the credit risk of the dealer and the prices at which the dealer can sell credit protection. As would be expected, the higher the dealer's credit risk, the lower is the price that the dealer can charge for selling credit protection. This confirms that prices in the CDS market respond rationally to the perceived counterparty risk of dealers selling credit protection.

Second, although there is a significant relation between dealer credit risk and the cost of credit protection, we show that the effect on CDS spreads is vanishingly small. In particular, an increase in the dealer's credit spread of 645 basis points only translates into a one-basis-point decline on average in the dealer's spread for selling credit protection. This small effect is an order of magnitude smaller than what would be expected if swap liabilities were uncollateralized. In contrast, the size of the pricing effect is consistent with the standard practice among dealers of having their counterparties fully collateralize swap liabilities.

Third, the Lehman bankruptcy in September 2008 was a major counterparty credit event in the financial markets. Accordingly, we examine how the pricing of counterparty credit risk was

Foreign Relations on March 10, 2009. For an in-depth discussion of the economics of CDS clearinghouse mechanisms, see Duffie and Zhu (2011).

affected by this event. We find that counterparty credit risk was priced prior to the Lehman bankruptcy. After the Lehman event, the point estimate of the effect increases but remains very small in economic terms. The increase is significant at the 10% level (but not at the 5% level).

Fourth, we study whether the pricing of counterparty credit risk varies across industries. In theory, the default correlation between the firm underlying the CDS contract and the CDS dealer selling protection on that firm should affect the pricing. Clearly, to take an extreme example, no investor would be willing to buy credit protection on Citigroup from Citigroup itself. Similarly, to take a less extreme example, we might expect the pricing of CDS dealers' credit risk to be more evident in selling credit protection on other financial firms. Surprisingly, we find that counterparty credit risk is priced in the CDS spreads of all firms in the sample except for the financials.

These results have many implications for current proposals to regulate the CDS market. As one example, they argue that market participants may view current CDS risk mitigation techniques such as the overcollateralization of swap liabilities and bilateral netting as largely successful in addressing counterparty credit risk concerns. Thus, proposals to create a central CDS exchange may not actually be effective in reducing counterparty credit risk further.

This paper contributes to an extensive literature on the effect of counterparty credit risk on derivatives valuation. Important research in this area includes Cooper and Mello (1991), Sorensen and Bollier (1994), Duffie and Huang (1996), Jarrow and Yu (2001), Hull and White (2001), Longstaff (2004) and Longstaff (2010), and many others. The paper most closely related to our paper is Duffie and Zhu (2011) who study whether the introduction of a central clearing counterparty into the CDS market could improve on existing credit mitigation mechanisms such as bilateral netting. They show that a central clearing counterparty might actually increase the amount of credit risk in the market. Thus, our empirical results support and complement the theoretical analysis provided in Duffie and Zhu.

The remainder of this paper is organized as follows. Section 1.2 provides a brief introduction to the CDS market. Section 1.3 discusses counterparty credit risk in the context of the CDS markets. Section 1.4 describes the data. Section 1.5 examines the effects of dealers' credit risk on spreads in the CDS market. Section 1.7 summarizes the results and presents concluding remarks.

1.2 The credit default swap market

In this section, we review briefly the basic features of a typical CDS contract. We then discuss the institutional structure of the CDS market.

1.2.1 CDS contracts

A CDS contract is best thought of as a simple insurance contract on the event that a specific firm or entity defaults on its debt. As an example, imagine that counterparty A buys credit protection on Amgen from counterparty B by paying a fixed spread of, say, 225 basis points per year for a term of five years. If Amgen does not default during this period of time, then B does not make any payments to A. If there is a default by Amgen, however, then B pays A the difference between the par value of the bond and the post-default value (typically determined by a simple auction mechanism) of a specific Amgen bond. In essence, the protection buyer is able to put the bond back to the protection seller at par in the event of a default. Thus, the CDS contract 'insures' counterparty A against the loss of value associated with default by Amgen[4].

1.2.2 The structure of the CDS market

Like interest rate swaps and other fixed income derivatives, CDS contracts are traded in the over-the-counter market between large financial institutions. During the past 10 years, CDS contracts

[4]For a detailed description of CDS contracts, see Longstaff, Mithal and Neis (2005).

have become one of the largest financial products in the fixed-income markets. As of June 30, 2008, the total notional amount of CDS contracts outstanding was $57.325 trillion. Of this notional, $33.083 trillion is with dealers, $13.683 trillion with banks, $0.398 trillion with insurance companies, $9.215 trillion with other financial institutions, and $0.944 trillion with nonfinancial customers[5].

Early in the development of the CDS market, participants recognized the advantages of having a standardized process for initiating, documenting, and closing out CDS contracts. The chartering of the International Swaps and Derivatives Association (ISDA) in 1985 led to the development of a common framework which could then be used by institutions as a uniform basis for their swap and derivative transactions with each other. Currently, ISDA has 830 member institutions. These institutions include virtually every participant in the swap and derivatives markets. As the central organization of the privately negotiated derivatives industry, ISDA performs many functions such as producing legal opinions on the enforceability of netting and collateral arrangements, advancing the understanding and treatment of derivatives and risk management from public policy and regulatory capital perspectives, and developing uniform standards and guidelines for the derivatives industry[6].

1.3 Counterparty credit risk

In this section, we first review some of the sources of counterparty credit risk in the CDS market. We then discuss ways in which the industry has attempted to mitigate the risk of losses stemming from the default of a counterparty to a CDS contract.

[5]Data obtained from table 4 of OTC Derivatives Market Activity for the First Half of 2008, Bank for International Settlements.

[6]This discussion draws on the information about ISDA provided on its website www.isda.org.

1.3.1 Sources of counterparty credit risk

There are at least three ways in which a participant in the CDS market may suffer losses when their counterparty enters into financial distress. First, consider the case in which a market participant buys credit protection on a reference firm from a protection seller. If the reference firm underlying the CDS contract defaults, the protection buyer is then owed a payment from the counterparty. If the default was unanticipated, however, then the protection seller could suddenly be faced with a large loss. If the loss was severe enough, then the protection seller could potentially be driven into financial distress. Thus, the protection buyer might not receive the promised protection payment.

Second, even if the reference firm underlying the CDS contract does not default, a participant in the CDS market could still experience a substantial loss in the event that the counterparty to the contract entered financial distress. The reason for this is that while CDS contracts initially have value of zero when they are executed, their mark-to-market values may diverge significantly from zero over time as credit spreads evolve. Specifically, consider the case where counterparty A has an uncollateralized mark-to-market liability of X to counterparty B. If counterparty A were to enter bankruptcy, thereby canceling the CDS contract and making the liability immediately due and payable, then counterparty Bs only recourse would be to attempt to collect its receivable of X from the bankruptcy estate. As such, counterparty B would become a general unsecured creditor of counterparty A. Given that the debt and swap liabilities of Lehman Brothers were settled at only 8.625 cents on the dollar, this could result in counterparty B suffering substantial losses from the default of counterparty A[7].

A third way in which a market participant could suffer losses through the bankruptcy of a

[7] The settlement amount was based on the October 10, 2008 Lehman Brothers credit auction administered by Creditex and Markit and participated in by 14 major Wall Street dealers. See the Lehman auction protocol and auction results provided by ISDA.

counterparty is through the collateral channel. Specifically, consider the case where counterparty A posts collateral with counterparty B, say, because counterparty B is counterparty A's prime broker. Now imagine that the collateral is either not segregated from counterparty B's general assets (as was very typical prior to the Lehman default), or that counterparty B rehypothecates counterparty A's collateral (also very common prior to the Lehman default). In this context, a rehypothecation of collateral is the situation in which counterparty B transfers counterparty A's collateral to a third party (without transferring title to the collateral) in order to obtain a loan from the third party. Buhlman and Lane (2009) argue that under certain circumstances, the rehypothecated securities become part of the bankruptcy estate. Thus, if counterparty B filed for bankruptcy after rehypothecating counterparty A's collateral, or if counterparty A's collateral was not legally segregated, then counterparty A would become a general unsecured creditor of counterparty B for the amount of the collateral, again resulting in large potential losses. An even more precarious situation would be when the rehypothecated collateral itself was seized and sold by the third party in response to counterparty B's default on the loan obtained using the rehypothecated securities as collateral. Observe that because of this collateral channel, counterparty A could suffer significant credit losses from counterparty B's bankruptcy, even if counterparty B does not actually have a mark-to-market liability to counterparty A stemming from the CDS contract.

1.3.2 Mitigating counterparty credit risk

One of the most important ways in which the CDS market attempts to mitigate counterparty credit risk is through the market infrastructure provided by ISDA. In particular, ISDA has developed specific legal frameworks for standardized master agreements, credit support annexes, and auction, closeout, credit support, and novation protocols. These ISDA frameworks are widely used by market participants and serve to significantly reduce the potential losses arising from the default of a counterparty in a swap or derivative contract[8].

Master agreements are encompassing contracts between two counterparties that detail all aspects of how swap and derivative contracts are to be executed, confirmed, documented, settled, etc. Once signed, all subsequent swaps and derivative transactions become part of the original master swap agreement, thereby eliminating the need to have separate contracts for each transaction. An important advantage of this structure is that it allows all contracts between two counterparties to be netted in the event of a default by one of the counterparties. This netting feature implies that when default occurs, the market value of all contracts between counterparties A and B are aggregated into a net amount, leaving one of the two counterparties with a net liability to the other. Without this feature, counterparties might have incentives to demand payment on contracts on which they have a receivable, but repudiate contracts on which they have a liability to the defaulting counterparty.

Credit support annexes are standardized agreements between counterparties governing how credit risk mitigation mechanisms are to be structured. For example, a specific type of credit risk mitigation mechanism is the use of margin calls in which counterparty A demands collateral from counterparty B to cover the amount of counterparty B's net liability to counterparty A. The credit support annex specifies details such as the nature and type of collateral to be provided, the minimum collateral transfer amount, how the collateral amount is to be calculated, etc.

ISDA protocols specify exactly how changes to master swap agreements and credit support annexes can be modified. These types of modifications are needed from time to time to reflect changes in the nature of the markets. For example, the increasing tendency among market participants to closeout positions through novation rather than by offsetting positions motivated the development

[8] Bliss and Kaufman (2006) provide an excellent discussion of the role of ISDA and of netting, collateral, and closeout provisions in mitigating systemic credit risk.

of the 2006 ISDA Novation Protocol II. Similarly, the creation of a standardized auction mechanism for settling CDS contracts on defaulting firms motivated the creation of the 2005 - 2009 ISDA auction protocols and the 2009 ISDA closeout amount protocol.

An important second way in which counterparty credit risk is minimized is through the use of collateralization. Recall that the value of a CDS contract can diverge significantly from zero as the credit risk of the reference firm underlying the contract varies over time. As a result, each counterparty could have a significant mark-to-market liability to the other at some point during the life of the contract. In light of the potential credit risk, full collateralization of CDS liabilities has become the market standard. For example, the ISDA (2009) reports that 74% of CDS contracts executed during 2008 were subject to collateral agreements and that the estimated amount of collateral in use at the end of 2008 was approximately $4.0 trillion. Typically, collateral is posted in the form of cash or government securities. Participants in the Margin Survey indicate that approximately 80% of the ISDA credit support agreements are bilateral, implying two-way transfers of collateral between counterparties. Of the 20 largest respondents to the survey (all large CDS dealers), 50% of their collateral agreements are with hedge funds and institutional investors, 15% are with corporations, 13% are with banks, and 21% are with others.

The data set used in this study represents the CDS spreads at which the largest Wall Street dealers actually sell, or are willing to sell, credit protection. Both discussions with CDS traders and margin survey evidence indicate that the standard practice by these dealers is to require full collateralization of swap liabilities by both counterparties to a CDS contract. In fact, the CDS traders we spoke with reported that the large Wall Street dealers they trade with typically require that their non-dealer counterparties overcollateralize their CDS liabilities slightly. This is consistent with the ISDA (2009) that documents that the 20 largest firms accounted for 93% of all collateral received, but only 89% of all collateral delivered, suggesting that there was a net inflow of collateral to the largest CDS dealers. Furthermore, the degree of overcollateralization required can vary over time. As an example, one reason for the liquidity problems at AIG that led to emergency loans by the Federal Reserve was that AIG would have been required to post additional collateral to CDS counterparties if AIG's credit rating had downgraded further[9].

At first glance, the market standard of full collateralization seems to suggest that there may be little risk of a loss from the default of a Wall Street credit protection seller. This follows since the protection buyer holds collateral in the amount of the protection sellers CDS liability. In actuality, however, the Wall Street practice of requiring non-dealer protection buyers to slightly overcollateralize their liabilities actually creates a subtle counterparty credit risk. To illustrate this, imagine that a protection buyer has a mark-to-market liability to the protection seller of $15 per $100 notional amount. Furthermore, imagine that the protection seller requires the protection buyer to post $17 in collateral. Now consider what occurs if the protection seller defaults. The bankruptcy estate of the protection seller uses $15 of the protection buyers collateral to offset the $15 mark-to-market liability. Rather than returning the additional $2 of collateral, however, this additional capital becomes part of the bankruptcy estate. This implies that the protection buyer is now an unsecured creditor in the amount of the $2 excess collateral. Thus, in this situation, the protection buyer could suffer a significant loss even though the buyer actually owed the defaulting counterparty on the CDS contract.

This scenario is far from hypothetical. In actuality, a number of firms experienced major losses on swap contracts in the wake of the Lehman bankruptcy because of their net exposure (swap liability and offsetting collateral) to Lehman[10].

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[9]For example, see the speech by Federal Reserve Chairman Ben S. Bernanke before the Committee on Financial Services, U.S. House of Representatives, on March 24, 2009.

[10]From the October 7, 2008 Financial Times: 'The exact amount of any claim is determined by the difference between the value of the collateral and the cost of replacing the contract.. . . Moreover, many

1.4 The data

Fixed-income securities and contracts are traded primarily in over-the-counter markets. For example, Treasury bonds, agency bonds, sovereign debt, corporate bonds, mortgage-backed securities, bank loans, interest rate swaps, and CDS contracts are all traded in over-thecounter markets. Because of the inherent decentralized nature of these markets, however, actual transaction prices are difficult to observe. This is why most of the empirical research in the financial literature about fixed-income markets has typically been based on the quotation data available to participants in these markets.

We were fortunate to be given access to an extensive proprietary data set of CDS prices by one of the largest fixed-income asset management firms in the financial markets. A unique feature of this data set is that it contains both actual CDS transaction prices for contracts entered into by this firm as well as actionable quotations provided to the firm by a variety of CDS dealers. These quotations are actionable in the sense that the dealers are keenly aware that the firm expects to be able to trade (and often does) at the prices quoted by the dealers (and there are implicit sanctions imposed on dealers who do not honor their quotations). Thus, these quotations should more closely represent actual market prices than the indicative quotes typically used in the fixed-income literature.

In this paper, we study the spreads associated with contracts in which 14 major CDS dealers sell five-year credit protection to the fixed-income asset management firm on the 125 individual firms in the widely followed CDX index. The sample period for the study is March 31, 2008 to January 20, 2009. This period covers the turbulent Fall 2008 period in which Fannie Mae, Freddie Mac, Lehman Brothers, AIG, etc. entered into financial distress and counterparty credit fears reached their peak. Thus, this sample period is ideally suited for studying the effects of counterparty credit

counterparties to Lehman who believe it owes them money have joined the ranks of unsecured creditors.'

risk on financial markets.

The transactions data in the sample are taken from a file recording the spreads on actual CDS contracts executed by the firm in which the firm is buying credit protection. There are roughly 1,000 transactions in this file. The average transaction size is $6.5 million and the average maturity of these contracts is 4.9 years. All 14 of the major CDS dealers to be studied in this paper are included in this file. Thus, all 14 of these dealers sold credit protection to the asset management firm during the sample period. Of these transactions, however, most involve either firms that are not in the CDX index, or contracts with maturities significantly different from five years. Screening out these trades results in a sample of several hundred observations.

To augment the sample, we also include quotes provided directly to the firm by the CDS dealers selling protection on the firms in the CDX index. As described above, these quotes represent firm offers to sell protection and there can be sanctions for dealers who fail to honor their quotes. For example, if the asset management firm finds that a dealer is often not willing to execute new trades (or unwind existing trades) at quoted prices, then that dealer could be dropped from the list of dealers that the firms traders are willing to do business with. Given the large size of the asset management firm providing the data, the major CDS dealers included in the study have strong incentives to provide actionable quotes.

There are a number of clear indications that the dealers respond to these incentives and provide reliable quotes. First, the dealers included in the study frequently update their quotes throughout the trading day. The total number of quotations records in the data set for firms in the CDX index is 673,060. This implies an average of 2.19 quotations per day per dealer for each of the firms in the sample. Thus, quotes are clearly being refreshed throughout the trading day. Second, the fact that all 14 of the CDS dealers sold protection to the asset management firm during the sample period suggests that each was active in providing competitive and actionable quotes during

Table 1: The distribution of dealer prices and quotations

Notes: This table provides summary statistics for the distribution of dealer prices or quotations for CDS contracts referencing the firms in the CDX index. The panel on the left summarizes the distribution in terms of the number of dealer prices and quotations on a given day for a CDS contract referencing a specific firm. The panel on the right summarizes the distribution in terms of the range R of prices and quotations (measured in basis points) provided by dealers on a given day for a CDS contract on a specific reference firm. Only days on which two or more simultaneous prices or quotations are available for a specific firm are included in the sample as an observation. The sample period is March 31, 2008 to January 20, 2009.

Number	Observations	Percentage	Range	Observations	Percentage
2	4907	36.66	0	1175	8.78
3	4518	33.78	$0 < R \leq 1$	1952	14.59
4	2566	19.17	$1 < R \leq 2$	2298	17.17
5	1012	7.56	$2 < R \leq 3$	1925	14.38
6	267	1.99	$3 < R \leq 4$	1065	7.96
7	84	0.62	$4 < R \leq 5$	1800	13.44
8	21	0.16	$5 < R \leq 10$	2209	16.51
9	8	0.06	$10 < R \leq 20$	748	5.59
			$20 < R$	211	1.58
Total	13,383	100.00		Total 13,383	100.00

this period. Third, we compare our sample of transaction prices directly to the quotes available in the market on the same day. This comparison is necessarily a little noisy since the transaction prices are not time-stamped within the day, and we are comparing them to quotes available in the market at roughly 11:30 AM. Despite this, however, the average transaction price is only 0.26 basis points below the minimum quote available in the market. The standard deviation of the difference is 5.87 basis points and the difference between the mean transaction price and minimum quote is not statistically significant.

As mentioned, dealers frequently update their quotations throughout the day to insure that they are current. Since our objective is to study whether the cross-sectional dispersion in dealer prices is related to counterparty credit risk, it is important that we focus on dealer prices that are as close to contemporaneous as possible. To this end, we extract quotes from the data set in the following way. First, we select 11:30 AM as the reference time. For each of the 14 CDS dealers, we then include the quote with time-stamp nearest to 11:30 AM, but within 15 minutes (from 11:15 to 11:45 AM). In many cases, of course, there may not be a quote within this 30-minute period. Thus, we will generally have fewer than 14 prices or quotes available for each firm each day. For a firm to be included in the sample for a particular day, we require that there be two or more prices or quotes for that firm. We repeat this process for all days and firms in the sample.

This algorithm results in a set of 13,383 observation vectors of synchronous prices or quotations by multiple CDS dealers for selling protection on a common underlying reference firm. Since there are 212 trading days in the sample period, this implies that we have data for multiple CDS dealers for an average of 63.13 firms each day. Table 1 presents summary statistics for the data. As shown, the number of synchronous quotes ranges from two to nine. On average, an observation includes 3.073 dealer quotes for the reference firm for that day. Table 1 also shows that the variation in the quotes provided by the various dealers is relatively modest. For most of the observations, the range of CDS quotations is only on the order of two to three basis points, and the median range is three basis points.

In addition to the prices and quotes provided by the dealers selling protection, we also need a measure of the counterparty credit risk of the dealers themselves. To this end, we obtain daily midmarket five-year CDS quotes referencing each of the 14 major CDS dealers in the study. The midmarket spreads for these CDS contracts are obtained from the Bloomberg system and reflect the markets perception of the counterparty credit risk of the dealers selling credit protection to the asset management firm.

Table 2 reports summary statistics for the CDS spreads for these dealers. As shown, the average CDS spread ranges from a low of 59.40 basis points for BNP Paribas to a high of 355.10 basis points for Morgan Stanley. Note that CDS data for Lehman Brothers and Merrill Lynch are included in the data set even though these firms either went bankrupt or merged during the sample period. The reason for including these firms is that both were actively making markets in selling credit protection through much of the sample period. Thus, their spreads may be particularly informative about the impact of perceived counterparty credit risk on CDS spreads.

1.5 Empirical analysis

In this section, we begin by briefly describing the methodology used in the empirical analysis. We then test whether counterparty credit risk is reflected in the prices of CDS contracts. Finally, we study whether the pricing of counterparty credit risk by dealers varies by industry as would be implied by a correlation-based credit model.

Table 2: Summary statistics for CDS contracts referencing dealers

Notes: This table provides summary statistics for the CDS spreads (in basis points) for contracts referencing the dealers listed below. The spreads are based on daily observations obtained from the Bloomberg system. N denotes the number of days on which Bloomberg quotes are available for the indicated dealer. The sample period is March 31, 2008 to January 20, 2009.

Dealer	Mean	σ	Min	Median	Max	N
Barclays	122.65	43.33	53.27	122.17	261.12	212
BNP Paribas	59.40	13.29	34.24	59.08	107.21	212
Bank of America	121.60	35.77	61.97	119.75	206.85	209
Citigroup	180.67	71.13	87.55	162.90	460.54	207
Credit Suisse	111.66	37.20	57.59	101.40	194.22	212
Deutsche Bank	96.88	29.70	51.92	90.11	172.00	212
Goldman Sachs	230.58	110.62	79.83	232.69	545.14	177
HSBC	75.41	21.94	41.84	67.59	128.30	212
JP Morgan	110.86	27.96	62.54	107.68	196.34	209
Lehman	291.79	89.01	154.04	285.12	641.91	84
Merrill Lynch	243.19	71.34	114.35	218.43	472.72	193
Morgan Stanley	355.10	236.22	108.06	244.98	1360.00	187
RBoS	116.45	45.16	55.17	110.69	304.89	212
UBS	139.09	56.81	55.45	126.24	320.80	212

1.5.1 Methodology

For each reference firm and for each date t in the sample, we have simultaneous prices from multiple CDS dealers for selling five-year credit protection on that firm. Thus, we can test directly whether counterparty credit risk is priced by a straightforward regression of the price of protection sold or quoted by a dealer for a reference firm on the price of protection for the dealer itself providing that quotation. In this panel regression framework, we allow for reference-firm-specific date fixed effects. Specifically, we estimate the following regression:

$$CDS_{i,j,t} = \alpha_{i,t} + \beta Spread_{j,t-1} + \epsilon_{i,j,t} \tag{1}$$

where $CDS_{i,j,t}$ denotes the CDS spread for credit protection on reference firm i sold or quoted by dealer j at date t, $\alpha_{i,t}$ is a fixed effect parameter specific to firm i at time t, and $Spread_{j,t-1}$,is the CDS spread for dealer j as of the end of the previous day[11]. Under the null hypothesis that counterparty credit risk is not priced, the slope coefficient β is zero. The t-statistics for β reported in the tables are based on the White (1980) heteroskedastic-consistent estimate of the covariance matrix.

As shown in table 1, there are a total of 13,383 observation vectors in the sample. On average, each observation vector consists of 3.073 distinct quotations for selling credit protection on the reference firm, giving a total of 41,122 observations collectively. Thus, there are 339.85 observations on average for each of the 121 reference firms in the sample.

[11]We use the dealers spread as of $t-1$ rather than t since the dealer data are as of the end of the day while the CDS quotation data are taken from a narrow timeframe centered at 11:30 AM. Thus, using the dealers spread as of the end of day $t-1$ avoids using ex post data in the regression

1.5.2 Is counterparty credit risk priced?

Although a formal model of the relation between a dealers credit risk and the price at which the dealer could sell credit protection could be developed, the underlying economics of the transaction makes it clear that there should be a negative relation between the two. Specifically, as the credit risk of a protection seller increases, the value of the protection being sold is diminished and market participants would not be willing to pay as much for it. Thus, if counterparty credit risk is priced in the market, the slope coefficient β in the regressions should be negative.

Table 3 reports the results from estimating the regression in Equation (1) (which is designated specification I). The slope coefficient β is -0.001548 with a t-statistic of -7.31. Thus, the empirical results strongly support the hypothesis that counterparty credit risk is priced in the CDS market. Furthermore, the sign of the coefficient is negative, consistent with economic intuition. We acknowledge, however, that we cannot completely rule out the possibility that the relation between CDS spreads and the credit risk of protection sellers may actually be due to some other factor that is correlated with dealer spreads[12]. For example, since CDS contracts are traded in over-the-counter markets, the search costs associated with finding trading partners could play a role in determining equilibrium CDS spreads (see Duffie, Garleanu and Pedersen (2002), Duffie, Garleanu and Pedersen (2005), Duffie, Garleanu and Pedersen (2008), and others). If these search costs were inversely related to dealer CDS spreads, then they could potentially affect CDS spreads in a way consistent with the results reported in table 3. We will explore some of these possibilities in a later section on robustness.

[12]We are grateful to the referee for raising this issue

Table 3: Results from the regression of CDS spreads on the CDS spread of the corresponding dealer

Notes: This table reports the results from the regressions of CDS prices or quotations for the firms in the CDX Index on the CDS spread of the dealer providing the CDS price or quotation. The sample period is March 31, 2008 to January 20, 2009. Regression specification II includes a dummy variable I_L that takes value one for the post-Lehman period beginning September 15, 2008, and zero otherwise. The t-statistics are based on White (1980) heteroskedasticity-consistent estimate of the covariance matrix. The superscript ** denotes significance at the 5% level; the superscript * denotes significance at the 10% level.

$$I : CDS_{i,j,t} = \alpha_{i,t} + \beta Spread_{j,t-1} + \epsilon_{i,j,t}$$

$$II : CDS_{i,j,t} = \alpha_{i,t} + \beta Spread_{j,t-1} + \gamma I_{L,t} \epsilon_{i,j,t}$$

	Regression specification I		Regression specification II	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic
$Spread$	-0.001548	-7.31**	-0.000991	-3.73**
I_L $Spread$			-0.000713	-1.92*
N		41,122		41,122

1.5.3 Why is the effect so small?

Although statistically very significant, the slope coefficient is relatively small in economic terms. In particular, the value of -0.001548 implies that the credit spread of a CDS dealer would have to increase by nearly 645 basis points to result in a one-basis-point decline in the price of credit protection. As shown in table 2, credit protection on most of CDS dealers in the sample never even reached 645 basis points during the period under study. These results are consistent with the results in table 1 suggesting that the cross-sectional variation in the dealers' quotes for selling credit protection on a specific reference firm is only on the order of several basis points.

A number of papers have explored the theoretical magnitude of counterparty credit risk on the pricing of interest rate swaps. Important examples of this literature include Cooper and Mello (1991), Sorensen and Bollier (1994), and Duffie and Huang (1996). Typically, these papers find that since the notional amount is not exchanged in an interest rate swap, the effect of counterparty credit risk on an interest rate swap is very small, often only a basis point or two.

Unlike an interest rate swap, however, a CDS contract could involve a very large payment by the protection seller to the protection buyer. For example, sellers of protection on Lehman Brothers were required to pay \$91.375 per \$100 notional to settle their obligations to protection buyers. Thus, the results from the interest rate swap literature may not necessarily be directly applicable to the CDS market.

A few recent papers have focused on the theoretical impact of counterparty credit risk on the pricing of CDS contracts. Important examples of these papers include Jarrow and Yu (2001), Hull and White (2001), Brigo and Pallavicini (2006), Kraft and Steffensen (2007), Segoviano and Singh (2008), and Blanchet-Scalliet and Patras (2008). In general, estimates of the size of the effect of counterparty credit risk in this literature tend to be orders of magnitude larger than those in the literature for interest rate swaps. For example, estimates of the potential size of the pricing effect range from 7.0 basis points in Kraft and Steffensen to more than 20 basis points in Hull and White (2001), depending on assumptions about the default correlations of the protection seller and the underlying reference firm. Thus, this literature tends to imply counterparty credit risk pricing effects many times larger than those we find in the data.

It is crucial to recognize, however, that this literature focuses almost exclusively on the case in which CDS contract liabilities are not collateralized. As was discussed earlier, the standard market practice during the sample period would be to require full collateralization by both counterparties to a CDS contract. This would be particularly true for CDS contracts in which one counterparty was a large Wall Street CDS dealer.

In theory, full collateralization of CDS contract liabilities would appear to imply that there should be no pricing of counterparty credit risk in CDS contracts. In reality, however, there are several reasons why there might still be a small pricing effect even if counterparties require full collateralization. First, as became clear after the Lehman bankruptcy, counterparties who post collateral in excess of their liabilities risk becoming unsecured creditors of a defaulting counterparty for the amount of the excess collateral. As discussed earlier, however, Wall Street CDS dealers often require a small amount of overcollateralization from their counterparties (typically on the order of several percent) thus creating the possibility of a slight credit loss (ironically, however, only when the counterparty owes the bankrupt firm money). Second, the Lehman bankruptcy also showed that there were a number of legal pitfalls that many market participants had not previously appreciated. These include the risk of unsegregated margin accounts or the disposition of rehypothecated collateral.

In summary, the size of the counterparty pricing effect in the CDS market appears too small to be explained by models that abstract from the collateralization of CDS contracts. Rather, the small size of the pricing effect appears more consistent with the standard market practice of full collateralization, or even overcollateralization, of CDS contract liabilities.

1.5.4 Did pricing of counterparty credit risk change?

The discussion above suggests that the Lehman bankruptcy event may have forced market participants to reevaluate the risks inherent in even fully collateralized counterparty relationships. If so, then the pricing of counterparty credit after the Lehman bankruptcy might differ from the pricing in the CDS market previous to the bankruptcy. To explore this possibility, we reestimate the regression described above using a dummy slope coefficient for the post-Lehman period. Specifically, we estimate the regression

$$CDS_{i,j,t} = \alpha_{i,t} + \beta Spread_{j,t-1} + \gamma I_{L,t} Spread_{j,t-1} + \epsilon_{i,j,t} \tag{2}$$

where I_L is a dummy variable that takes value one for the post-Lehman period beginning September 15, 2008, and zero otherwise. Table 3 also reports the results from this regression (which is designated specification II). Note that in this specification, the coefficient β represents the regression slope during the pre-Lehman period, while the coefficient γ measures the change in the slope after the Lehman bankruptcy. Thus, we can test for whether there was a significant change in the pricing of counterparty credit risk after the Lehman bankruptcy by simply testing whether γ is statistically significant. The regression slope during the post-Lehman period can be obtained by simply summing the pre-Lehman slope coefficient β and the post-Lehman change in the slope coefficient γ.

The results provide some support for the hypothesis that the pricing of counterparty credit risk changed after the Lehman bankruptcy. Specifically, the pre-Lehman slope coefficient is -0.000991 and has a t-statistic of -3.73. After the Lehman bankruptcy, the change in the slope coefficient is -0.000713, making the pricing of counterparty credit risk in the post-Lehman period roughly twice as large as in the pre-Lehman period. The t-statistic for the change, however, is only -1.92. Thus, the change is significant at the 10% level, but not the 5% level.

1.5.5 Robustness of the results

To provide some robustness checks for these results, we also estimate several alternative specifications. In the first of these, we include the total number of trades executed by each dealer each day as a control for trading activity. Specifically, we estimate the following regression specifications:

$$\begin{aligned} CDS_{i,j,t} &= \alpha_{i,t} + \beta Spread_{j,t-1} + \eta Volume_{j,t} + \epsilon_{i,j,t} \qquad (3) \\ CDS_{i,j,t} &= \alpha_{i,t} + \beta Spread_{j,t-1} + \gamma I_{L,t} Spread_{j,t-1} + \eta Volume_{j,t} + \epsilon_{i,j,t} \end{aligned}$$

where $Volume_{j,t}$ denotes the total number of trades executed by dealer j on date t. Table 4 reports the results from the regressions.

Even after controlling for dealer trading activity, table 4 shows the regression coefficients and t-statistics for the dealers CDS spreads are virtually the same as they are in table 3. Thus, the results provide evidence that the dealer spread is not simply proxying for dealer liquidity effects.

As another robustness check, we reestimate the regressions in table 3, but with dummy variables for individual dealers. This specification controls for dealer fixed effects. Thus, the relation between CDS spreads for the firms in the CDX index and dealer CDS spreads is identified using only the times-series variation in spreads. The regressions estimated are:

$$\begin{aligned} CDS_{i,j,t} &= \alpha_{i,t} + \beta Spread_{j,t-1} + \sum_{j=1}^{13} \delta_j I_j + \epsilon_{i,j,t} \qquad (4) \\ CDS_{i,j,t} &= \alpha_{i,t} + \beta Spread_{j,t-1} + \gamma I_{L,t} Spread_{j,t-1} + \sum_{j=1}^{13} \delta_j I_j + \sum_{j=1}^{13} \eta_j I_j I_L + \epsilon_{i,j,t} \end{aligned}$$

where I_j is the dummy variable for the j^{th} dealer. Note that we only include 13 dealer dummies rather than all 14. This is because inclusion of all 14 dummies results in a collinearity with the firm

Table 4: Results from the regression of CDS spreads on the CDS spread of the corresponding dealer with control for dealer trading volume

Notes: This table reports the results from the regressions of CDS prices or quotations for the firms in the CDX index on the CDS spread of the dealer providing the CDS price or quotation and on the total number of trades executed by the dealer in all CDX index firms that day as a control variable (denoted as volume). The sample period is March 31, 2008 to January 20, 2009. The t-statistics are based on the White (1980) heteroskedasticity-consistent estimate of the covariance matrix. The superscript ** denotes significance at the 5% level; the superscript * denotes significance at the 10% level.

$$I : CDS_{i,j,t} = \alpha_{i,t} + \beta Spread_{j,t-1} + \eta Volume_{j,t} + \epsilon_{i,j,t}$$

$$II : CDS_{i,j,t} = \alpha_{i,t} + \beta Spread_{j,t-1} + \gamma I_{L,t} + \eta Volume_{j,t} + \epsilon_{i,j,t}$$

	Regression specification I		Regression specification II	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic
$Spread$	-0.001548	-7.3**	-0.000990	-3.73**
I_L $Spread$			-0.000714	-1.92*
N		41,122		41,122

Table 5: Results from the regression of CDS spreads on the CDS spread of the corresponding dealer with fixed effects for individual dealers

Notes: This table reports the results from the regression of CDS prices or quotations for the firms in the CDX index on the CDS spread of the dealer providing the CDS price or quotation. The regression also includes a separate fixed effect dummy variable for each dealer (except for the dealer with the largest number of quotes, arbitrarily designated dealer 14). The sample period is March 31, 2008 to January 20, 2009. Regression specification II includes a dummy variable I_L that takes value one for the post-Lehman period beginning September 15, 2008, and zero otherwise. The t-statistics are based on the White (1980) heteroskedasticity- consistent estimate of the covariance matrix. The superscript ** denotes significance at the 5% level; the superscript * denotes significance at the 10% level.

$$CDS_{i,j,t} = \alpha_{i,t} + \beta Spread_{j,t-1} + \sum_{j=1}^{13} \delta_j I_j + \epsilon_{i,j,t}$$

	Regression specification I		Regression specification II	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic
$Spread$	-0.001338	-4.49**	-0.001786	-2.35**
I_1	-1.4154	-3.87**	-0.113	-0.23
I_2	0.6574	4.17**	0.7774	4.34**
I_3	0.1707	1.56	0.1923	1.88*
I_4	0.4062	4.95**	0.5837	7.50**
I_5	0.2106	1.95*	0.0086	0.09
I_6	0.0326	0.64	-0.0461	-0.82
I_7	0.4728	2.28**	0.4227	2.07**
I_8	0.6006	6.03**	0.2026	2.28**
I_9	-0.1701	-1.66*	-0.1136	-0.82
I_{10}	0.1041	1.49	0.396	3.75**
I_{11}	0.1862	3.60**	0.1982	3.05**
I_{12}	0.9453	6.96**	0.6462	3.74**
I_{13}	0.1922	1.64	0.0659	0.65
N	41,122		41,122	

and date fixed effects. Thus, the regression coefficients for dealer dummies have the interpretation of the marginal effect relative to that of the omitted dealer, which is chosen to be the dealer with the highest trading activity throughout the sample period.

The results from these regressions are reported in tables 5 and 6. The results indicate that the previous results are robust to the inclusion of dealer fixed effects. The coefficient for dealer CDS spread is -0.001338 for the first specification, which is only slightly less than the corresponding estimate in table 3. The t-statistic for dealer CDS spread in this regression is -4.49. In the second specification with the post-Lehman dummy variable, the CDS spread of the dealer is again significantly negative during the pre-Lehman period, and there is no significant change in the variable after the Lehman bankruptcy. This again provides support for the result that dealer credit risk is priced in the market, although the effect is very small.

The coefficients for the individual dealer dummy variables are also interesting. Although many of the coefficients in the first specification are significant, almost all of them are much less than one basis point in magnitude. The same is also true for the pre-Lehman coefficients for the second specification. On the other hand, the results indicate that a number of the coefficients change in the post-Lehman period by one or more basis points. These changes, however, are essentially equally divided between positive and negative values. Thus, these results provide some evidence of greater heterogeneity in dealer fixed effects in the post-Lehman period[13].

1.5.6 Are there differences across firms?

A number of recent papers have emphasized the role that the default correlation between the protection seller and the reference firm should play in determining CDS spreads. To illustrate the importance of correlation, let us take it to an extreme and imagine that Citigroup is willing to

[13] We are grateful to the referee for suggesting the robustness checks discussed in this section

Table 6: Results from the regression of CDS spreads on the CDS spread of the corresponding dealer with fixed effects for individual dealers

Notes: This table reports the results from the regression of CDS prices or quotations for the firms in the CDX index on the CDS spread of the dealer providing the CDS price or quotation. The regression also includes a separate fixed effect dummy variable for each dealer (except for the dealer with the largest number of quotes, arbitrarily designated dealer 14). The sample period is March 31, 2008 to January 20, 2009. Regression specification II includes a dummy variable I_L that takes value one for the post-Lehman period beginning September 15, 2008, and zero otherwise. The t-statistics are based on the White (1980) heteroskedasticity- consistent estimate of the covariance matrix. The superscript ** denotes significance at the 5% level; the superscript * denotes significance at the 10% level.

$$CDS_{i,j,t} = \alpha_{i,t} + \beta Spread_{j,t-1} + \gamma I_{L,t} Spread_{j,t-1} + \sum_{j=1}^{13} \delta_j I_j + \sum_{j=1}^{13} \eta_j I_j I_L + \epsilon_{i,j,t}$$

	Regression specification I		Regression specification II	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic
I_L $Spread$			0.000347	0.36
$I_1 I_L$			−1.4112	-2.21**
$I_2 I_L$			−1.0839	-2.78**
$I_3 I_L$			−0.0857	-0.3
$I_4 I_L$			−0.7415	-2.90**
$I_5 I_L$			0.4342	1.47
$I_6 I_L$			0.728	2.58**
$I_7 I_L$			0.5204	0.32
$I_8 I_L$			1.6748	4.68**
$I_9 I_L$				
$I_{10} I_L$			−1.101	-4.79**
$I_{11} I_L$			0.0423	0.17
$I_{12} I_L$			0.6155	2.08**
$I_{13} I_L$			2.6544	1.87*
N	41,122		41,122	

sell credit protection against the event that Citigroup itself defaults. Clearly, no one would be willing to pay Citigroup for this credit protection[14]. Similarly, a financial institution selling credit protection on another financial institution might not be able to charge as much as a nonfinancial seller might[15].

To explore the effects of correlation on the price of credit protection, we do the following. First, we classify the firms in the CDX index that are in our sample into one of five broad industry sectors or categories: consumer, energy, financials, industrials, and technology. We then re-estimate the regressions using the following specifications:

$$
\begin{aligned}
CDS_{i,j,t} &= \alpha_{i,t} + \sum_{k=1}^{5} \beta_k I_{Sector_k} Spread_{j,t-1} + \epsilon_{i,j,t} \qquad (5) \\
CDS_{i,j,t} &= \alpha_{i,t} + \sum_{k=1}^{5} \beta_k I_{Sector_k} Spread_{j,t-1} + \sum_{k=1}^{5} \gamma_k I_{Sector_k} I_L Spread_{j,t-1} + \epsilon_{i,j,t}
\end{aligned}
$$

where I_{Sector_k} are dummy variables that take value one if firm i is in sector k, and zero otherwise. The regression results are reported in table 7. As shown in the first specification, counterparty credit risk is priced for the consumer, energy, industrial, and technology firms in the sample. The t-statistics for the corresponding coefficients are -4.83, -7.25, -3.61, and -5.41, respectively. These results are clearly consistent with the previous results.

The most puzzling result, however, is that for the financial sector. As described above, the correlation argument suggests that the counterparty credit risk for the CDS dealers should be most evident when they are selling protection on firms in the financial industry. In contrast to this intuition, however, the results show that the CDS dealers' counterparty credit risk is not priced in

[14]It is interesting to note, however, that a number of European banks sell credit protection on the iTraxx index which includes these banks as index components.

[15]Examples of recent papers discussing the role of correlation in the pricing of CDS contracts include Hull and White (2001), Jarrow and Yu (2001), Longstaff, Mithal and Neis (2005), Yu (2007), and many others

Table 7: Results from regression of CDS spreads on the CDS spreads of the corresponding dealer interacted with sector dummy variables for the underlying firms

Notes: This table reports the results from the regression of CDS prices or quotations for the firms in the CDX index on the CDS spread of the dealer providing the CDS price or quotation interacted with five sector dummy variables where the dummy variables take value one if firm i is in the consumer, energy, financial, industrial, or technology sectors, respectively, and zero otherwise. The sample period is March 31, 2008 to January 20, 2009. Regression specification II includes a dummy variable I_L that takes value one for the post-Lehman period beginning September 15, 2008, and zero otherwise. The t-statistics are based on the White (1980) heteroskedasticity-consistent estimate of the covariance matrix. The superscript ** denotes significance at the 5% level; the superscript * denotes significance at the 10% level.

$$CDS_{i,j,t} = \alpha_{i,t} + \sum_{k=1}^{5} \beta_k I_{Sector_k} Spread_{j,t-1} + \epsilon_{i,j,t}$$

$$CDS_{i,j,t} = \alpha_{i,t} + \sum_{k=1}^{5} \beta_k I_{Sector_k} Spread_{j,t-1} + \sum_{k=1}^{5} \gamma_k I_{Sector_k} I_L Spread_{j,t-1} + \epsilon_{i,j,t}$$

	Regression specification I		Regression specification II	
Variable	Coefficient	t-Statistic	Coefficient	t-Statistic
$I_{Consumer}$ $Spread$	-0.001161	-4.83**	-0.000015	-0.04
I_{Energy} $Spread$	0.002313	-7.25**	-0.002253	-5.14**
$I_{Financial}$ $Spread$	0.001097	0.77	-0.000910	-0.67
$I_{Industrial}$ $Spread$	0.001324	-3.61**	-0.001245	-2.42**
$I_{Technology}$ $Spread$	0.002553	-5.41**	-0.003173	-4.69**
$I_{Consumer}$ I_L $Spread$			0.001719	-3.65**
I_{Energy} I_L $Spread$			0.000079	-0.09
$I_{Financial}$ I_L $Spread$			0.003183	1.27
$I_{Industrial}$ I_L $Spread$			0.000096	-0.14
$I_{Technology}$ I_L $Spread$			0.000674	0.80
N	41,122		41,122	

the spreads of CDS contracts on financial firms. Furthermore, likelihood ratio tests strongly reject the hypotheses that the slope coefficient for the financial sector is equal to that of the consumer, energy, industrial, and technology sectors, with p-values of 0.00026, 0.00000, 0.00012, and 0.00000, respectively. Thus, the pricing of counterparty credit risk for financial firms is significantly different from that of the other four categories of firms in the sample. In summary, far from being the most sensitive to counterparty credit risk, financial firms in the CDX index represent the only category in the sample for which counterparty credit risk is not priced.

These patterns are repeated in the second specification. As shown, counterparty credit risk is significantly priced for the energy, industrial, and technology firms during the pre-Lehman period. Furthermore, there is no significant change in how counterparty credit risk is priced for these firms in the post-Lehman period. Counterparty credit risk for firms in the consumer sector is not priced during the pre-Lehman period, but there is a significant change in pricing for these firms after the Lehman event. The results also show that counterparty credit risk for the financial firms is not priced in the pre-Lehman period, and that there is no significant change in this relation after the Lehman event.

What factors might help account for the evidence that counterparty credit risk is not priced for the financial firms? First of all, the financial firms in the CDX index consist primarily of insurance firms, industrial lenders, consumer finance firms, and real estate companies. Thus, it is possible that the default risk of these firms in the CDX index may actually be much less correlated with that of the CDS dealers than one might expect based on their designation as financials. Second, counterparty credit risk might not be priced in the cost of selling protection on the large financial firms in the CDX index if the market believed that the CDS dealers would not fail when the large financial firms in the CDX index became vulnerable to default. Thus, this possibility suggests that there might be a state-contingent aspect to the default risk of CDS dealers. Finally, it is important to acknowledge that there is actually little empirical evidence in the literature about default correlations. Thus, while intuition suggests that the default correlation between financial firms should be higher than the default correlation between financial and nonfinancial firms, there is no direct empirical evidence supporting this intuition. For this reason, the analysis in this section should be viewed more as an exploratory investigation, rather than as a test rejecting specific empirical hypotheses about default correlations.

1.6 Comparison to model-implied values

The empirical results demonstrate that counterparty credit risk is priced by the market, but that the size of the effect is very small. A natural question to ask is whether these empirical results can be reconciled with those implied by theoretical models of counterparty credit risk[16].

There is a large and rapidly growing literature on the valuation of counterparty credit risk in CDS contracts which is far too extensive for us to review fully here. Gregory (2010) provides an excellent summary of the literature and discusses a number of the modeling approaches that have been applied to the problem of valuing counterparty credit risk. In this section, we compare our empirical results with those implied by a simple simulation-based model of the effects of counterparty credit risk. A key feature of this framework is that it allows us to quantify the size of the effect when CDS counterparties collateralize their mark-to-market liabilities.

In this model, we take the perspective of the protection buyer and model the losses arising from the default of the protection seller. To model default, we use the reducedform framework of Duffie and Singleton (1997) and Duffie and Singleton (1999) in which the default of a firm is triggered by the realization of a jump process. Let λ_t and ν_t denote the risk-neutral intensity processes of the firm underlying the CDS contract and the firm selling credit protection (the CDS counterparty),

[16] We are grateful to the referee for raising this issue

respectively. The risk-neutral dynamics for these intensity processes are given by:

$$d\lambda = (\alpha - \beta\lambda)dt + \sigma\sqrt{\lambda}dZ_\lambda \quad (6)$$

$$d\nu = (\alpha - \beta\nu)dt + s\sqrt{\nu}dZ_\nu \quad (7)$$

$$\quad (8)$$

where α, β, σ, μ, γ, and s are constant parameters, and $Corr(dZ_\lambda, dZ_\nu) = \xi$. Given this model, the marginal distribution for the default time of the underlying firm has a hazard function equal to the realized path of the intensity (see Lando (1998)) and similarly for the firm selling default protection. Modeling the simultaneous distribution of defaults would require a specification of the probability of simultaneous defaults. We will specify the joint distribution of defaults in our discrete-time simulation.

Following Gregory (2010), we distinguish between three types of default scenarios. The first is the case in which the underlying firm defaults but not the counterparty. In this case, the protection buyer receives the protection payment from the protection seller and does not suffer any counterparty credit losses.

The second case is when the counterparty defaults, but the underlying firm does not. For simplicity, we assume that both counterparties are required to post full collateral daily for CDS liabilities, where the mark-to-market liability is computed under the assumption that both counterparties are default free[17]. In addition, we assume that there is zero recovery of uncollateralized liabilities in the event that the protection seller defaults[18]. Given the square-root dynamics in Equation (6), the value of a CDS contract can be obtained directly from the CDS valuation model

[17]This assumption greatly simplifies the analysis but has virtually no effect on the total amount of collateral required

[18]This is consistent with the Lehman default in which CDS contracts referencing Lehman were settled at 8.625 cents on the dollar.

in (Longstaff, Mithal and Neis (2005) , pp. 2221-2222). There are now two ways in which a protection buyer can suffer a loss when the protection seller defaults. If the mark-to-market value is positive, but the collateral posted the previous day (which equals the previous days mark-to-market value of the CDS contract) is insufficient, then the buyers loss is the difference between the two. As discussed earlier, however, the buyer can also lose from a counterparty default when he owes the counterparty on the CDS contract and the amount of collateral posted with the defaulting protection seller exceeds the amount of the buyers liability. In this situation, the excess collateral becomes part of the bankruptcy estate and represents the protection buyers loss. Note that the loss of excess collateral does not occur when CDS liabilities are uncollateralized. Thus, there are states in which a protection buyer may be worse off with full bilateral collateralization of CDS liabilities.

The third case occurs when both the underlying firm and the counterparty default at the same time. We will make the assumption that joint default occurs if both the firm and the counterparty default within a two-businessday timeframe. This assumption reflects the reality that a discrete period of time is required operationally to post collateral and settle trades. With collateralization, the protection buyers loss is the difference between the loss on the underlying firm and the amount of collateral held. Again, since the buyer may have posted collateral with the defaulting counterparty, the buyer could actually be worse off in some states in this joint default scenario than without collateralization.

Since we are simulating changes in the intensity processes and the realization of defaults at each time step, we only need to specify local or one-step joint probabilities to simulate joint default events. In particular, conditional on no default having occurred before time t, the marginal probability of the underlying firm defaulting between time t and $t + \Delta t$ is $\lambda_t \Delta t$. Similarly, the marginal probability of the firm selling credit protection defaulting between time t and $t + \Delta t$ is $\nu_t \Delta t$. Let a, b, c, and d denote the joint probabilities that neither firm defaults, that only the underlying firm defaults, that only the firm selling credit protection defaults, and that both firms default between time t and $t + \Delta t$, respectively. The Appendix shows that these joint probabilities are completely determined by the two marginal probabilities and a default correlation parameter ρ. Thus, we are in essence assuming that the local joint distribution of default events is given by a simple multinomial distribution. Furthermore, this approach explicitly allows for correlated defaults to occur. Given these joint probabilities, we simulate the model in steps of Δt and sample the four joint events based on their multinomial probabilities. We repeat this process at each time step along a simulated path until the first default occurs[19].

Turning to the issue of calibration, it is important to stress that our objective is simply to provide general estimates of the size of counterparty default effects rather than to model specific contracts. As such, we adopt a generic parameterization and estimate counterparty default costs under a broad range of assumptions about default intensities and correlations. The average value of the CDX index during the sample period is 95 basis points, while the average CDS spread for the dealers during the same period is 145 basis points. These values, of course, are high by historical standards but they do provide a realistic benchmark for the calibration of the risk-neutral intensity processes. Accordingly, we parameterize the long-run values of λ_t and ν_t to be 100 and 150 basis points, respectively. Furthermore, we assume $\beta = \gamma = 0.50$ and $\sigma = s = 0.20$. These parameters are consistent with the longer-term properties of the CDX index[20]. We also assume that the spread correlation parameter ξ takes on values of 2%, 6%, or 10%. Similarly, we assume that the default correlation ρ takes on values of 2%, 6%, or 10%. These values essentially bracket the default

[19]Note that the limiting distribution of this multinomial distribution would likely be of the form of a bivariate exponential distribution as the number of time steps increases (see Johnson and Kotz (1972). We are grateful to the referee for this insight.

[20]Specifically, the moments of normalized monthly changes in the CDX index from 2004 to 2009 imply $\beta = 0.54$ and $\sigma = 0.18$.

correlations reported by Longstaff and Wang (2008) implied from the prices of CDX index tranches and the CDS spreads for the constituents of the CDX index[21].

Table 8 reports the estimated basis-point cost of counterparty default for a range of scenarios. Specifically, we compute the cost of events in which only the counterparty defaults, the cost of joint events in which both the underlying firm and the counterparty default, and the total of these two costs. The default intensity for the underlying firm takes values of 100 or 300 basis points, essentially bracketing the CDX index values during the sample period. Similarly, the default intensity for the counterparty selling protection takes values of 100, 300, and 500 basis points, again paralleling the behavior of broker CDS spreads during the sample period. The results are based on 100,000 simulations for a five-year CDS contract. The details on how the joint distribution of defaults is simulated are described in the Appendix.

The results in table 8 imply counterparty credit risk pricing effects that are very consistent with those documented in previous sections of this paper. For example, a 400-basis-point increase in the CDS spread of the protection seller from 100 to 500 basis points maps into an increase in counterparty credit costs of roughly 0.5, 1.0, and 2.0 basis points in the cases where the default correlation is 2%, 6%, and 10%, respectively. Thus, the empirical estimates of the size of the effect of counterparty credit risk on CDS spreads given in this paper harmonize well with those implied by a model in which average default correlations are in the range of, say, zero to 4%.

1.7 Conclusion

We examine the extent to which the credit risk of a dealer offering to sell credit protection is reflected in the prices at which the dealer can sell protection. We find strong evidence that counterparty

[21] For a few of the 100,000 simulated paths, we assume a smaller value of ρ to insure that simulated joint default probabilities remain positive. See the discussion in the Appendix.

credit risk is priced in the market; the higher the credit risk of a dealer, the lower is the price at which the dealer can sell credit protection in the market. The magnitude of the effect, however, is extremely small. In particular, an increase in the credit spread of a dealer of about 645 basis points maps into only a one-basis-point decline in the price of credit protection.

The price of counterparty credit risk appears to be too small to be explained by models that assume that CDS liabilities are unsecured. The pricing of counterparty credit risk, however, seems consistent with the standard market practice of requiring full collateralization, or even the overcollateralization of CDS liabilities. These results also have implications for current proposals about restructuring derivatives markets. For example, since market participants appear to price counterparty credit risk as if it were only a relatively minor concern, this suggests that attempts to mitigate counterparty credit risk through alternative approaches, such as the creation of a central clearinghouse for CDS contracts, may not be as effective as might be anticipated. This implication parallels and complements the conclusions in the recent paper Duffie and Zhu (2011).

1.8 Appendix

To simulate correlated defaults in the model presented in the paper, we do the following. First, we define the discretization interval for the simulation to be two days; $\Delta t = 2/260$ (there are approximately 260 trading days per year). Let I_1 denote a random binomial variable that takes value one if the underlying firm defaults during the two-day window, and zero otherwise. Similarly, let I_2 denote a random binomial variable that takes value one if the counterparty defaults during the two-day window, and zero otherwise. Let $\pi_1 = \lambda \Delta t$ denote the probability that the underlying firm defaults during the two-day window, and $\pi_2 = \nu \Delta t$ denote the probability that the counterparty defaults during the two-day window. Thus, with this notation, $E[I_1] = \pi_1$ and $E[I_2] = \pi_2$. Also, $Var[I_1] = \pi_1 - \pi_1^2$ and $Var[I_2] = \pi_2 - \pi_2^2$.

Table 8: Basis point cost of CDS counterparty credit risk

Notes: This table reports the basis point cost to the protection buyer from the potential default of the protection seller. The central panel reports the costs when CDS liabilities are not collateralized; the right panel reports the costs when CDS liabilities are collateralized. CP default denotes the cost of events where only the counterparty defaults. Joint default denotes the cost of events where both the underlying firm and the counterparty default together. Total denotes the sum of the costs of the two types of events. The parameter ρ denotes the default correlation between the underlying firm and the counterparty. The parameters λ and η denote the basis point default intensities for the underlying firm and the counterparty, respectively.

Parameters			Uncollateralized			Collateralized		
ρ	λ	η	CP default	Joint default	Total	CP default	Joint default	Total
0.02	100	100	0.69	0.89	1.58	0.07	0.88	0.95
		300	0.98	1.02	2.00	0.10	1.00	1.10
		500	1.31	1.21	2.52	0.14	1.18	1.32
	300	100	0.68	1.16	1.84	0.08	1.14	1.22
		300	1.16	1.50	2.66	0.13	1.48	1.61
		500	1.62	1.56	3.18	0.18	1.53	1.71
0.06	100	100	0.68	2.50	3.18	0.07	2.43	2.50
		300	0.99	3.35	4.34	0.10	3.27	3.37
		500	1.32	3.52	4.83	0.13	3.43	3.56
	300	100	0.69	3.24	3.93	0.08	3.18	3.26
		300	1.16	4.15	5.31	0.13	4.07	4.20
		500	1.63	4.48	6.11	0.18	4.38	4.56
0.10	100	100	0.71	3.82	4.53	0.07	3.73	3.80
		300	1.02	5.17	6.19	0.10	5.04	5.14
		500	1.35	5.99	7.34	0.13	5.87	6.00
	300	100	0.69	5.11	5.80	0.08	5.00	5.08
		300	1.15	6.89	8.04	0.13	6.75	6.88
		500	1.65	7.70	9.35	0.18	7.55	7.73

Now let a denote the probability that neither the underlying firm nor the counterparty defaults during the two-day window. Let b denote the probability that the underlying firm defaults during the two-day window, but the counterparty does not. Let c denote the probability that the counterparty defaults during the two-day window, but the underlying firm does not. Finally, let d denote the probability that both the underlying firm and the counterparty default during the two-day window. It is easily shown that the correlation ρ between I_1 and I_2 is given by:

$$Corr[I_1, I_2] = \frac{d - \pi_1\pi_2}{\sqrt{(\pi_1 - \pi_1^2)(\pi_2 - \pi_2^2)}} \tag{9}$$

Solving this expression for d gives:

$$d = \rho\sqrt{\pi_1\pi_2(1-\pi_1)(1-\pi_2)} + \pi_1\pi_2 \tag{10}$$

Since the marginal probabilities of default are π_1 and π_2, and since the total probability must equal one, we have:

$$a = 1 - b - c - d \tag{11}$$

$$b = \pi_1 - d \tag{12}$$

$$c = \pi_2 - d \tag{13}$$

Thus, given λ, ν, and ρ, we can solve for the probabilities a, b, c, and d that define the joint default distribution for each two-day window.

To simulate default outcomes for a five-year CDS contract, we simulate a path for the default intensity processes λ and ν using the dynamics given in the above equations. In doing this, we use two-day discretization intervals. For each two-day window along the path, we then apply the above algorithm to simulate the joint default outcome (neither defaults, both default, etc.). We then use the simulated joint default probabilities to define the cash flows along the path and evaluate the default costs. We repeat this process using 100,000 simulated paths.

Finally, we note that there is a minor restriction on ρ that is needed to insure that b and c take positive values:

$$\rho < \frac{min(\pi_1(1-\pi_2)\pi_2(1-\pi_1))}{\sqrt{\pi_1\pi_2(1-\pi_1)(1-\pi_2)}} \tag{14}$$

Whenever ρ exceeds this bound for a two-day window, we set ρ equal to this bound in solving for the joint default probabilities for that two-day window. This restriction, however, only affects a small fraction of the 100,000 simulated paths.

2 Chapter 2: Size Anomalies in Bank Stock Returns: A Fiscal Explanation

2.1 Introduction

Banks are different from non-financial firms in many ways. One of the most salient distinctions is that banks are subject to bank runs during banking panics and crises, not just by depositors, but also by other creditors (see Gorton and Metrick (2009) and Duffie (2010)). Because financial crises are high marginal utility states for the average investor, the expected return on bank stocks should be especially sensitive to variation in the anticipated financial disaster recovery rates of bank shareholders related to bank size, the regulatory regime, implicit government guarantees and other characteristics. For example, if a bank is deemed too-big-to-fail, the expected return on its stock is lower in equilibrium than that of smaller banks holding the exact same assets in their portfolio, as the government absorbs some of the large bank's tail risk. We find evidence that the pricing of bank-specific tail risk in the stock market depends on all of these bank characteristics.

To explore the asset pricing implications of financial disasters, our paper studies historical bank stock returns in the U.S. We find that there is a size effect in bank stock returns that is different from the market capitalization effects that have been documented in non-financial stock returns (see Banz (1981) and many others). All else equal, a 100% increase in a bank's book value lowers its annual return by 2.45% per annum. For non-financial stocks, there is no similar relation between book value and returns (Berk (1997)).

These return differences cannot be imputed to differences in standard risk exposure. A long position in the stock portfolio of largest commercial banks, measured by deciles of total book value, and a short position in the stock portfolio of the smallest banks under-performs an equally risky portfolio of all (non-bank) stocks and government and corporate bonds by more than 5.85% per annum. The average alphas are large and positive for commercial banks in the first five deciles and then decrease for the largest banks in the top three deciles.

Small banks differ from large banks in many ways, but these differences should not lead to differences in average risk-adjusted returns on bank portfolios unless there is bank-specific tail risk that is priced but not spanned by the traded returns on other stocks in the sample. We found evidence of such a risk factor in bank stock returns: The second principal component (p.c.) of the risk-adjusted returns on size-sorted portfolios of commercial banks is a size factor that has the exactly the right covariance with the portfolio returns to account for most of this pricing anomaly. By construction, this size factor is orthogonal to the stock and bond risk factors.

This size portfolio, determined by the second p.c., which goes long in small bank stocks and short in large bank stocks, loses an average of 61 cents during NBER (National Bureau of Economic Research) recessions per dollar invested at the start, after hedging out exposure to standard stock and bond risk. We attribute the cyclical banking size factor in the data to size-dependent differences in the perceived shareholder recovery rates on these bank portfolios during financial disasters.

In a version of the Barro (2006), Rietz (1988) and Longstaff and Piazzesi (2004) asset pricing model with a time-varying probability of rare events, developed by Gabaix (2008), Wachter (2008), and Gourio (2008), financial disasters which disproportionately impact bank cash flows contribute an additional bank-specific risk factor. These rare events are priced into expected returns on portfolios of banks, but are not fully spanned by the returns on other assets in a small sample. A general equilibrium version of our model that is calibrated to match the equity premium can match the average alphas in a sample without disasters if the financial disaster recovery rate is 35 cents higher for large banks, in line with the failure rate of banks in the lowest decile during the latest crisis.

Historically, the probability of a financial disaster increases during recessions. Because of the size-contingent nature of the the recovery rate for bank stockholders in case of a financial disaster, the variation in the probability of a financial disaster generates a common business cycle factor in the normal-risk-adjusted returns of size-sorted bank stock portfolios; the loadings of bank stock portfolio returns on this size factor are determined by the recovery rates and hence by size. Small banks have positive loadings while large banks have negative loadings. As the probability of a financial disaster increases, the expected return gap between small and large banks grows.

Shareholder recovery rates for banks depend on size. During financial disasters, large banks fare much better, even though they are more levered than their smaller counterparts. A total of 30% of publicly traded commercial banks in the first size decile were delisted in 2009 alone although there were none in the last decile. During the recent U.S. financial crisis, the size portfolio of commercial banks, hedged against exposure to commercial banks, lost 90 cents per dollar invested at the start of the crisis, while the same hedged size portfolio of all banks lost all of its value during the Great Depression.

To back out the implicit financial tail risk premium or discount charged by the shareholders of commercial banks, we multiply the loadings on the size factor by its market risk price. The implicit insurance provided against financial disaster risk lowers the expected equity return for the largest U.S. commercial banks by 3.10%, but the additional exposure to bank-specific tail risk increases the expected return on the smallest bank stocks by 3.25%, compared to a portfolio of non-bank stocks and bonds with the same standard risk characteristics. The largest banks have an average market capitalization of $152 bn in 2005 dollars.[22] For the largest commercial banks, this amounts to an annual savings of $4.71 bn per bank. The market imposes large financial tail risk 'subsidies'

[22]This number only includes the market capitalization of the commercial bank, not the bank holding company.

(‘taxes’) on large (small) bank stocks compared to a portfolio of stocks and bonds with the same observed risk profile. There is direct evidence from option markets: Kelly, Lustig and Nieuwerburgh (2011) find that out-of-the-money put options on large banks were cheap during the crisis.

The pricing of financial tail risk depends not only on bank size. We relate the financial disaster premium of banks to the regulatory regime. Commercial banks, who have access to the discount window and benefit from deposit insurance, and Government-sponsored enterprises (GSE), who benefit from an explicit guarantee, are imputed a large financial tail risk subsidy while investment and foreign banks are not. On the other hand, hedge funds are imputed a financial tail risk tax, just like small banks.

After the repeal of key provisions in the Glass-Steagall Banking Act in 1999, we find large across-the-board increases in the size of the subsidy for large commercial, investment banks and GSE. For example, the Fannie Mae subsidy tripled to 6.57% in 2000-2005. This period also coincides with the dramatic growth in securitization, which allows financial institutions to benefit from the collective bailout option more aggressively by eliminating idiosyncratic risk exposure (see Brunnermeier and Sannikov (2008) for a clear description of this effect of securitization).

Furthermore, we provide a direct link to bailouts; we show that the financial disaster subsidy of the largest 10 banks increases immediately after bailout announcements. O’Hara and Shaw (1990) document large positive wealth effects for shareholders of banks who were declared ‘too-big-to-fail’ by the Comptroller of the Currency in 1984, and negative wealth effects for those banks that were not included. Consistent with this, we document large increases in the implicit financial disaster subsidy to these too-big-to-fail banks after this announcement, and six other bailout announcements prior to the recent financial crisis that were identified by Kho, Lee and Stulz (2000). Furthermore, we find large increases after announcements that benefited large banks during the recent financial crisis as well.

The rest of this paper is organized as follows. The first section discusses the related literature. In Section 2.3 we construct portfolios of commercial U.S. bank stocks sorted by size. Section 2.4 describes the size effect in bank stock returns. Section 2.5 establishes that there is a pro-cyclical size factor in the normal-risk-adjusted returns of these portfolios. Section 2.6 relates the pricing of bank tail risk to government announcements and the regulatory environment. We use a calibrated version of the model to back out the implied differences in recovery rates in section 2.7. Section 2.8 concludes.

2.2 Related literature

There is obviously a large literature on size effects in stock returns (see Banz (1981), Basu (1983), Lakonishok, Shleifer and Vishny (1993), Fama and French (1993), Berk (1995) and others), but most of these papers actually do not include financial stocks, presumably because of their high leverage. Our paper is the first to document that the size effect in financial stocks is really about size, rather than market capitalization. We attribute the size effect to how tail risk is priced in financial stocks.

There is direct evidence from option markets that tail risk in the financial sector is priced differently. Kelly, Lustig and Nieuwerburgh (2011) find that the out-of-the-money index put options of bank stocks were relatively cheap during the recent crisis, as a consequence of the government absorbing sector-wide tail risk. In related work on bank stock returns, Fahlenbrach, Prilmeier and Stulz (2011) document that those banks which incurred substantial losses during previous crises were more likely to incur losses during the recent crisis. If some banks benefit from a larger perceived tail risk subsidy, they have an incentive to load up on this type of risk risk. In fact, shareholder value maximization requires that they do so, as pointed out by Panageas (2010a) who analyzes optimal risk management in the presence of guarantees. Interestingly, Fahlenbrach and Stulz (2011) find some evidence that banks whose managers' interests were more aligned with shareholders actually performed worse during the recent financial crisis.

Our work contributes to the important task of measuring systemic risk in the financial sector. Acharya, Pedersen, Philippon and Richardson (2010), Adrian and Brunnermeier (2008) and Huang, Zhou and Zhu (2011) develop novel methods for measuring systemic risk. Our measure of the banking tail risk premium is determined by the bank's loading on the size factor, which gauges a firm's systemic risk exposure. Firms that are deemed systemically important have large negative loadings on the size factor, because these are less likely to be allowed to fail in the event of a financial disaster, and they trade at a premium as a result. As far as we know, our paper is the first to link the subsidy that accrues to banks who are deemed systemically important with exposure to systemic risk. To the extent that these differences in bank tail risk pricing are directly attributable to government policies, they are an ex ante measure of the distortion created by the implicit guarantee extended to some U.S. financial institutions.[23]

Why study the effect of bailouts on bank equity? The anticipation of future bailouts of bondholders and other creditors always benefits shareholders (see Kareken and Wallace (1978)) ex ante. Furthermore, during the crisis, there may be massive uncertainty about the resolution regime, especially for large financial institutions. As a result, government guarantees will inevitably tend to benefit shareholders ex post as well. Clearly, the U.S. government and regulators are willing to let small banks fail, not so for large banks. Of course, ex ante, one could have expected that the government would wipe out shareholders of large financial institutions in case of a bailout.[24]Our

[23]Estimating the entire ex post, realized cost of the various measures implemented by the U.S. Treasury, the Federal Reserve system, the FDIC and other regulators in the face of the recent crisis is hard. Veronesi and Zingales (2010) estimate the cost to be between \$21 and \$44 billion, with a benefit of more than \$86 billion.

[24]The key to activating the collective bailout clause is common variation in bank payoffs. In a recent paper,

evidence suggests that this is not what market participants expected. A number of events have been important in creating and sustaining the too-big-too fail perception in the market. Among these are the Federal Deposit Insurance Corporation's intervention to prevent the failure of Continental Illinois National Bank in 1984, Federal Deposit Insurance Corporation Improvement Act of 1991, and the Federal Reserve's intervention in 1998 to save Long Term Capital Management.

Finally, our findings suggests that cost of capital distortions might have contributed to the pre-crisis growth in the size of the financial sector relative to the overall economy. Philippon (2008) has argued that much of the variation in the size of the U.S. financial sector can be imputed to standard corporate finance forces. However, he notes the 2002-2007 period as an exception, which is exactly when we measure the largest distortions.

2.3 Size effect in bank stock returns.

This section reports the returns on size-sorted portfolios of bank stocks. We also show the results of a cross-sectional regression of returns on firm characteristics that confirms the portfolio results.

2.3.1 Data

We collect data on equity returns from the Center for Research in Security Prices (CRSP) for all firms with Standard Industrial Classification (SIC) codes 60, 61, and 62. The data starts in January 1970 and ends in December 2009. Firms with these SIC codes are defined as commercial

Acharya and Yorulmazer (2007) and Farhi and Tirole (2009) explore the incentives for banks in this type of environment to seek exposure to similar risk factors. The government's guarantee creates complementarities in firm payoffs. In earlier work, Schneider and Tornell (2004) explain the currency mismatch on firm balance sheets in emerging markets endogenously by means of a bailout guarantee for the non-tradeables sector. Ranciere and Tornell (2011) discuss how to design regulation in the context of government bailout guarantees. Panageas (2010b) explores the optimal taxation implications of bailouts.

banks, non-depository credit institutions, and investment banks respectively. Henceforth, we refer to commercial banks, credit institutions, and investment banks collectively as banks. We exclude data for all financial firms that are inactive and/or not incorporated in the U.S., and we also exclude financial firms not incorporated in the U.S. because these financial firms will be influenced by regulations applicable both in the country of operation and the country of incorporation. Since these policies vary across countries, our focus on financial firms operating and incorporated inside the U.S. ensures that all firms in our analysis are subject to a uniform regulatory regime.

We start by focusing on portfolios of commercial bank stocks. We employ the standard portfolio formation strategy of Fama and French (1993). We rank all bank stocks by market capitalization as of January of each year. The stocks are then allocated to 10 portfolios based on their market capitalization. We calculate value-weighted returns for each portfolio for each month over the next year. At the end of this exercise, we have monthly value-weighted returns for each size-sorted portfolio of banks.

While the CRSP data are available from 1926, our main sample only begins only in 1970 for banks, as there are not enough publicly traded commercial banks prior to 1970. Only a small fraction of all banks that operate in the U.S. are publicly listed. For instance, for the years 2000 to 2008, data are available from CRSP for approximately 630 banks, as compared to more than 7000 FDIC-insured banks operating in the U.S. over the same period. However, the largest 600 banks control more than 88% of all commercial bank assets in the U.S. Most of these large banks are publicly listed. To the extent that small banks that are not publicly listed are very different from those that are, some of our results need to be qualified.

We also use book value data from the CRSP-Compustat merged data-set. While our market capitalization results are based on 15,536 bank-years, the book-value results are based on only 12,556 bank-years. The reduction in the number of banks is primarily due to missing balance sheet data in the CRSP-Compustat merged data-set.

2.3.2 Summary statistics

Table 9 reports the total market capitalization of banks in each of 10 size-sorted portfolio as a fraction of the total market capitalization of the banking sector in January of each year. The numbers are reported in percentages. We also report the the average number of banks in the portfolio.

Panel A in Table 9 shows that during the 1970 - 1980 subsample the smallest banks (those in portfolio 1) on average represented just 0.36% of the total market capitalization of all commercial banks, as compared to 49.78% represented by the largest banks (those in portfolio 10). During any year between 1970 and 1980, the banks in portfolio 1 at most accounted for 0.57% of the total market capitalization of the commercial banking sector.

Table 9 clearly shows the increasing concentration of the U.S commercial banking sector. The top 10% of banks account for nearly 50% of the total sector market capitalization in the 70s while they account for more than 90% during the 2000-2009; nearly 84% of this accounted for by the largest 1/2 in this group. In any given year between 1970 and 1980, there are at least 9 banks per size-sorted portfolio, which increases to 62 banks for any year between 2000 and 2009.

Panel B of Table 9 reports the total book value of banks in each size-sorted portfolio as a fraction of the total asset value of the banking sector in January of each year. Total book value is the better measure of size. These results are very close to those obtained by sorting on market capitalization. We also report leverage. Leverage is computed as total book value divided by the book value of equity. Bank leverage clearly increases with bank size. Between 1980 and 1990, the average leverage in the first decile is 13.55, and it gradually increases to 22.37 in the last decile. We document the same pattern in subsequent decades.

Table 9: Market capitalization and book value for size-sorted portfolios of commercial banks

Notes: This table presents the total market capitalization (book value) of firms in each size-sorted portfolio as a percentage of total market capitalization (book value) for the entire banking sector. The market values (book values) are measured in January of each year. Mean represents the average value of this percentage over the years specified. N is the average number of banks in each portfolio over the same period.

	1	2	3	4	5	6	7	8	9	10
Panel A: Market Capitalization										
1970-1980										
Mean	0.36	0.92	1.50	1.95	3.50	4.67	7.61	11.51	18.21	49.78
N	8.00	9.00	9.00	9.00	9.00	8.00	9.00	9.00	9.00	9.00
1980-1990										
Mean	0.33	0.72	1.10	1.66	2.39	3.61	5.71	8.84	17.28	58.34
N	26.00	27.00	26.00	27.00	27.00	26.00	27.00	26.00	26.00	27.00
1990-2000										
Mean	0.17	0.34	0.52	0.76	1.10	1.56	2.32	3.99	8.52	80.71
N	57.00	57.00	57.00	57.00	57.00	57.00	57.00	57.00	57.00	57.00
2000-2009										
Mean	0.13	0.24	0.35	0.50	0.68	0.95	1.42	2.33	4.62	88.78
N	62.00	62.00	62.00	62.00	62.00	62.00	62.00	62.00	62.00	63.00
Panel B: Book Value										
1980-1990										
Mean	0.34	1.04	1.83	2.44	3.39	4.33	6.06	9.90	18.72	51.94
N	10.00	11.00	11.00	11.00	11.00	11.00	11.00	11.00	11.00	11.00
Leverage	13.55	15.86	16.04	16.42	16.59	17.22	17.67	17.73	18.54	22.37
1990-2000										
Mean	0.13	0.31	0.50	0.73	1.02	1.46	2.41	4.14	10.75	78.56
N	45.00	46.00	45.00	46.00	45.00	45.00	46.00	45.00	45.00	46.00
Leverage	11.42	11.16	12.17	11.82	14.03	13.56	13.73	14.40	13.83	15.86
2000-2009										
Mean	0.08	0.14	0.20	0.27	0.36	0.51	0.79	1.35	3.33	92.96
N	61.00	61.00	61.00	61.00	61.00	61.00	61.00	62.00	61.00	62.00
Leverage	8.38	10.82	5.86	14.36	11.64	11.97	12.35	12.27	10.77	14.01

2.3.3 Returns on commercial bank stock portfolios

When we report portfolio return averages, we exclude the recent financial crisis, as we consider samples that exclude realizations of the rare events in the model. However, the results that we report are quite robust to extending the sample.

Table 10 provides mean returns for the size-sorted portfolios of banks over the 1970-2005 sample. In panel A, the stocks are sorted into deciles by market capitalization. The mean monthly returns for all portfolios are annualized by multiplying by 12 and are expressed in percentages. The last column reports the difference in mean annual returns between portfolio 10 and portfolio 1. Over the entire sample, a portfolio that goes long in a basket of large banks and short in a basket of small banks on average loses 4.47% per annum. The average returns on the first (last) portfolio are 17.47% (13.01%). There is a monotonic decline in average returns from the first to the last portfolio.

Market cap measures size, but it also measures expected returns. Firms which generate more cash flows will tend to have higher market cap, but firms with lower expected returns, holding cash flows constant, also have larger market capitalization. As a result, Berk (1995) argues that there should be a relation between expected returns and market capitalization. Of course, this argument does not apply to other measures of size such as book value. A priori, there is no reason to expect a relation between book values and expected returns.

In Panel B of Table 10, we sort stocks into deciles by total book value. The pattern in realized returns is quite different. There is an inverted U-shaped pattern. The average returns between 1980 and 2005 increase from 16% in the first portfolio to 21.75% in the sixth portfolio, and then decline to 13.68% in the last portfolio. The difference between the sixth and the 10th portfolio is 8.07% per annum. This is remarkable because the largest commercial banks are more levered than medium-sized banks, and hence, if anything, one would expect to see the opposite pattern.

Table 10: Mean returns for size-sorted portfolios of commercial banks

Notes: This table presents the mean returns for each size-sorted portfolio of banks sorted by market capitalization in the top panel and by total balance sheet in the bottom panel. The first column indicates the years over which mean returns were computed. The monthly mean returns have been annualized by multiplying by 12 and are expressed in percentages.

Panel A: Market Capitalization										
Year	1	2	3	4	5	6	7	8	9	10
1970 – 2005	17.47	16.73	16.15	15.96	16.05	17.03	15.89	14.37	13.77	13.26
1980 – 2005	19.81	19.18	18.09	17.84	18.31	19.94	19.38	17.15	16.31	16.17
1990 – 2005	19.61	20.90	18.24	17.67	20.32	19.15	18.69	17.34	16.62	16.90
Panel B: Book Value										
Year	1	2	3	4	5	6	7	8	9	10
1980 – 2005	16.36	17.57	19.46	18.84	20.68	21.75	20.12	16.89	13.95	13.68
1990 – 2005	13.65	18.03	19.44	18.76	20.54	20.00	21.34	17.96	13.67	11.00

2.3.4 Characteristics regression

The portfolio results in table 10 suggest there is a negative relation between total book value and returns for commercial banks, at least for the largest banks. We investigated this relation in the 1970-2005 sample. When we run a cross-sectional regression of average annual returns on firm characteristics: the log of market capitalization, the log of book value, book-to-market, and leverage, we obtain a large and significant negative coefficient for log book value (-2.45) and a positive coefficient for market capitalization (2.76). These coefficients are significant at the 1% level. The detailed results are in the appendix in section 2.9.3.

This pooled regression explains 0.38% of the variation in annual returns. Thus a 100% increase in book value above the sample average lowers annual returns by 245 bps for a typical bank, holding all variables, including market capitalization, fixed. Leverage and book-to-market ratio seem to have no additional explanatory power for returns. We obtain identical results when we exclude leverage and book-to-market ratios from the regression. When we drop book value, the regression only accounts for 0.004% of the variation in annual returns. Hence, this size effect in bank stock returns is very different from the market capitalization effect first documented by Banz (1981).

2.3.5 Returns on size-sorted portfolios of non-financials

What we usually refer to as a size effect is really a market capitalization effect in most industries. Berk (1997) points out that there is only a moderate size effect in the raw returns of non-financials when size is measured by book value rather than market capitalization. The same conclusion applies when other measures of actual firm size are used, such as the number of employees (Berk (1997)). When we perform the same sorting exercise using book values for non-financials, we do not find similar patterns.

Panel A of Table 11 reports the average returns on portfolios of non-financial firms sorted by market capitalization. The average returns on firms in the first decile of market capitalization are high (24.51%). These small cap stocks have smaller market capitalization than the smallest banks, are highly illiquid and hence earn much higher expected returns. Between the second and the tenth portfolio, average returns gradually decline from 15.76% to 11.39%.

The book-sorting results are reported in Panel B of Table 11. Between 1970 and 2005, the average returns in the first decile are 276 bps higher than the average returns in the last portfolio. The average returns on the the first portfolio are 16.05% per annum. Returns increase to 16.75% in the second portfolio and subsequently decrease to 13.29% in the last portfolio. The difference between the sixth and the tenth portfolio is only 2.10 % per annum (compared to 8.07% for non-financials).

Table 11: Mean returns for size-sorted portfolios of non-financial firms

Notes: This table presents the mean returns for each size-sorted portfolio of non-financial firms sorted by market capitalization in the top panel and by total balance sheet in the bottom panel. Non-financial firms are defined as those for which the SIC code lies outside 6000 - 6799. The first column indicates the years over which mean returns were computed. The monthly mean returns have been annualized by multiplying by 12 and are expressed in percentages. The first column indicates the years over which mean returns were computed. The monthly mean returns have been annualized by multiplying by 12 and are expressed in percentages.

Year	1	2	3	4	5	6	7	8	9	10
Panel A: Market Capitalization										
1970 − 2005	24.51	15.76	13.38	12.41	11.61	12.12	12.21	12.55	13.30	11.39
1980 − 2005	26.29	15.47	13.25	12.02	11.27	11.51	12.07	12.57	14.32	13.18
1990 − 2005	30.13	17.75	14.96	14.11	12.43	12.04	11.47	10.65	12.56	10.61
Panel B: Book Values										
1970 − 2005	16.05	16.75	15.90	15.15	14.90	15.39	15.63	15.26	15.02	13.29
1980 − 2005	16.08	17.14	16.59	15.65	15.19	15.81	16.52	15.92	15.94	14.74
1990 − 2005	21.06	19.68	18.32	17.62	16.28	16.43	16.24	15.80	14.75	12.56

2.4 Size effect in normal risk-adjusted bank stock returns

We start by adjusting the portfolio returns for exposure to the standard risk factors that explain cross-sectional variation in average returns on other portfolios of non-financial stocks and bonds. We do so by comparing the performance of the bank portfolio to the performance of a portfolio of non-bank stocks with the same exposure to normal risk factors.

A bank manages a portfolio of bonds of varying maturities and credit risk.[25] Therefore, we also include two bond risk factors in addition to three stock risk factors. The vector of normal risk factors:

$$\boldsymbol{f}_t = \begin{bmatrix} market & smb & hml & ltg & crd \end{bmatrix}, \tag{15}$$

is 5×1. $market$, smb, and hml represent the returns on the three Fama-French stock factors: the market, small minus big, and high minus low respectively. The Fama/French factors are constructed using the 6 value-weight portfolios of all stocks on NYSE, AMEX And NASDAQ (including financials) formed on size and book-to-market. $market$ is the value-weight return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate (from Ibbotson Associates). We use ltg to denote the excess returns on an index of 10-year bonds issued by the U.S. Treasury as our first bond risk factor. The USA 10-year Government Bond Total Return Index (ltg) is downloadable from Global Financial Data. In addition, active participation by banks in markets for commercial, industrial, and consumer loans exposes them to credit risk. We use crd to denote the excess returns on an index of investment grade corporate bonds, maintained by Dow Jones, as our second bond risk factor. To compute excess returns, we use the one-month risk-free rate.[26]

[25] Longstaff and Myers (2009) also show that banks can be treated as active managers of fixed income portfolios.

[26] Data for the risk-free rate and the Fama-French factors was collected from Kenneth French's website.

2.4.1 Returns on commercial bank stock portfolios

We regress monthly excess returns for each size-sorted portfolio on the three Fama-French factors and two bond factors. For each portfolio i we run the following time-series regression to estimate the vector of betas $\boldsymbol{\beta}_i$:

$$R^i_{t+1} - R^f_{t+1} = \alpha^i + \boldsymbol{\beta}^{i,\prime} \boldsymbol{f}_{t+1} + \varepsilon^i_{t+1}, \tag{16}$$

where R^i_{t+1} is the monthly return on the i^{th} size-sorted portfolio. Since all of the risk factors in $\boldsymbol{f}_t$ are traded returns, the estimated residuals in the time series regression are estimates of the normal-risk-adjusted returns $\widehat{R}^i_{t+1}$.

Table 12 provides the results of the regression specified in equation (16). Panel A reports the results based on sorting by market capitalization. The table reports the regression coefficients for each size-sorted portfolio, along with their statistical significance and the adjusted R^2. Table 12 excludes the recent financial crisis. The estimated intercepts decrease nearly monotonically with bank size from 5.45% for the first portfolio to -2.53% for the tenth portfolio. The implicit risk prices for the factors $\boldsymbol{f}_t = \begin{bmatrix} market & smb & hml & ltg & crd \end{bmatrix}$ are given by:

$$\boldsymbol{\lambda}_t = \begin{bmatrix} 5.80 & 0.88 & 6.62 & 2.92 & 4.01 \end{bmatrix}.$$

A long-short position that goes long one dollar in a portfolio of the largest market capitalization banks and short one dollar in a portfolio of the smallest market capitalization banks loses 7.97% over the non-disaster sample. This return spread is statistically significant at the 1% level. The average normal-risk-adjusted return on a 9-minus-2 position is -6.62% per annum, and -3.95% per annum for the 8-minus-3 portfolio. These are statistically significant at the 1% and the 5% level respectively. The differences in risk-adjusted portfolio returns tend to be larger than the differences in raw portfolio returns, because larger banks are more levered and hence impute higher market

The Dow Jones Corporate Bond Return Index (crd) is downloadable from Global Financial Data.

betas to large bank stock portfolios. The market beta increases from 0.36 for the first decile to 1.07 in the last decile. However, this effect is attenuated by the lower credit risk exposure for the larger banks.

The second row of Table 12 reports the coefficient on excess market return, *market*, for each size-sorted portfolio. The market beta increases monotonically with bank size. Over the entire sample, a portfolio of large banks has a market β of 1.07, as compared to a β of 0.36 for a portfolio of the smallest banks. The largest banks were 2.9 times more exposed to market risk as compared to the smallest banks. This difference can be attributed to differences in leverage.

The loadings on *smb* and *hml* also depend systematically on size. We first look at the exposure to the size factor. Contrary to what one expects to find, over the entire sample, the loading on smb_{t+1} actually increases from 0.39 for the first portfolio to 0.50 for the fifth portfolio, and then it drops to -0.03 for the tenth portfolio. Clearly, the common variation in stock returns of banks along the size dimension is very different from that in other industries. The same pattern holds true for the loadings on *hml* which increase from 0.32 for the first portfolio to 0.42 for the last portfolio.

There is a clear size pattern in the loadings on the bond risk factors as well. *ltg*, the slope coefficient on the excess return on an index of 10-year bonds issued by the U.S. Treasury, is negative and statistically insignificant for small banks and is positive and almost always statistically significant for large banks. The loadings vary monotonically in size. A \$1 long position in large banks and a \$1 short position in small banks results in a net exposure of 30 cents to long-term government bonds over the entire sample. On the other hand, the loadings on the credit risk factor, *crd*, are surprisingly small for large banks and positive for small banks. A long-large-banks-short-small-banks position delivers a net negative exposure to credit markets of 38 cents per dollar invested.

Panel B reports the results obtained by sorting by book value. The pattern in risk-adjusted

Table 12: Mean risk-adjusted returns in size-sorted portfolios of commercial banks

Notes: This table presents the estimates from an OLS regression of monthly excess returns on each size-sorted portfolio of banks on the Fama-French stock and bond risk factors. *market*, *smb*, and *hml* are the three Fama-French stock factors: the market, small minus big, and high minus low respectively. *ltg* is the excess return on an index of long-term government bonds and *crd* is the excess return on an index of investment-grade corporate bonds. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels respectively. The alphas have been annualized by multiplying by 12 and are expressed in percentages. The standard errors were adjusted for heteroscedasticity and auto-correlation using Newey-West with 3 lags. The sample is 1970-2005.

	1	2	3	4	5	6	7	8	9	10	8 - 3	9 - 2	10 - 1
Panel A: Market Capitalization													
α	5.45**	4.11*	3.25	2.05	1.75	2.11	0.64	-0.70	-2.51	-2.53	-3.95**	-6.62***	-7.97***
market	0.36***	0.44***	0.49***	0.55***	0.59***	0.63***	0.69***	0.71***	0.87***	1.07***	0.23***	0.43***	0.71***
smb	0.39***	0.44***	0.41***	0.47***	0.50***	0.47***	0.47***	0.44***	0.43***	-0.03	0.02	-0.01	-0.42***
hml	0.32***	0.38***	0.39***	0.50***	0.52***	0.53***	0.54***	0.55***	0.57***	0.42***	0.15**	0.19*	0.09
ltg	-0.16	-0.11	-0.05	0.10	0.15	0.12	0.07	0.12	0.26**	0.15	0.17	0.37***	0.30*
crd	0.51***	0.41***	0.35**	0.21	0.17	0.29*	0.30**	0.18	0.11	0.13	-0.17	-0.30*	-0.38*
R^2	29.12	40.47	42.80	53.16	53.56	55.36	61.49	62.99	65.09	63.62	6.21	18.83	27.91
Panel B: Book Value													
α	3.29	3.98	4.91*	4.54**	3.80	4.53*	2.12	-1.39	-3.17	-2.56	-6.30**	-7.15***	-5.85*
market	0.49***	0.50***	0.56***	0.54***	0.69***	0.74***	0.81***	0.83***	0.85***	0.91***	0.27**	0.35***	0.41***
smb	0.50***	0.51***	0.46***	0.51***	0.60***	0.57***	0.55***	0.59***	0.32***	0.05	0.13	-0.19***	-0.45***
hml	0.44***	0.45***	0.50***	0.51***	0.65***	0.65***	0.64***	0.72***	0.57***	0.42***	0.22**	0.12	-0.02
ltg	0.17	0.19	0.09	0.14	0.00	0.03	0.21*	0.29***	0.19	0.18	0.20	-0.00	0.00
crd	0.06	0.14	0.26	0.19	0.43**	0.40***	0.31**	0.16	0.16	0.07	-0.09	0.03	0.01
R^2	38.53	44.04	46.66	52.12	53.17	60.49	63.50	54.84	62.13	46.24	8.04	15.03	14.46

returns is different from the one obtained when sorting by the market capitalization of banks. The risk-adjusted returns remain around 400 bps for the first six portfolios. The seventh portfolio posts average risk-adjusted returns of 212 bps. After that, the the average risk-adjusted returns decline to -139 bps for portfolio 8, -317 bps for portfolio 9, and - 256 bps for portfolio 10. A long-short position that goes long one dollar in a portfolio of the largest banks and short one dollar in a portfolio of the smallest banks loses 5.85% over the non-disaster sample. This return spread is statistically significant at the 1% level. The average normal-risk-adjusted return on a 9-minus-2 position is -7.15% per annum, and -6.30% per annum for the 8-minus-3 portfolio. These are statistically significant at the 1% and 5% levels respectively.

Larger banks have higher market betas, consistent with leverage increasing in size, although the increase is smaller than the difference in leverage suggests. However, the negative effect of higher market betas on risk-adjusted returns is partly offset by a strong inverse U-shaped pattern in the credit risk loading. The loading increases from 0.06 in the first portfolio to 0.43 in the fifth portfolio, and then it declines to 0.07 in the tenth portfolio.

2.4.2 Returns on portfolios of non-financial stocks

Table 13 provides the results of the regression specified in equation (16) for non-financials sorted by market capitalization (Panel A) and book value (Panel B). The table reports the regression coefficients for each size-sorted portfolio along with their statistical significance and the adjusted R^2. Table 12 excludes the recent financial crisis.

In the top panel, stocks with market capitalization in the lowest decile earn much higher risk-adjusted returns. This is not surprising. These small cap stocks are typically highly illiquid stocks. It has been documented that illiquid stocks earn abnormal returns (see, e.g., Brennan and Subrahmanyam (1996)). However, these are stocks with very small market capitalization, which are much smaller than the banks in the first portfolio. In 1980, the average market capitalization of a firm in the first portfolio is only \$22.8 million, compared to \$75.9 million for the banks in the first portfolio in 1980. The average market capitalization in the second portfolio is much larger (\$ 65.7 million in 1980). Other than this illiquidity effect in the first decile, the risk-adjusted returns are small and statistically insignificant. In Panel B, we sort by book values. While smaller firms seem to earn higher risk-adjusted returns, the effects do not exceed 300 bps, and are statistically insignificant.

2.4.3 Robustness

These results are robust. First, we checked the robustness of our results by building three portfolios of all banks, including investment banks, sorted by market capitalization, starting in 1927. This is when the CRSP data starts. There are only a few banks in each portfolio at the start of the sample in 1927. Over the entire 1927-2009 sample, the banks in the first portfolio earned 5.48% per annum more than banks in the last portfolio after adjusting for exposure to the same five stock and bond risk factors.

Second, we also split the 1970-2005 benchmark sample to check the stability of our results. In particular, we want to make sure that our results are not driven by the banking merger and acquisition wave of the 1990's. In fact, we find that the differences in the normal-risk-adjusted returns are fairly constant throughout our 1970-2005 sample.

Third, when we extend the sample to include the recent financial crisis (1970-2009), we obtain a 778 bps spread in risk-adjusted returns on commercial bank portfolios between the first and the last market decile. This spread is statistically significant at the 1% level. Hence, our findings are quite robust.

Table 13: Mean risk-adjusted returns in size-sorted portfolios of non-financial firms

Notes: This table presents the estimates from an OLS regression of monthly excess returns on each size-sorted portfolio of non-financials on the Fama-French stock and bond risk factors. *market*, *smb*, and *hml* are the three Fama-French stock factors: the market, small minus big, and high minus low respectively. *ltg* is the excess return on an index of long-term government bonds and *crd* is the excess return on an index of investment-grade corporate bonds. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The alphas have been annualized by multiplying by 12 and are expressed in percentages. The standard errors were adjusted for heteroscedasticity and auto-correlation using Newey-West with 3 lags. The sample is 1970-2005.

Year	1	2	3	4	5	6	7	8	9	10	8 - 3	9 - 2	10 - 1
Panel A: Market Capitalization													
α	11.17***	1.55	-1.22	-2.10	-3.03**	-2.36**	-2.02**	-1.06	0.20	0.61	0.16	-1.35	-10.56***
market	0.77***	0.89***	0.95***	0.99***	1.05***	1.13***	1.14***	1.12***	1.10***	0.95***	0.17***	0.21***	0.19*
smb	0.82***	0.96***	1.02***	0.97***	0.94***	0.90***	0.80***	0.67***	0.41***	-0.14***	-0.35***	-0.55***	-0.96***
hml	0.34**	0.37***	0.36***	0.29**	0.27**	0.25**	0.18	0.11	0.09	-0.10***	-0.25***	-0.29***	-0.44***
ltg	-0.47***	-0.37***	-0.36***	-0.31***	-0.24**	-0.20**	-0.18**	-0.14*	-0.07	-0.10***	0.21*	0.30***	0.37***
crd	0.36*	0.23	0.24	0.25	0.19	0.05	0.09	0.09	0.03	0.13***	-0.15	-0.20	-0.23
R^2	52.70	67.11	74.48	76.89	82.69	86.57	89.16	89.62	91.22	97.03	17.42	22.76	34.76
Panel B: Book Value													
α	3.02	2.91	2.16	1.13	0.62	1.00	0.73	0.80	0.55	-0.07	-1.36	-2.36	-3.09
market	0.99***	1.02***	1.04***	1.06***	1.09***	1.12***	1.16***	1.14***	1.14***	0.98***	0.10	0.12	-0.01
smb	0.92***	0.97***	1.00***	0.99***	0.94***	0.87***	0.80***	0.66***	0.45***	-0.05	-0.35***	-0.51***	-0.97***
hml	0.14	0.23	0.18	0.20	0.22*	0.24**	0.29***	0.31***	0.31***	0.27***	0.13	0.08	0.13
ltg	-0.42**	-0.39***	-0.30***	-0.32***	-0.29***	-0.23***	-0.16***	-0.06	-0.03	-0.07*	0.25***	0.37***	0.35**
crd	0.23	0.20	0.16	0.19	0.17	0.08	0.04	-0.11	-0.09	0.07	-0.27*	-0.29	-0.15
R^2	55.54	67.97	75.48	83.02	86.01	88.98	91.62	92.07	93.97	93.32	14.89	16.70	27.23

2.5 Size factor in bank stock returns

The second principal component of normal-risk-adjusted returns on size-sorted portfolios of bank stocks has loadings that depend monotonically on size. The covariance between the returns on size-sorted portfolios of banks stocks and the size factor can explain the size pattern in average risk-adjusted returns. In the next section, we interpret this slope factor in normal-risk-adjusted returns as a measure of financial tail risk.

2.5.1 Constructing the size factor

We compute the residuals from the time series regression of returns of each size-sorted portfolio on the equity and bond risk factor in 16. We extract the loadings for the principal components $(\boldsymbol{w}_1, \boldsymbol{w}_2)$ and we report the results in Table 14. This table only shows the loadings for the first two principal components. The other eight are plotted in figure 1. Together, these two principal components explain 66% of the residual variation over the entire sample.

The first two columns in the Table shows results for market capitalization sorts; the last two columns show results for book sorts. They are very similar. We focus on the results obtained using the market capitalization sort, mainly because this sort provides more observations.

The first principal component is a banking industry ('level') factor with roughly equal weights on all 10 portfolios. The second principal component is a size factor that loads positively on portfolios of small banks and negatively on portfolios of large banks. The loadings vary monotonically in size. This is a candidate risk factor because the loadings align with the average normal-risk-adjusted returns that we want to explain.

Next, we take our $(T \times 10)$ matrix of estimated residuals, $\boldsymbol{\epsilon}_t$, and multiply it by the (10×10) loadings of the principal components, to construct the asset pricing factors. The weights $(\boldsymbol{w}_1, \boldsymbol{w}_2)$

Table 14: Principal components of size-sorted portfolios of commercial bank stock returns

Notes: This table presents the loadings for the first and second principal components ($\boldsymbol{w}_1, \boldsymbol{w}_2$) extracted from the residuals of the regression specified in equation 16. The last row indicates the % explained by each principal component.

	Market Capitalization 1970 - 2009		Book Value 1980 - 2009	
Portfolio	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$
1	0.31	0.42	0.21	0.34
2	0.29	0.35	0.25	0.30
3	0.28	0.31	0.31	0.26
4	0.28	0.26	0.28	0.19
5	0.33	0.16	0.38	0.20
6	0.34	0.00	0.37	-0.01
7	0.35	-0.21	0.36	-0.11
8	0.32	-0.26	0.40	-0.19
9	0.32	-0.37	0.30	-0.24
10	0.33	-0.51	0.23	-0.74
%	47.63	18.37	47.56	15.39

are re-normalized to $(\widehat{\boldsymbol{w}}_1, \widehat{\boldsymbol{w}}_2)$ so that they sum to 1.[27] This results in a $(T \times 10)$ linear combination of the residuals. We focus on the first two principal components, denoted $PC_t^1 = \widehat{\boldsymbol{w}}_1' \boldsymbol{\epsilon}_t$ and $PC_{2,t} = \widehat{\boldsymbol{w}}_2' \boldsymbol{\epsilon}_t$.

The size factor not only has an appealing macro-economic interpretation, but it also is a natural candidate for explaining the size pattern in normal-risk-adjusted returns, because the average normal-risk-adjusted returns align with the covariance between the size factor (second principal component) and the returns on the portfolios. This is not the case for any of the other principal components, as is clear from Figure 1. This figure plots the average normal-risk-adjusted returns (labeled x) against the covariance of that return with the n-th principal component (labeled o). The second principal component is the only candidate factor, because the second p.c. is the only one for which the covariances line up with the average excess returns, suggesting that the common variation in banks stock returns captured by the second principal component can explain the size anomaly in bank stock returns.

To check whether the size factor actually explains the average normal-risk-adjusted returns, we define a new independent variable. We take the $(T \times 10)$ matrix of returns for each of the size-sorted portfolio of banks and multiply this by the (10×1) loading of the second principal component. We re-normalize the loadings of the second principal component so that they sum to one. As above, we use $\widehat{\boldsymbol{w}}_2$ to denote the re-normalized weights. Then: $R[PC_2]_{t+1} = \widehat{\boldsymbol{w}}_2 \boldsymbol{R}_t$ denotes the results of our multiplication and is a $(T \times 1)$ vector of the returns weighted by the second principal component. Thus for each month, the returns of each of the 10 portfolios are multiplied by their corresponding weights in the second principal component and added together. This portfolio is long in small banks

[27] $\boldsymbol{w}_2$ is given by:

$$\begin{bmatrix} 2.70 & 2.24 & 1.94 & 1.68 & 1.00 & 0.00 & -1.31 & -1.65 & -2.34 & -3.26 \end{bmatrix}$$

.

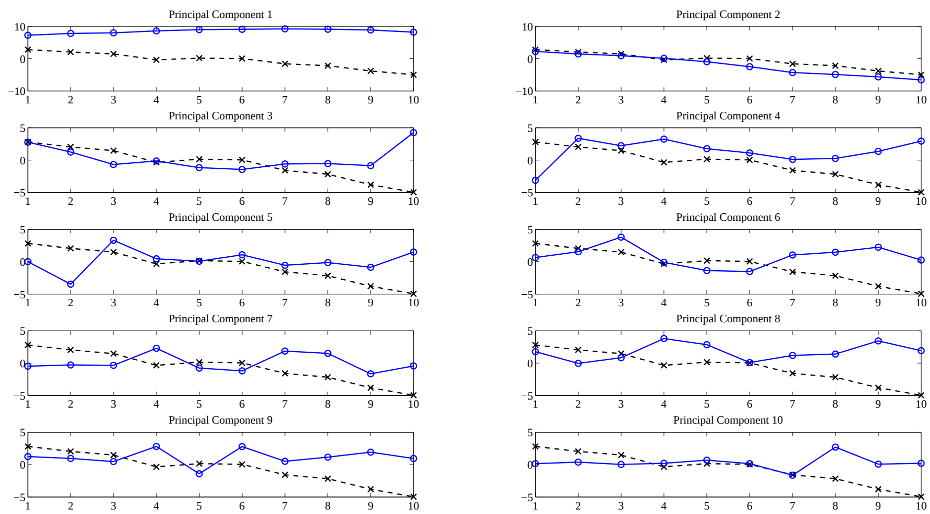

Figure 1: Covariances between risk adjusted returns and principal components

Each panel corresponds to a principal component. The upper left panel uses the first principal component. The black 'X' represent the average risk adjusted returns for the 10 size-sorted portfolios of banks. Each blue circle represents a covariance between a given principal component and a given bank portfolio. The covariances are re-scaled. The normal-risk-adjusted returns are annualized (multiplied by 12) and reported in percentage points.

and short in large banks. The weights of the portfolio are given by the second principal component loadings, re-normalized to sum to one. We then run a time-series regression of the returns on the size-sorted bank portfolios on the equity and bond factors, and the size factor $R[PC_2]$:

$$R^i_{t+1} - R^f_{t+1} = \alpha^i + \boldsymbol{\beta}^{i,\prime}\boldsymbol{f}_{t+1} + \beta^i_{PC,2} R[PC_2]_{t+1} + \varepsilon^i_{t+1}. \tag{17}$$

The tail-and-normal-risk-adjusted returns or α's from this regression are presented in Panel A of Table 15. The risk-adjusted returns on all portfolios are smaller than 250 bps over the entire sample. The average risk-adjusted return on the long-short position is reduced to 20 bps. Not only does the magnitude of the alphas change, but all of them are statistically insignificant. In addition, there is no discernible size-related pattern in these normal-risk-adjusted returns.

2.5.2 What is the size factor?

PC_2 is the normal-risk-adjusted return on a portfolio that is long small banks and short large banks. The weights of the portfolio are given by the second principal component. Figure 2 plots the 12-month moving average (months $t-11$ through t) of PC_2 series along with a plot of the index for industrial production. The units are monthly returns. The gray-shaded regions represent NBER recessions and the light-shaded regions represent banking crisis. The NBER recession dates are published by the NBER Business Cycle Dating Committee. The dates for the Mexico and LTCM crisis were obtained from Kho et al. (2000) and the FDIC (for the Less-Developed-Country debt crisis of 1982).

The size factor, which by construction is orthogonal to the bond and equity pricing factors, declines during recessions and financial crises. Moreover, it is very sensitive to large slowdowns in the growth rate of industrial production. We plot a backward looking 12-month moving average, which explains why the returns appear to drop a couple of months after the start of the NBER

Table 15: Size-factor-adjusted returns for size-sorted portfolios of commercial banks

Notes: This table presents the estimates from OLS regression of monthly excess returns on each size-sorted portfolio of commercial banks on the Fama-French stock factors, bond factors, and the second principal component weighted returns. mkt, smb, and hml are the three Fama-French factors: the market, small minus big, and high minus low respectively. ltg is the excess return on an index of long-term government bonds and crd is the excess return on an index of investment-grade corporate bonds. R^{PC_2} is the time-series of the returns of the size-sorted portfolios weighed by the loadings of the second principal component $\widehat{\boldsymbol{w}}_2$. The weights of the second principal component have been re-normalized so that they sum to 1. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels respectively. The alphas have been annualized by multiplying by 12 and are expressed in percentages. The standard errors were adjusted for heteroscedasticity and auto-correlation using Newey-West with 3 lags. The last two lines show the loadings on the size factor and the implicit tax (risk price times loading on PC_2). The annualized risk price is 38.93% in the sample ending in 2005.

Year	1	2	3	4	5	6	7	8	9	10
					Risk-adjusted Returns					
1970 - 2005	0.78	0.60	0.26	-0.41	0.56	2.28	1.77	0.87	0.27	1.66
					Loading on 2nd PC					
1970 - 2005	0.08***	0.06***	0.05***	0.04***	0.02**	0.00	-0.02**	-0.03***	-0.05***	-0.07***
					Size Factor Adjustment					
1970 – 2005	3.25	2.44	2.08	1.71	0.83	-0.12	-0.79	-1.10	-1.94	-2.92

recessions. The returns also tends to increase before the end of the NBER recession.[28] On average, during recessions, this normal-risk-adjusted return drops by an average of 3.30% per month or 39.57% per annum. During the most recent recession, which coincides with financial crisis, the size factor lost 89% of its value, after adjusting for risk exposure.

We also extended our sample to the pre-war era by including all banks and sorting these by market capitalization. We used the same principal component weights on this sample; see Figure 4 in the appendix. We observe the same pattern in the size factor in risk-adjusted returns. In every NBER recession that we examined, the size factor decreases substantially; the largest losses in this sample are incurred towards the end of the Great Depression.

Panel A in Table 16 shows the value at the trough of the NBER cycle (the end of the banking crisis) of a \$100 invested at the peak of the NBER cycle (the start of the banking crisis) in the slope portfolio – the weights are given by the normalized second principal component. The second column reports the dollar value after subtracting the performance of a benchmark portfolio with the same exposure to the bond and equity factors ($\$100 + x$ means the a cumulative return of x% in excess of the benchmark portfolio). This is the return on a portfolio that is hedged to have zero betas with respect to the standard risk factors. The third column reports the dollar value without risk-adjustment. On average, the unhedged size portfolio loses \$35 during a recession or banking crisis. The fourth column column reports the returns on the same investment strategy after hedging out the exposure to the standard equity and bond factors. That hedged strategy loses

[28] There are two exceptions to this cyclical pattern. One is the double-dip recession in the early eighties. Small banks stocks were already recovering from the huge declines suffered relative to large bank stocks, and hence starting from very low valuations, when the second recession started. The second is the 2001 recessions in the wake of the Long Term Capital Management crisis. Moreover, in 2001, the NBER chose the starting point of the recessions well after the decline in industrial production started (in other recessions, the starting date coincides with the decline in industrial production.)

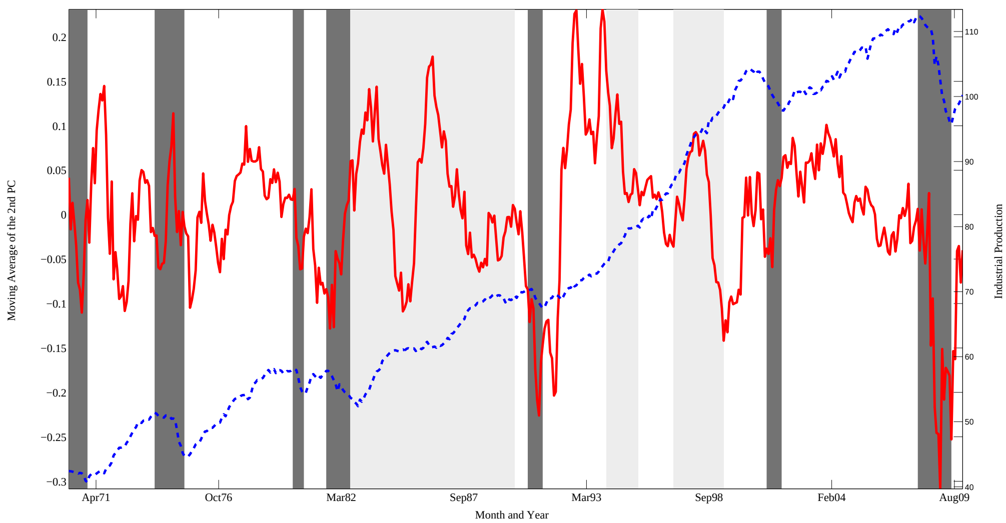

Figure 2: Size factor in normal risk-adjusted returns of commercial banks

The solid line plots the 12-month (backward looking) moving average (months $t-11$ through t) of the time-series of the weighted sum of the residuals from the OLS regression of monthly excess stock returns for each size-sorted portfolio of commercial banks on the Fama-French and bond risk factors. The weights are given by the second principal component and sum to 1. The dashed line represents the growth of index of industrial production. The gray-shaded regions represent NBER recessions and the light-shaded regions represent banking crisis. The NBER recession dates are published by the NBER Business Cycle Dating Committee. The dates for the Mexico and LTCM crisis were obtained from Kho et al. (2000) and the FDIC (for the Less-Developed-Country debt crisis of 1982). The left-axis references the moving average of the residuals and the right-axis references the index of industrial production.

more than \$60 per recession. As is clear from panel B, the largest losses are concentrated in the first six months of the NBER recessions, just under \$30 in normal-risk-adjusted terms. Moreover, this portfolio (both hedged and unhedged) experienced steep declines during the Less Developed Country and the LTCM crises.

Panel B in Table 16 shows the average value of the portfolio n months into a recession. The hedged portfolio gradually drops more in value. Twelve months after the peak it has lost almost \$63 dollars of its value.

The size factor appears to be a reliable measure of bank-specific tail risk. During the most recent U.S. recession, a full-fledged banking crisis, the hedged size portfolio of commercial banks lost close to 90 cents on the dollar (see Table 16). This is not a surprise. In 2008, 18% of the commercial banks in the first market capitalization decile were delisted, followed by another 30% in 2009. We also went back to 1926 by including all banks in our sample. During the Great Depression (NBER recession dates), the hedged size portfolio of all financials was trading at -44 cents at the end of the recession per \$100 invested at the peak.

In the data, there is a strong connection between the business cycle and the incidence of banking panics. We examined the U.S. banking panics starting in 1873, as well as the NBER business cycle peaks and troughs. Except for the first banking panic, all of these occur during the contraction phase of the U.S. business cycle. The dates of the banking panics were taken from Gorton (1988, p. 223) and Wicker (1996, p. 155). The details are provided in Table 22 in the separate appendix. This is not the case for non-financials. Longstaff (2010) examine 150 years of U.S. corporate history and they find a weak relation between the business cycle and corporate bond defaults.

Table 16: Cumulative return on the 2nd pc portfolio in recessions and financial crises

Notes: This table shows the value of a \$100 invested in a portfolio that goes long in small banks and shorts large banks. The weights of the portfolio are given by the second principal component, re-normalized so that they sum to 1 ($\widehat{\boldsymbol{w}}_2$). \$100 is invested in this portfolio at the 'Start' date and its value, given in columns 3 and 4, is measured on the 'End' date. The column labeled Value represents the value of \$100 invested at the peak (or start of the crisis) at the trough (or end of the crisis) on this portfolio and the column labeled Hedged Value represents the normal-risk-adjusted returns on this portfolio. The average is computed for all NBER recessions only using the NBER dating conventions. The bottom panel shows the value of a \$100 investment n months into the recession. The first two columns use all portfolios. The last two columns exclude the first portfolio containing the smallest banks.

Panel A: Portfolio Value at NBER Trough			
Start	End	Value	Hedged Value
NBER Recessions			
01: 1970	11: 1970	-12.23	32.74
11: 1973	03: 1975	-17.10	26.50
01: 1980	11: 1982	47.34	8.51
07: 1990	03: 1991	19.54	17.05
03: 2001	11: 2001	287.33	138.48
12: 2007	06: 2009	63.53	11.77
Average		64.73	39.17
Panel B: Average Portfolio Value n months after NBER Peak			
		Value	Hedged Value
Month 1		128.26	112.52
Month 2		88.76	86.04
Month 3		105.17	84.70
Month 4		86.36	65.93
Month 5		75.06	60.55
Month 6		99.79	65.32
Month 12		8.80	37.21

2.5.3 Alternative explanations

Large idiosyncratic shocks can cause bank failures. If the volatility of these shocks increases more in recessions for small banks, that could explain some of our findings. Smaller banks are much more exposed to idiosyncratic risk than large banks, but the amount of idiosyncratic risk exposure of small banks does not seem to increase very much during recessions. During NBER recessions, the standard deviation ranges from 38% for the smallest banks to 26% for the largest banks as compared to 36% and 20% respectively in the whole sample. The details are in the separate appendix (section 2.9.2). Hence, the largest percentage point increase in volatility during recessions is noted for the largest banks: from 20% to 26%. For the smallest banks, the increase is less than two percentage points. There is no evidence to suggest that the cyclicality of the size factor is due to idiosyncratic banks risk. While smaller banks are more exposed to idiosyncratic risk, we do not see large increases in this type of risk during recessions.

There is no evidence that business cycle variation in cash flows can explain our findings. If anything, the evidence suggests that large financial institutions are more exposes to business cycle risk. Boyd and Gertler (1993) analyze the impact of size on the performance of banks as measured by accounting data. They show that increased competition and financial innovation have induced the largest banks to participate in riskier investments.[29] We examined bank performance during the last two recessions by studying the Quarterly Banking Reports issued by the FDIC, and we found that small banks tend to outperform large banks during recessions. Section 2.9.2 of the separate appendix contains the details.

[29] This is consistent with the findings of Gatev et al. (2007); they document a reverse bank-run phenomenon for large deposit-taking institutions in periods of tight aggregate liquidity. In related work, Gatev and Strahan (2006) find that large banks provide aggregate liquidity insurance to non-financial corporations.

2.6 The pricing of bank tail risk and the government

The average return of this size factor is the price of banking tail risk insurance, and it can be measured for individual banks as the loading on this factor times this risk price. When the price of tail risk measured by the size factor is negative, we will refer to this as a tail risk subsidy. If not, it is a tail risk tax. This section examines how bank-specific tail risk is priced in the stock market, and relates it to the regulatory regime and to government announcements.

2.6.1 Size of largest banks

The events immediately after the collapse of Lehman in September 2008 confirm the commonly-held view that the U.S. government and monetary authorities are reluctant to let large financial institutions fail collectively, even though they may be occasionally willing to let individual institutions fail. For example, over the course the recent financial crisis, the Federal Reserve made emergency loans totaling about $9.99 trillion to 10 of the largest U.S. financial institutions, which accounted for 83% of the emergency credit extended to all U.S. institutions.[30] Moreover, even if regulators are willing to let these large banks fail, the uncertainty about the resolution regime for distressed banks clearly favors the creditors and shareholders of large financial institutions.

Consistent with this view, even in the highest market capitalization decile of commercial banks, we find a strong negative relation between the market capitalization of individual firms relative to GDP and the loading on the size factor. We chose banks that were in portfolio 10 in each year of our sample and then computed the loadings on PC_2 over the subsequent five-year window. As

[30]Data from the Term Auction Facility (TAF) (provided emergency loans to commercial banks), the Primary Dealer Credit Facility (PDCF)(provided emergency loans to investment banks and other broker-dealers, which typically do not have access to Fed funds) and the Term Securities Lending Facility (TSLF)(which allowed financial firms to borrow Treasury securities).

individual banks grow larger over time relative to GDP, their loadings on this size factor clearly tend to increase. The slope coefficient in the regression of PC_2 loadings on market capitalization/GDP is 0.018, meaning that a 100% increase in the size of market capitalization relative to GDP raises the loading by 0.018 in absolute value or, equivalently, it increases the tail risk subsidy by 68 bps per annum.

2.6.2 Regulatory regime

We want to relate the pricing of tail risk, as captured by the size factor, to the regulatory regime of different banks. Commercial banks and GSEs benefit from special provisions: deposit insurance[31], access to the discount window at the Federal reserve and other special lending facilities in the case of commercial banks, and widely acknowledged debt guarantees in the case of GSEs. Foreign banks and investment banks do not enjoy the same level of protection.

Table 17 compares the results for a value-weighted index of commercial banks, investment banks, foreign banks, and GSEs. The first row reports the value-weighted average market capitalization for each index. For foreign banks, this only includes the market capitalization of U.S. listed shares.[32] Investment and foreign banks do not benefit from the tail risk subsidy to commercial banks, but the GSEs (Fannie Mae and Freddie Mac) clearly do. Over the entire sample, the subsidy to commercial banks is 2.32% and the subsidy to GSEs is 1.95%. The loadings on $R[PC_2]$ are much smaller (investment banks) or positive (foreign banks) and not statistically significant.

Table 17 shows the same results for the largest commercial, investment banks and GSEs. Panel A shows the results for the entire sample excluding the crisis. The tail risk subsidy is largest for

[31] The FDIC Improvement Act of 1991 limits the protection of creditors, but it provides a systemic risk exception.

[32] The worldwide market-cap for just the 6 largest banks included in the index of foreign banks is $330.21 billion in 2010

the large commercial banks. For BoA (1973-2009), we estimate a tail risk subsidy of 3.12% per annum, for Wells Fargo (1970-2009) it is 3.27%, and for Citibank (1986-2009) it is 1.94 %. For investment banks, these effects are much smaller and not statistically significant. Lehman is the only exception.

As a benchmark, we also computed the loading on $R[PC_2]$ for an index of hedge fund returns. Hedge funds do not benefit from the umbrella extended to large banks. We used the HFRI fund-weighted hedge fund index. These results are not reported. Over the entire sample (from 1991 - 2005) the loading for hedge fund returns on $R[PC2]$ is 0.02 (t-stat 2.66) and this reduces to 0.01 (t-stat 0.91) over 2000 - 2005. Hence, as expected, hedge funds face a tail risk tax, because the loadings are positive, just like small banks.

These results lend some support to a government-based interpretation of the size factor, as commercial banks and GSEs benefit from more extensive government guarantees than other financial institutions.[33]

2.6.3 Elimination of Glass-Steagall

The Glass-Steagall Act (1933) effectively separated U.S. commercial banking from investment banking. The provisions of this act preventing bank holding companies from owning financial companies were repealed in 1999. Its repeal allowed large commercial banks to originate and trade collateralized debt obligations.

After 2000, the tail risk subsidy to commercial banks more than doubled to 4.76%, and the subsidy to GSEs more than tripled to 6%. These numbers were determined by multiplying the loadings with the same risk price (38.93%) computed over the entire sample. There was also a marked increase in the exposure of investment and foreign banks to the size factor.

[33] The GSEs and foreign banks were suggested to us by Martin Bodenstein.

Table 17: Bank tail risk pricing for investment banks, foreign banks, and GSEs.

Notes: This table presents the estimates from OLS regression of monthly excess returns on a value-weighted index of commercial banks, investment banks, and GSEs on the Fama-French stock factors, bond factors, and the second principal component weighted returns. The table also reports results for individual banks. Foreign banks were selected based on the share-code in CRSP. Investment banks are those with SIC code 62. A share-code ending in two indicates that firms were incorporated outside the US. For individual banks, the longest available sample for each bank till 2009 was selected. The starting year for each bank is mentioned in parentheses under the name of the bank. PC_2 is the time-series of the returns of the size-sorted portfolios weighed by the loadings of the second principal component $\widehat{\boldsymbol{w}}_2$. The weights of the second principal component have been re-normalized so that they sum to 1. Statistical significance is indicated by *, **, and *** at the 10%, 5%, and 1% levels respectively. The alphas have been annualized by multiplying by 12 and are expressed in percentages. The standard errors were adjusted for heteroscedasticity and auto-correlation using Newey-West with 3 lags. The implicit subsidy is the risk price (38.93%) times (minus) loading on PC_2). The risk price is fixed in the different subsamples.

	Index of Banks				Individual Banks								
	Commercial	Investment	Foreign	GSE	BoA	Citi	GS	LEH	ML	MS	WFC	FNM	FRE
Market Cap(Jan 05)	118.57	24.12	44.71	50.61	187.30	254.56	52.22	34.33	55.78	61.25	103.71	62.48	44.95
start					(1973)	(1986)	(1999)	(1994)	(1971)	(1986)	(1970)	(1970)	(1989)
Panel A: Full Sample													
market	0.83***	1.65***	0.97***	0.82***	1.12***	1.37***	1.50***	1.54***	1.85***	1.63***	0.82***	0.8***	0.68***
smb	0.17**	0.14	0.36	-0.01	0.08	-0.17	0.21	-0.09	0.06	-0.15	-0.12	-0.07	0.38
hml	0.41***	0.13	0.54	0.16	0.56***	0.17	-0.28	-0.10	0.20	-0.12	0.39***	0.16	0.43**
ltg	0.04	0.09	0.07	1.39***	0.08	-0.07	1.09	-0.08	-0.31	-0.16	-0.01	1.34***	1.23***
crd	0.26**	-0.25	-1.24	-0.22	0.44	0.44	-0.66	0.91	0.37	-0.20	0.44*	-0.15	-0.25
PC_2	-0.06***	-0.02	0.01	-0.05***	-0.08***	-0.05**	-0.07	-0.09*	-0.02	-0.04**	-0.08***	-0.05***	-0.10***
size	2.32	0.77	-0.38	1.95	3.12	1.94	2.57	3.43	0.70	1.47	3.27	1.83	3.94
Panel B: Subsamples													
1990-2005													
PC_2	-0.07***	-0.03**	-0.02	-0.09***	-0.08**	-0.06**	-0.07	-0.09*	-0.02	-0.04**	-0.11***	-0.08***	-0.11***
size	2.58	1.13	0.84	3.57	3.17	2.18	2.57	3.43	0.61	1.55	4.40	3.39	4.06
2000-2005													
PC_2	-0.12***	-0.07***	-0.06**	-0.16***	-0.12***	-0.12***	-0.06	-0.16***	-0.04	-0.11***	-0.16***	-0.17***	-0.14***
size	4.76	2.59	2.23	6.07	4.53	4.59	2.53	6.22	1.61	4.12	6.15	6.57	5.37

The loadings for the largest commercial banks increased dramatically in the last decade. The BoA tail risk subsidy increased from 3.17% to 4.53% in 2000-2005, while the Citi subsidy increased from 2.18% to 4.59%. This is exactly what one would have expected to see given the enormous increase in total asset size realized by these banks. Wells Fargo collected a subsidy of 6.15% in 2000-2005, compared to 4.40% in the 1990-2005 sample. The largest subsidy is collected by Fannie Mae (6.57%), in spite of its smaller size. Lehman also collect a large subsidy in this period. Both Lehman and Fannie Mae were building up substantial exposure to the subprime mortgage market during this period. Note that there is no mechanical connection between our size factor and the subprime exposure, since we exclude the financial crisis from the sample. Exposure to the size factor seems a good yardstick of systemic risk exposure.

2.6.4 Announcement effects

In September 1984, the Comptroller of the Currency announced a list of 10 banks that were deemed too big to fail. We examine the pricing of the financial tail risk embedded in the stocks of these 10 banks around this announcement date. Table 24 in the appendix lists all the announcement dates.

Pre-crisis announcement dates We also look at six other announcement dates listed by Kho et al. (2000). Tables 18 and 19 report the results. We report regressions for windows of 30, 45, 60, 90, and 105 days around the announcement date. Panel A lists results from a pooled regression for all seven announcement dates. In the 30-day window after the Comptroller announcements, the loading increases by 0.12. This amounts to an annualized 4.56 % tail risk subsidy. This effect gradually decreases as we increase the window around the event. We find slightly smaller effects for the LTCM, Brazilian, Mexican and South-Korean crisis. The average effect is a 1.14 pps (0.03 times 38%) increase in the tail risk subsidy. This average effect is roughly constant across the windows. These effects are economically and statistically significant.

Crisis announcement dates In the crisis sample, we identified announcements that increased the likelihood of a bailout for all banks, for large banks and, finally, we also looked at events that decreased the likelihood of a bailout. These are listed in Panel B of Table 24 in the separate appendix.

Panel B looks at the financial crisis announcements. Only the positive announcements for large banks have an economically and statistically significant effect on the pricing of tail risk. The tail risk subsidy for the too-big-to-fail banks increases by 2.66 pps in a 30-day window around these announcements. The other announcements have small or negative effects that are not statistically significant.

2.7 Recovery rates and equilibrium pricing of tail risk in the banking sector

To help us interpret our empirical findings, we use a stylized dynamic asset pricing model with time-varying probability of banking panics that reproduces the size anomalies, as well as the size factor in returns. The driving force is the size variation in recovery rates.

2.7.1 A simple model of the size anomaly in bank stock returns

The model yields a key testable prediction: a size factor in normal-risk-adjusted returns on banking portfolios that is tied to the U.S. business cycle.

We adopt a version of the models with time-varying probabilities of financial disasters proposed by Gabaix (2008) and Wachter (2008). These are extensions of the rare event models developed by Barro (2006) and Rietz (1988). In our model, the stochastic discount factor has two components:

Table 18: Bailout announcements

Notes: This table presents the results of the regression $R_t^{TBTF} - R_t^f = \alpha + \beta_1 PC_2 + \beta_2 PC_2 D + \epsilon$. $TBTF$ represents the value-weighted return of the 10 banks that were announced to be by the Comptroller of Currency in September of 1984. PC_2 represents the daily return of the portfolio that goes long in small banks and shorts large banks. The weights for the portfolio are given by the second principal component and sum to 1. D represents a dummy variable that equals 1 after the announcement date and 0 otherwise. The regression is estimated over a 30-, 60-, 90-, and a 105-day window around the announcement date. A 7-day window around the exact announcement date was excluded from the sample while estimating coefficients. Dates for the announcements are from O'Hara and Shaw (1990) and Kho et al. (2000).

Coeff	30D	45D	60D	90D	105D
Panel A: Pre-crisis Announcements					
9/19/1984; Comptroller of Currency					
PC_2	-0.19***	-0.19***	-0.20***	-0.21***	-0.20***
PC_2D	-0.12*	-0.05	-0.03	-0.02	0.00
9/24/1998; LTCM					
PC_2	-0.22***	-0.23***	-0.24***	-0.23***	-0.24***
PC_2D	-0.05	-0.05	-0.05	-0.05	-0.05*
9/15/1998; Brazilian Crisis					
PC_2	-0.24***	-0.25***	-0.25***	-0.26***	-0.26***
PC_2D	-0.03	-0.03	-0.03	-0.02	-0.03
10/08/1998; Brazilian Crisis					
PC_2	-0.24***	-0.24***	-0.25***	-0.25***	-0.25***
PC_2D	-0.08*	-0.09**	-0.09***	-0.08***	-0.06**
11/13/1998; Brazilian Crisis					
PC_2	-0.27***	-0.26***	-0.27***	-0.25***	-0.25***
PC_2D	-0.06	-0.05	-0.03	-0.05	-0.03
11/14/1997; South Korean Crisis					
PC_2	-0.27***	-0.27***	-0.27***	-0.26***	-0.26***
PC_2D	-0.01	0.00	0.00	0.00	0.00
01/25/1995; Mexico Crisis					
PC_2	-0.17*	-0.11*	-0.12***	-0.15***	-0.14***
PC_2D	-0.06	-0.12*	-0.08	-0.05	-0.05
Pooled Regression					
PC_2	-0.24***	-0.24***	-0.24***	-0.24***	-0.24***
PC_2D	-0.03**	-0.04***	-0.04***	-0.04***	-0.04***

Table 19: Bailout announcements

Notes: This table presents the results of the regression $R_t^{TBTF} - R_t^f = \alpha + \beta_1 PC_2 + \beta_2 PC_2 D + \epsilon$. $TBTF$ represents the value-weighted return of the 10 banks that were announced to be by the Comptroller of Currency in September of 1984. PC_2 represents the daily return of the portfolio that goes long in small banks and shorts large banks. The weights for the portfolio are given by the second principal component and sum to 1. D represents a dummy variable that equals 1 after the announcement date and 0 otherwise. The regression is estimated over a 30-, 60-, 90-, and a 105-day window around the announcement date. A 7-day window around the exact announcement date was excluded from the sample while estimating coefficients. Dates for the announcements are from O'Hara and Shaw (1990) and Kho et al. (2000).

Coeff	30D	45D	60D	90D	105D
Panel B: Crisis Announcements					
Positive Announcements: All Banks					
PC_2	-0.17***	-0.17***	-0.17***	-0.16***	-0.16***
PC_2D	0.00	-0.00	-0.01	-0.01	-0.01
Positive Announcements: Large Banks					
PC_2	-0.11***	-0.15***	-0.16***	-0.15***	-0.14***
PC_2D	-0.07***	-0.04**	-0.02	-0.02	-0.03*
Negative Announcements					
PC_2	-0.15***	-0.15***	-0.16***	-0.16***	-0.16***
PC_2D	-0.01	-0.01	0.00	-0.01	-0.01

a standard normal component and a disaster component:

$$\begin{aligned} M_{t+1} &= M_{t+1}^{G} \times 1 \textit{ in states without a financial disaster} \\ M_{t+1} &= M_{t+1}^{G} \times M_{t+1}^{D} \textit{ in states with a financial disaster.} \end{aligned} \tag{18}$$

M_{t+1}^{G} denotes the representative investor's intertemporal marginal rate of substitution (IMRS) in normal times, i.e., in states without a disaster. In the simplest version of his model, Gabaix (2008) defines $\Delta \log C_{t+1} = g_C + \sigma\eta_{t+1}$ as the growth rate of consumption in normal times, and $\Delta \log C_{t+1} = g_C + \sigma\eta_{t+1} + \log F_t^c$ as the consumption growth rate in the financial disaster state, where $1 \geq F_t^c > 0$. η_{t+1} is Gaussian white noise. p_t denotes the probability of a financial disaster.

In the absence of a financial disaster, the IMRS is completely determined by normal risk. We assume that the normal component of the stochastic discount factor is linear in the normal risk factors:

$$M_{t+1}^{G} = \boldsymbol{b}'\boldsymbol{f}_{t+1}. \tag{19}$$

We use $\boldsymbol{\beta}_t^i$ to denote the vector of conditional normal risk factor betas for the returns on asset i, and we use $\boldsymbol{\lambda}_t$ to denote the vector of normal risk prices. We make some additional simplifying assumptions in order to characterize disaster risk premia analytically. First, we assume that the conditional distribution of the normal risk factors $\boldsymbol{f}_t$ is independent of the disaster realization. Second, we assume that p_t does not co-vary with the normal risk factors f_t. This second assumption implies that the recession risk itself is not priced, only the financial disaster risk itself is.

The dividend process of a portfolio of bank stocks of size i is given by:

$$\begin{aligned} \Delta \log D_{t+1}^{i} &= \Delta \log D_{t+1}^{i,G} \textit{ in states without banking crisis} \\ \Delta \log D_{t+1}^{i} &= \Delta \log D_{t+1}^{i,G} + \log F_t^i \textit{ in states with banking crisis} \end{aligned}$$

$\Delta \log D_{t+1}^{i,G}$ is the Gaussian component of dividend growth. $1 \geq F_t^i > 0$ can be thought of as the recovery rate; in case the rare event is realized, a fraction F^i of the dividend gets wiped out

(See Longstaff and Piazzesi (2004) and Barro (2006)). This recovery rate will vary across banks depending on size, partly because the realization of this rare event can trigger a collective bailout of larger banks, but not necessarily of smaller banks. There is strong empirical evidence for size-dependent variation in disaster recovery rates. In our sample (1970-2009), the average delisting rate for banks in the first market capitalization decile is 1.77%, compared to 0.018% for the ninth decile and 0% for the tenth decile. During 2008, 18% of banks in the first decile were delisted, another 30% were delisted in 2009, and, finally, 10% in 2010. None of the commercial banks in the highest decile were delisted. Including acquisitions increases these numbers to 19% and 32% respectively.

The resilience of banks is defined as the marginal-utility-weighted recovery rate in disaster states (Gabaix (2008)): $H_t^i = p_t E_t \left[M_{t+1}^D F^i - 1 \right]$. In the simplest CCPAM case, this would be $H_t^i = p_t E_t \left[(F_{t+1}^c)^{-\gamma} F_{t+1}^i - 1 \right]$. As the economy enters into a recession, p_t increases and the resilience of large banks H_t^B increases relative to small banks H_t^S if $F_{t+1}^B > F_{t+1}^S$. In fact, we assume that the recovery rate $F_t^n > F_t^{n-1}$ increases monotonically in size.

The expected return on asset i, conditional on no disaster realization, after adjusting for normal risk exposure, becomes $E_t[\widehat{R}_{t+1}^i] = \exp(r - h_t^i)$, where $E_t[\widehat{R}_{t+1}^i] = E_t[R_{t+1}^i] - \boldsymbol{\beta_t^i \lambda_t}$, and r denotes $\log R_t = \log E_t[M_{t+1}^G]^{-1}$, and h_t^i denotes $\log(1 + H_t^i)$. The proof is in the Appendix .

To derive a simple expression for average normal-risk-adjusted returns, we abstract from variation in normal betas and risk prices. In the interest of tractability, we assume that the recovery rates F^i are constant over time, and we also assume that the size of the consumption disaster F^C is constant over time. The conditional beta $\boldsymbol{\beta}_t$ and the conditional risk prices $\boldsymbol{\lambda}_t$ are constant. In a sample without a disaster realization, the average normal-risk-adjusted return will be given by:

$$E[\widehat{R}_{t+1}^i] = E[R_{t+1}^i] - \boldsymbol{\beta^i \lambda} = exp(\overline{r} - \overline{h}^i),$$

where $\overline{h}^i = E[\log\left(1 + H^i\right)]$. The difference in alphas in a sample without a rare event realization measures the differences in average resilience between different bank stock portfolios: $\log \alpha^B - \log \alpha^S = \overline{h}^S - \overline{h}^B$. Hence, we can interpret the 6% difference between small and large bank portfolios in the normal-risk-adjusted returns as measuring differences in the resilience of these bank portfolios to banking crises.

A key prediction of this model is that this variation in the probability of a financial disaster in turn imputes common variation to the normal-risk-adjusted stock returns along the size dimension, since we assumed that the recovery rate depends on size, even in a sample without disasters. The loadings on this common factor are proportional to $F^i - 1$. To see why, note that $\log(1 + H^i_t) \approx p_t E_t\left[M^D_{t+1} F^i - 1\right]$. This is a size factor because the loadings depend on the recovery rates and hence (by assumption) on size. The conditional normal-risk-adjusted multiplicative risk premium on a long-short portfolio is given by the following expression:

$$\log E_t\left[\widehat{R}^B_{t+1}\right] - \log E_t\left[\widehat{R}^S_{t+1}\right] = h^S_{t+1} - h^B_{t+1}.$$

As p_t increases during recessions, the risk premium on this long-short portfolio becomes more negative. This variation in risk premia is the driving force. The size factor tracks the variation in p_t.

The characteristic (the size of the bank) actually determines the financial disaster risk premium, because of the collective bailout guarantee for large banks. This creates an opening for arbitrage opportunities. Let us assume that there is a single critical size threshold. In this case, the low recovery rate ($F^i = \underline{F}$) applies for all bank portfolios with size below the cutoff. Also, suppose banks do not switch between portfolios as a result of growth, mergers or acquisitions. For banks in portfolios above the cutoff, the higher recovery rate applies: $F^i = \overline{F}$. The baseline model predicts large positive, but constant, $\underline{\alpha}$'s for all the banks in size-sorted portfolios below the threshold, and much smaller, negative $\overline{\alpha}$'s for all banks above the threshold. In that sense, the pattern we found in the data is surprising. However, this stark $(\underline{\alpha}, \overline{\alpha})$ outcome can only be an equilibrium if there are prohibitively large costs associated with merging and acquiring banks.

Suppose there are no such costs. Consider two banks (A and B) just below the threshold with recovery rates $F^A = F^B = \underline{F}$. By bundling the cash flows of these two banks (A and B), the recovery rate increases to $F^{A+B} = \overline{F}$, and the value of a claim to the cash flows of A and B will exceed the sum of the value of these cash flows: $P(A) + P(B) \leq P(A+B)$. In the absence of costs, this represents an arbitrage. However, if there are positive costs C, then the value of A and B has to increase such that $P(A) + P(B) \geq P(A+B) - C[A, B]$ to eliminate the arbitrage opportunities. This increase reflects the probability that these banks end up crossing the size threshold because of growth or because of a future merger or acquisition. Hence, the α's for these banks (A and B) will decrease, as their value rises, even though they do not directly benefit from the guarantee yet. Alternatively, A and B will actually merge right away.

There was a large amount of concentration in the banking sector in the last decades. Table 9 reports an increase from 50% (in the 1970's) to 90 % (in the last decade) in the share of total market capitalization accounted for by the top decile. The increase in the share of total balance sheet accounted for by the top decile is from 52% to 95%. Kane (2000) and Brewer and Jagtiani (2007) document acquiring banks are willing to pay larger premiums for banks that put them over critical size thresholds, consistent with our hypothesis. By backward induction, the same argument applies to smaller banks in other portfolios. However, the costs of bundling the cash flows ($C[D, E, F, \ldots, Z]$) of many smaller banks to reach this critical threshold increase, and this mitigates the effect on the average risk-adjusted returns. This can account for the decreasing pattern in the alphas that we have found in the data.

2.7.2 Calibrated GE asset pricing model

Obviously, the independence of risk factors and p_t that we need to derive simple, analytical characterizations of the risk-adjusted returns is very restrictive. This section develops a general equilibrium version of this model, in which these restrictions are relaxed. We show there is a qualitatively similar relation between the average risk-adjusted returns and the financial disaster recovery rates provided that the market itself is not as exposed to financial disaster risk as banks.

We use a modified version of Gourio (2008)'s model. The stand-in agents has Epstein-Zin utility over non-durable consumption streams:

$$V_t(C^t) = \left[(1-\beta)C_t^{1-\alpha} + \beta(\mathcal{R}_t V_{t+1})^{1-\alpha}\right]^{\frac{1}{1-\alpha}}, \tag{20}$$

where $\mathcal{R}$ denotes the following operator: $\mathcal{R}_t V_{t+1} = \left(E_t V_{t+1}^{1-\theta}\right)^{1/1-\theta}$. This agent cares about the intertemporal composition of risk. α^{-1} controls the intertemporal elasticity of substitution, while θ controls risk aversion. When $\alpha = \theta$, preferences are time-separable. The equilibrium SDF is given by:

$$M_{t+1} = \beta^{\frac{1-\theta}{1-\alpha}} \left(\frac{C_{t+1}}{C_t}\right)^{-\alpha\frac{1-\theta}{1-\alpha}} R_{w,t+1}^{\frac{\alpha-\theta}{1-\alpha}}, \tag{21}$$

where R^w denotes the return on a claim to aggregate consumption.

The process for aggregate consumption growth is given by:

$$\Delta \log C_{t+1} = g_C + \sigma\eta_{t+1}, \textit{ in states without financial disaster}$$

$$\Delta \log C_{t+1} = g_C + \sigma\eta_{t+1} + \log F^c, \textit{ in states with financial disaster.}$$

When p is i.i.d., this model can be solved analytically. We are interested in the case in which p varies over the business cycle. We solve a version of this model with two aggregate states.

We choose σ, the standard deviation of Gaussian aggregate consumption growth shocks, equal to 3%, and g_C equal to 2%. The time discount factor β is set to 0.975. Following Gourio (2008), we use a two-state discretization for the aggregate state of the economy. In the recession state, the probability of a financial disaster is high. In the expansion state, the probability of a financial disaster is low. The average length of an expansion is 44 months. The average length of a recession is 16 months. The ratio of the average length of an expansion to the average length of a recession is 2.62. We set the average probability of a banking crisis to 13%, because the U.S. spent 13% of all years since 1800 in a banking panic according to Reinhart and Rogoff (2009).[34] The aggregate state of the economy follows a 2-state Markov chain with transition probability matrix:

$$Q = \begin{bmatrix} \phi & 1-\phi \\ 1-\varphi & \varphi \end{bmatrix}$$

with stationary distribution $\{\frac{(1-\varphi)}{(1-\varphi)+(1-\phi)}, \frac{(1-\phi)}{(1-\varphi)+(1-\phi)}\}$. To match the average length of a recession (16 months), we set φ equal to 0.25. The same transition matrix Q applies in disaster and non-disaster states. To match the ratio, we choose ϕ equal to 0.71. In an expansion, the conditional probability of a banking panic $p_{ex} = 0$. In a recession, the conditional probability of a banking panic $p_{re} = 0.466$. Finally, we consider a cumulative consumption drop of 5% ($F^C = 0.95$) in the financial disaster state. This scenario matches the experience of all developed economies considered by Reinhart and Rogoff (2009) during banking crises. The market (equity) is a levered claim to aggregate consumption C^{λ}:

$$\begin{aligned} \Delta \log D^m_{t+1} &= \lambda^m g_C + \lambda^m \eta_{t+1}\sigma, \textit{ in states without financial disaster} \\ \Delta \log D^m_{t+1} &= \lambda^m g_C + \lambda^m \eta_{t+1}\sigma + \lambda^m \log F^c, \textit{ in states with financial disaster.} \end{aligned}$$

Bank cash flows are also a levered claim to aggregate consumption:

[34]This matches 13 U.S. financial crises over 210 years with an average length of 2.1 years.

$$\Delta \log D^i_{t+1} = \lambda^i g_C + \lambda^i \sigma \eta_{t+1}, \textit{ in states without financial disaster}$$

$$\Delta \log D^i_{t+1} = \lambda^i g_C + \lambda^i \sigma \eta_{t+1} + \lambda^i \log F^i, \textit{ in states with financial disaster.}$$

We assume that small and large banks have the same cash flow properties in normal times. However, small banks will have recovery rates below the $F^S < F^c$, and large banks will have recovery rates in excess of $F^L > F^c$.[35]

First, we consider the benchmark case in which the market is exposed to levered normal and disaster risk. Panel A in Table 20 reports the results for different values of the recovery rates. These results were generated by generating 25,000 draws from the model. The first column reports the equity premium conditional on no disaster in the sample ($E[R^{m,e}|\textit{no disaster}]$). The second column reports the actual equity premium ($E[R^{i,e}]$). The third and fourth column report the conditional equity premium in expansions and recessions. Finally, the last two columns report the average normal-risk-adjusted returns and the market beta.

We replicate the treatment of the actual data on model-generated data. To compute the alpha, we assume that the Gaussian component of the SDF is linear in the market excess return ($M^G = a + bR^{m,e}$), and hence we project the excess returns on the bank stocks on the excess return on the market in a sample without disasters. In a sample with disasters, the alphas are very close to zero, even though the CAPM does not hold exactly (see equation 21: The log SDF depends on the (unlevered) total wealth return and consumption growth).

The left panel of Table 20 considers the benchmark case of a 5% drop in aggregate consumption.

[35] One might conjecture that small banks simply under-perform during recessions. Although this should not lead to differences in α, but rather differences in exposure to the standard risk factors, we want to check this, because it might be important for how cash flows are modeled. Actually, we find small bank cash flows to be less exposed to aggregate risk. The evidence is reported in section 2.9.2 of the appendix.

The leverage of the market is 2.5. The banks have leverage of 2. With a 10% difference in the unlevered financial disaster recovery rate, the difference in the equity premium between small (7.11%) and large banks (2.29%) is 482 bps. However, most of this difference is accounted for by the higher beta, not by α differences.

As a result, the unlevered difference in the recovery rates needs to exceed 35% to match the spread in normal risk-adjusted returns we have observed in the data. Given that 32% of banks in the first decile were delisted in 2010 alone, that seems reasonable. When the difference in recovery rates is 35 cents, the differences in α is 551 bps. However, because the market itself is exposed to financial disaster risk, small banks have much higher loadings (2.10) on the market than large banks (0.59). This is at odds with the data.

The right panel Table 20 considers the case of a 2.5% drop in aggregate consumption. In this case, a smaller differences in recovery rates of 30% is sufficient to match the difference in normal-risk-adjusted returns.

The model can match the large betas of large banks and small betas of small banks, while still matching the average normal risk-adjusted-returns provided that the stock market is less exposed to financial disaster risk: The market (equity) is a levered claim to aggregate consumption C^{λ}, but the leverage only applies to the normal risk, not the disaster risk:

$$\begin{aligned}
\Delta \log D_{t+1}^{m} &= g_C + \lambda^{m} \sigma \eta_{t+1}, \textit{in states without financial disaster} \\
\Delta \log D_{t+1}^{m} &= g_C + \lambda^{m} \sigma \eta_{t+1} + \log F^{c}, \textit{in states with financial disaster.}
\end{aligned}$$

The dividend growth process for bank stocks is unchanged. In this calibration, we increased σ to 3.50 % and we increased θ to match the same ex-disaster equity premium of 5.80%. The results are shown in Panel II of Table 20. The top right panel considers the benchmark case of a 5%

Table 20: Baseline model with levered normal and financial disaster risk in the market

Calibrated version of model with Gaussian aggregate consumption growth shocks and two aggregate states. In Panel A, θ is 13.25 and α is 0.75. σ is 3% and μ is 2%. In Panel B, θ is 15 and α is 0.75. σ is 3.5% and μ is 2%. Results shown for $25,000$ random draws.

λ^i	F^i	$E[R^{i,e}\|nd]$	$E[R^{i,e}]$	$E[R^{i,e}\|exp]$	$E[R^{i,e}\|rec]$	$\alpha^i\|no\ dis.$	$\beta^i\|no\ dis$	$E[R^{i,e}\|nd]$	$E[R^{i,e}]$	$E[R^{i,e}\|exp]$	$E[R^{i,e}\|rec]$	$\alpha^i\|no\ dis.$	$\beta^i\|no\ dis$
Panel A: Baseline Model with Levered Normal and Financial Disaster risk in the Market													
		5% aggregate consumption drop						2.5% aggregate consumption drop					
		Market						Market					
2.5	0.95	5.80	4.09	3.49	5.64			4.21	3.33	3.19	3.71		
		Large Banks						Large Banks					
2	1.00	2.29	2.29	2.30	2.26	−0.63	0.59	2.44	2.44	2.45	2.43	−0.40	0.74
		Small Banks						Small Banks					
2	0.90	7.11	4.18	3.18	6.78	0.71	0.98	6.19	3.28	2.79	4.59	1.30	0.93
2	0.80	12.54	6.16	3.98	11.87	2.22	1.41	10.23	4.16	3.09	6.95	3.21	1.12
2	0.75	15.49	7.19	4.35	14.64	3.07	1.63	12.53	4.60	3.23	8.20	4.25	1.23
2	0.70	18.61	8.25	4.69	17.56	3.96	1.86	14.81	5.05	3.36	9.49	5.31	1.33
2	0.65	21.88	9.33	5.01	20.63	4.88	2.10	17.17	5.51	3.48	10.81	6.44	1.43
2	0.60	27.63	10.43	5.31	23.84	5.92	2.36	19.59	5.96	3.60	12.17	7.56	1.53
Panel B: Baseline Model with Levered Normal and Unlevered Financial Disaster risk in the Market													
		5% aggregate consumption drop						2.5% aggregate consumption drop					
		Market						Market					
2.5	0.95	5.83	5.12	4.87	5.75			5.23	4.88	4.83	5.03		
		Large Banks						Large Banks					
2	1.00	3.59	3.59	3.61	3.53	−0.59	0.76	3.78	3.78	3.79	3.75	−0.20	0.78
3	1.00	5.54	5.54	5.58	5.45	−0.85	1.17	5.75	5.75	5.76	5.76	−0.36	1.20
4								5.54	5.54	5.58	5.45	−0.56	1.56
		Small Banks						Small Banks					
2	0.90	10.5	5.80	4.68	8.74	2.32	0.89	7.69	4.76	4.19	6.24	2.05	0.84
2	0.80	14.63	8.13	5.63	14.64	5.48	1.03	12.02	5.77	4.55	8.96	4.56	0.89
2	0.75	17.84	9.35	6.09	17.87	7.23	1.11	14.33	6.28	4.71	10.40	5.86	0.93
2	0.70	21.24	10.62	6.51	21.31	9.03	1.19	16.73	6.81	4.87	11.90	7.21	0.97
1	0.70	10.32	5.27	3.34	10.34	4.50	0.56	8.33	3.43	2.47	5.94	3.71	0.46
1	0.65	12.13	5.98	3.62	12.17	5.57	0.60	9.66	3.74	2.58	6.77	4.50	0.47

drop in aggregate consumption. The leverage of the market is 2.5, but leverage only applies to the Gaussian component. This seems reasonable. Between June 2007 and March 2009, the market lost about 50% of its value, while the financial sector lost more than 80% of its value during the same period.

The key difference is that the equity premium contains a much smaller financial disaster risk premium. As a result, a larger fraction of the difference in risk premia ends up in the alpha. Consider the case of a 5% aggregate consumption drop. When bank leverage is equal to 2, and with a 20% difference in the unlevered financial disaster recovery rate, the difference in alphas exceeds 600 bps, while the betas for the large banks are larger than the betas for small banks. In fact, when we choose large bank leverage equal to 3, and small bank leverage equal to 1, there is a 57 bps spread in the betas, and a 642 basis point spread in the alphas. The required difference in the recovery rates is 35 cents on the dollar.

Figure 3 plots the simulated returns on a small-minus-big bank portfolio (dotted line) for this calibration. A period denotes one year. The dotted line plots the stock market return. The stock market return is driven by normal risk, while the small-minus-big portfolio responds mostly to the probability of a financial disaster, which increases in recessions. The shaded areas are recession states. The small-minus-big portfolio is a recession factor, as in the data. Moreover, this portfolio has negative market beta.

Finally, if we consider a 2.5% aggregate consumption drop, and we set the leverage of small banks equal to one, we can actually match the spread in betas of more than 100 bps between portfolio 1-10 observed in the data. However, the spread in alphas is only 500 bps.

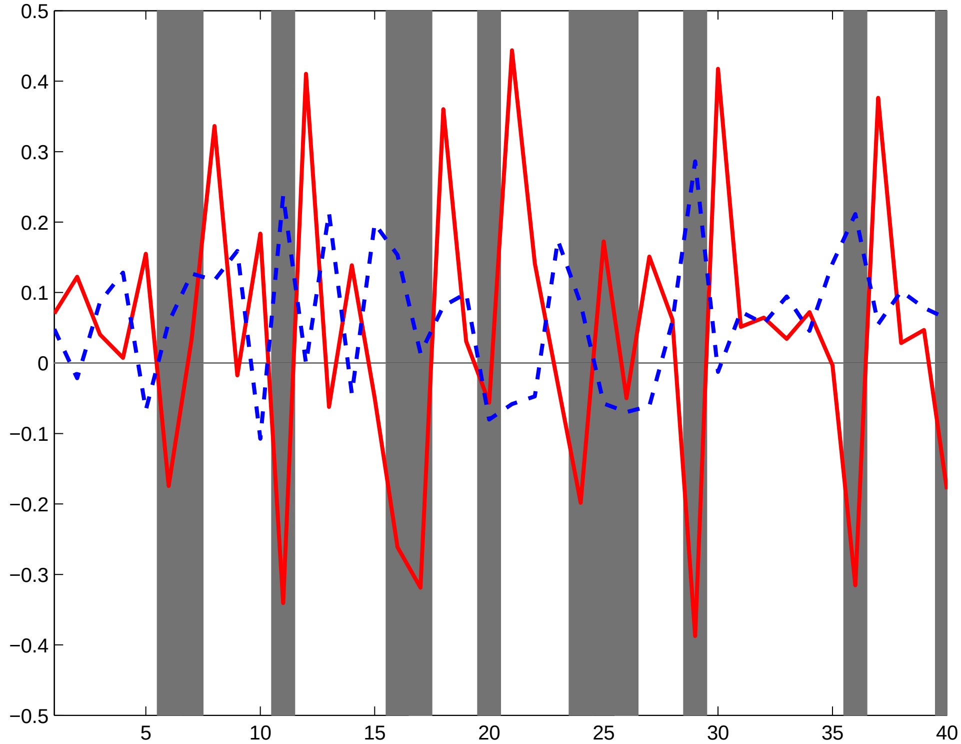

Figure 3: Size factor in bank stocks and recessions

Notes: Simulation of 40 years. The full line is Return on *smb*; the dotted line is Return on market. θ is 15 and α is 0.75. σ is 3.5% and μ is 2%. Small bank leverage is 1 and $F^S = 0.65$. Large bank leverage is 3 and $F^B = 1$. The shaded areas are recessions.

2.8 Conclusion

We document a size anomaly in bank stock returns that is different from the size effect that has been documented for non-financials. This size effect can be explained by the covariance with a new size factor that we extract from that component of bank stock returns that is orthogonal to standard risk factors. This size factor is a measure of bank-specific tail risk. Our evidence from bank stock returns reveals how the pricing of bank-specific tail risk in financial markets may depend on which bank is holding the risk. To the extent that these effects reflect implicit bailout guarantees in financial disasters, the government subsidizes large financial institutions to take on bank-specific tail risk.

2.9 Appendix

2.9.1 Derivation of tail risk premium expression

We use F to denote F^C. Consider the investor's Euler equation for asset i: $E_t[M_{t+1}R^i_{t+1}] = 1$.

The stand-in investor's SDF M_{t+1} is described in equation (19). This Euler equation can be decomposed as follows:

$$(1 - p_t)E_t[M^G_{t+1}R^i_{t+1}] + p_t E_t[M^G_{t+1}M^D_{t+1}R^{G,i}_{t+1}R^{D,i}] = 1.$$

We assume that the distribution of the Gaussian factors is (conditionally) independent of the realization of the disaster:

$$\left((1 - p_t) + p_t E_t[M^D_{t+1}R^{D,i}]\right) E_t[M^G_{t+1}R^{G,i}_{t+1}] = 1.$$

Given these assumptions, this expression can be further simplified to yield:

$$\left(1 + p_t E_t[M^D_{t+1}F^i - 1]\right) E_t[M^G_{t+1}R^i_{t+1}] = 1,$$

where we have substituted the recovery rate F^i for $R^{D,i}$. To see why, note that the Gaussian return on stock i can be stated as:

$$R_{t+1}^{G,i} = \frac{(P_{t+1}/D_{t+1})+1}{P_t/D_t}\frac{D_{t+1}}{D_t}$$

which can be stated as follows, in the case of no disaster: $R_{t+1}^{G,i} = \frac{(P_{t+1}/D_{t+1})+1}{P_t/D_t} \exp\left(g_D + \Delta \log D_{t+1}^{i,G}\right)$. In case of a disaster, the return is given by: $R_{t+1}^i = R_{t+1}^{G,i}F_{t+1}^i$, which only reflects the effect of the recovery rate on the dividend growth realization. Using the definition of resilience $p_t E_t[M_{t+1}^D F^i - 1]$, this yields the following expression:

$$\left(1+H_t^i\right) E_t[M_{t+1}^G R_{t+1}^{G,i}] = 1.$$

Decomposing this expectation into a covariance term and a cross-product produces:

$$E_t[M_{t+1}^G]E_t[R_{t+1}^i] + cov_t[M_{t+1}^G, R_{t+1}^{G,i}] = \left(1+H_t^i\right)^{-1}.$$

Given the linear specification of the stochastic discount factor, this equation can in turn be written in the conditional beta representation:

$$E_t[R_{t+1}^{G,i}] = E_t[M_{t+1}^G]^{-1}\left(1+H_t^i\right)^{-1} - \frac{cov_t[M_{t+1}^G, R_{t+1}^{G,i}]}{var_t[M_{t+1}^G]}\frac{var_t[M_{t+1}^G]}{E_t[M_{t+1}^G]},$$

or equivalently: $E_t[R_{t+1}^i] - \boldsymbol{\beta_t^i \lambda_t} = R_t\left(1+H_t^i\right)^{-1}$, where β_t^i is the vector of multiple regression coefficients in regression of returns on the factors and λ_t is the vector of risk prices, and $R_t = E_t[M_{t+1}^G]^{-1}$. Note that the variation in the p/d ratios induced by the variation in the probability of a disaster does not co-vary with the normal risk factors–by assumption– and hence is not priced in the normal risk premium. In addition, we assume that the market price of Gaussian risk is constant $\boldsymbol{\lambda}$ and that the Gaussian factor betas $\boldsymbol{\beta_t^i}$ are constant. In that case, the expected return on asset i, conditional on no disaster realization, after adjusting for Gaussian risk exposure, becomes: $E_t[\widehat{R}_{t+1}^i] = exp(r_t - h_t^i)$, where $E_t[\widehat{R}_{t+1}^i] = E_t[R_{t+1}^{G,i}] - \boldsymbol{\beta^i \lambda}$, and r_t denotes $\log R_t$, and h_t^i denotes $\log(1+H_t^i)$.

2.9.2 Other explanations

Business cycle variation in common and idiosyncratic risk Finally, there are factors other than financial disasters that could explain the cyclicality in the size factor. Large idiosyncratic shocks can cause bank failures. If the volatility of these shocks increases more in recessions for small banks, that could explain some of our findings. Table 21 measures the standard deviation of normal-risk-adjusted returns at the portfolio level (Panel A) and at the bank level (Panel B). The first one measures the quantity of residual common risk. The second one measures the quantity of residual idiosyncratic risk. The portfolio-level measure in Panel A is the time series standard deviation of normal risk-adjusted returns, reported for NBER expansions and recessions separately. The bank-level measure in panel B is the average over time of the cross-sectional standard deviation within each portfolio of normal-risk-adjusted returns.

During recessions, the exposure of the largest banks to residual common risk increases from 14.2 to 21.6%. For the smallest banks, the increase is only 3 percentage points. As expected, smaller banks are much more exposed to idiosyncratic risk than large banks, but the amount of idiosyncratic risk exposure of small banks does not seem to increase very much during recessions. The standard deviation ranges from 38% for the smallest banks to 26% for the largest banks during recessions, and from 36% to 20% in the whole sample. However, the largest percentage point increase in volatility during recessions is noted for the largest banks: from 20% to 26%. For the smallest banks, the increase is less than two percentage points. There is no evidence to suggest that the cyclicality of the size factor is due to idiosyncratic banks risk.

Business cycle variation in cash flows We analyzed the data in the report for the first three quarters of 2001 which corresponds to the recession dates provided by NBER. During this period, small banks outperform large banks on almost all 13 performance parameters measured.

Table 21: Measuring residual risk exposure

Notes: This table presents the standard deviation of the residuals from the OLS regression of monthly excess returns of each size-sorted portfolio of commercial banks on Fama-French factors and bond factors. In panel A the row labeled Recession computes the (time series) standard deviation of the residuals during recession months and the row labeled Entire Sample computes the (time series) standard deviation for the entire sample. In Panel B we examine the cross-sectional standard deviation of the residuals of banks in each bin for each period t. Panel B reports the time-series average of the cross-sectional standard deviation for each bin. The row labeled Recession lists the standard deviation of the residuals during recession months and the row labeled Entire sample lists the standard deviation for the entire sample. The standard deviations have been annualized by multiplying by $\sqrt{12}$ and are expressed in percentages.

Panel A: Portfolios										
Period	1	2	3	4	5	6	7	8	9	10
Recession	15.77	14.39	12.80	12.43	13.76	13.46	15.77	14.79	18.11	21.13
Entire Sample	13.18	11.92	11.43	10.54	10.93	11.17	11.38	10.96	11.95	14.26
Panel B: Individual Banks										
Recession	38.40	30.94	32.45	28.86	30.33	27.61	27.48	28.05	26.01	25.54
Entire Sample	36.36	30.05	28.79	27.45	25.88	25.13	24.68	24.03	22.43	20.83

Small banks had a higher return-on-equity (14.00% versus 13.80%), a higher return-on-assets (1.15 times that of large banks), a lower loan-loss-charge, a higher net-interest-margin (4.34% versus 3.62%), and comparable cost-of-funds (approximately 3.75% for both). During this recession, 70% of small banks and 60% of large banks reported earnings gains.

In 2008, large banks are again unable to match the performance of small banks on most measures. For the first-half 2008, small banks' ROE is 1.5 times and yield-on-assets is 50 basis-point higher than corresponding values for large banks. 14.16% of the 558 small banks and 26.72% of the 114 large banks were unprofitable. Finally, 41.22% of small banks reported an earnings gain as compared to 24.14% of large banks.

For the full-year 2008, 28.70% of small banks and 40.35% of large banks reported losses. Small banks do have lower return-on-assets and ROE for the full year, but it is not obvious if this is due to a higher cash flow risk. During second-half 2008, small banks not only earned a higher yield on assets and a higher net interest margin, but also provisioned more conservatively for losses. The ratio of loan-loss provisions to assets increases to 1.93% for small banks by 4Q 2008 from 0.76% during 1Q 2008 but this ratio hardly changes for the largest banks.

2.9.3 Additional tables

Table 22: NBER reference cycle peaks and banking panics

Notes: The dates of the banking panics were taken from Gorton (1988, p. 223) and Wicker (1996, p.155). Months before peak and Months after peak indicate the number of months relative to the peak when the banking crisis occurs.

Peak	Trough	Panic	Months before peak	Months after peak
October 1873	March 1879	September 1873	1	
March 1882	May 1885	May 1884		17
July 1890	May 1891	November 1890		4
January 1893	June 1894	February 1893		1
December 1895	June 1897	October 1896		10
May 1907	June 1908	October 1907		5
January 1913	December 1914	August 1914		20
August 1929	March 1933	October-November 1930		19
		September-October 1931		
		February-March 1933		
July 1981	November 1982	February-July 1982		8
December 2007		September-December 2008		9

Table 23: Coefficients for the cross-sectional regression of annual returns on size as measured by market capitalization

Notes: Pooled regression. The dependent variable is the annual return for each individual bank in our sample. The independent variables are the market capitalization of the bank, the book to market value for the bank, the book value of the bank, and the leverage of the bank. All variables are at date t. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors were adjusted for heteroscedasticity and auto-correlation using Newey-West with 3 lags. Annual data. The sample is 1970-2005.

constant	9.85 **	-0.14
$\log Book$	-2.45***	0.00
$\log Marketcap$	2.76***	0.54**
$\frac{Book}{Marketcap}$	0.00	
Leverage	0.00	-0.01
$adj-R^2$	0.0038	0.0004

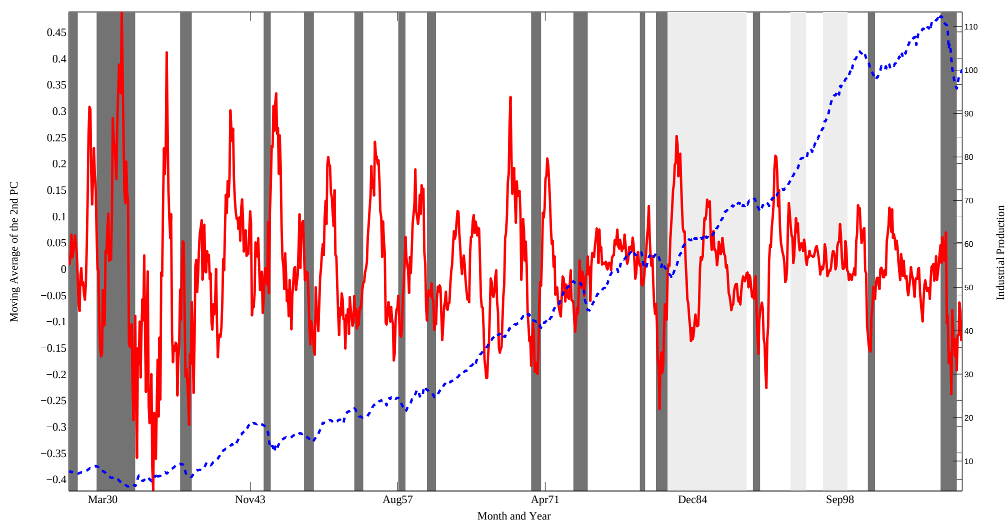

Figure 4: Size factor in normal risk-adjusted returns of all banks

The solid line plots the 12-month (backward looking) moving average (months $t-11$ through t) of the time-series of the weighted sum of the residuals from the OLS regression of monthly excess stock returns for each size-sorted portfolio of all financial firms on the Fama-French and bond risk factors. The weights are given by the second principal component and sum to 1. The dashed line represents the growth of index of industrial production. The dates are indicated on the x-axis. The left-axis references the moving average of the residuals and the right-axis references the index of industrial production.

Table 24: Announcement dates

Dates for the pre-crisis announcements are from O'Hara and Shaw (1990) and Kho et al. (2000). Dates for the crisis announcements are from the New York Fed Timeline of the Financial Crisis.

		+ All	+ large	- large
Panel A: Pre-Crisis Bailout Announcement Dates				
9/19/1984	Comptroller of Currency		x	
9/24/1998	LTCM		x	
9/15/1998	Brazilian Crisis		x	
10/08/1998	Brazilian Crisis		x	
11/13/1998	Brazilian Crisis		x	
11/14/1997	South Korean Crisis		x	
01/25/1995	Mexico Crisis			
Panel B: Crisis Announcement Dates				
2007/08/10	The FR provides liquidity	x		
2007/12/12	Term auction facility is announced	x		
2007/12/17	First Term auction takes place	x		
2007/12/21	Term auction facility is extended	x		
2008/03/11	Term securities lending facility is extended	x		
2008/03/14	Emergency lending from the Fed to Bear Stearns	x	x	
2008/03/17	Bear Stearns is bought for $2 per share			x
2008/03/17	Primary dealer credit facility is extended **delayed by a day*	x	x	
2008/05/02	TSLF collateral eligibility is expanded	x		
2008/07/15	Paulson requests govnmt funds for Fannie Mae and Freddie Mac	x	x	
2008/07/30	84-day TAF auctions are introduced	x		
2008/09/15	Lehman files for bankruptcy			x
2008/09/29	House votes down bailout plan			x
2008/10/03	Revised plan passes House	x		
2008/10/06	TALF increased to $900 billion	x		
2008/10/14	Treasury announces $250 billion capital injection			
2008/11/7	Bush Speech			x
2008/11/13	TARP not used for buying troubled assets from banks			x
2008/11/25	Term Asset-Backed Securities Loan Facility (TALF)	x		
2009/01/16	Treasury/ Federal Reserve and the FDIC Provide Assistance to Bank of America	x	x	
2009/02/10	The FRB expands TALF to as much as $1 trillion	x		
2009/03/18	The FRB purchases up to $300 billion of longer-term Treasury securities	x		

3 Chapter 3: The Relationship between Credit Growth and the Expected Returns of Bank Stocks

3.1 Introduction

A large literature in financial economics has established that aggregate bank credit level is highly pro-cyclical. Several papers have also analyzed the impact of variation in credit level on borrower firms' valuation and output. Given that banks' primary business is to produce credit, theory suggests that time-variation in the aggregate bank credit level should also have a first order effect on the valuation of banks. Yet, no one has documented such a relationship. While a few studies focus on exogenous shocks to banks to understand the connection between aggregate bank credit level and borrower firms' output, these isolated examples do not have much to say about the effect of credit level variation over the business cycle on banks.

In this paper, I study the empirical linkage between aggregate bank credit level and the expected returns of bank stocks. I estimate aggregate bank credit level by measuring aggregate bank credit growth (henceforth credit growth), where credit growth is defined using the monthly data on the assets and liabilities of all commercial banks in the U.S. issued by the Board of Governors of the Federal Reserve.

A key result is that credit growth and the expected returns of bank stocks are negatively correlated. A 1% increase in credit growth implies that excess returns of bank stocks over the next one year are lower by nearly 3%. Unlike most other forecasting relationships, credit growth tracks bank stock returns over the business cycle. The predictive power of credit growth for bank stock returns is economically large. The annual adjusted-R^2 of this regression is nearly 14% and it peaks at nearly 21% over 35 months. Over 1960 - 2009, the standard deviation of predicted returns is

8.37% and the unconditional equity premium of bank stocks is 9.67%. Hence, the expected return of bank stocks vary as much as its unconditional mean.

This effect is robust to the exclusion of data from the crisis years and to the inclusion of several popular forecasting variables used in the literature, such as lagged returns, dividend yield, term spread, default spread, size of the credit market, and the consumption-wealth ratio. Credit growth does not predict stock returns of any other asset class. It also does not predict future cash flows of bank stocks as measured by dividend growth rates. However, it does predict returns of investment banks and of bank-dependent firms.

I argue that this predictive variation in bank stock returns reflects the representative agent's rational response to a small time-varying probability of a tail event. A straightforward extension of the Rietz (1988) and Barro (2006) disaster framework, with a representative bank, produces the exact same negative correlation between credit growth and the expected returns of bank stocks. In the model, realization of a tail event results in a large loss of cash flows from projects funded by bank loans. The tail event may not impact other projects in the economy. Examples of such events (in the sample) are the Less Developed Country Debt crisis of 1982, the Mexico crisis of 1994, the East Asian crisis of 1997, and the Long-Term-Capital-Management crisis of 1998. Each of these events resulted in a large loss of cash flows from projects funded by bank loans and a significant drop in the profitability and valuation of banks. However, there was no measurable effect on the performance of other projects in the economy. These crises were not accompanied by a recession, and other important asset markets such as the stock and housing markets, were relatively unaffected[36].

Bank management is very sensitive to changes in the probability of a tail event. This high

[36] One implication of this hypothesis is that banks actively fund projects with higher exposure tail risk. I return to this question in section 3.3 below.

sensitivity arises from higher leverage, shorter debt maturity structure, and lower fraction of tangible assets that characterize the balance sheet of a typical bank. In concert, these characteristics increase the likelihood that a bank will enter distress upon the realization of a tail event. Hence, as the probability of a tail event increases, projects with lower expected cash flows are rejected by the bank, effectively raising the discount rate used by the bank to evaluate projects. This in turn contracts the supply of credit.

Simultaneously, the discount rate used by the bank's customers (the project manager) to evaluate projects also increases in the probability of a tail event. In fact, many projects with low expected cash flows that would customarily be taken to the bank for evaluation may be rejected at the outset by the project manager herself, thereby contracting the demand for credit. My mechanism does not require that I distinguish between credit supply and demand contraction, only that both credit supply and demand be negatively correlated with the probability of a tail event - a reasonable assumption. The actual fall in credit level attributed to supply or demand contraction may differ in each business cycle and may depend on the financial condition of the bank, the balance sheet strength of the project manager, and the exact nature of the tail event.

The standard disaster-risk asset pricing framework also implies that the expected returns required by the average investor to hold bank stocks increases in the probability of a tail event. This drives the observed negative correlation between credit growth and the expected returns of bank stocks. The disaster-risk framework also explains the fact that credit growth predicts the excess returns of investment banks (financial trading firms). This is because tail events that impact cash flows of bank-funded projects may also affect cash flows of projects funded by other intermediaries. Further, like banks, financial trading firms employ high leverage, rely on short-term debt, and do not own substantial tangible assets. An increase in the probability of a tail event should also increase the expected return of any direct equity claim on bank-funded projects and this explains the negative correlation between credit growth and expected returns of bank-dependent firms.

Consistent with this hypothesis, I show that the predictive power, as measured by the absolute magnitude of the coefficient on credit growth and the adjusted-R^2 at the the 1-year horizon, depends systematically on variables that regulate exposure to tail risk. Predictive power decreases monotonically in size, as measured by market capitalization, and increases in leverage and the proportion of short-term debt employed by the bank. This is because small banks, banks with more leverage, or more short-term debt are more exposed to tail risk. Here, I quantify higher exposure to tail risk by the slope coefficient in a regression of bank stock returns on changes in the implied volatility of the index options on the S&P500 (VIX) during economic expansions and recessions. In recessions, the slope coefficient of small banks increases by nearly 86% as compared to the slope coefficient of small industrial firms, which increases by only 4%.

Alternatively, one may attribute the predictive variation in bank stock returns to investor overreaction, or bank management's rational response to sources of variation in expected returns other than tail risk. Investor overreaction can explain my results if optimistic investors first overestimate the impact of new loans on future bank cash flows and drive up the current price of bank stocks (higher initial returns). Subsequently, when investors correct their beliefs, future bank stock prices fall (lower future returns). Arguably, investors should learn and not make such systematic errors over time. I find that the negative correlation between credit growth and expected returns of bank stocks increases over time. Over 1990 - 2009, a 1% increase in credit growth predicts that excess returns of bank stocks will be lower by 4.31% over the next one year. The adjusted-R^2 is now nearly 20%. While not conclusive, this argues against investor overreaction.

If bank management is responding to sources of variation in expected returns other than tail risk, then credit growth should be correlated either with the loadings of bank stock returns on standard risk factors, or with changes in aggregate risk-premium, or both. Credit growth is not significantly correlated with 3-year or 5-year rolling betas of bank stock returns on equity and bond market risk factors. If credit growth is correlated with changes in aggregate risk-premium, it should also predict returns for other assets. I find that credit growth does not significantly predict returns of treasury bonds, investment-grade corporate bonds, any other industry index, an index of non-financial stocks, or an index of non-financial stocks sorted by balance sheet characteristics. In all these cases, the small predictive power of credit growth, if any, arises from its correlation with business cycle variables, which are known to predict stock and bond market returns over the long horizon. The coefficient on credit growth is economically and statistically insignificant once these other business-cycle variables are directly included in the forecasting regression for these other assets.

Finally, it is plausible that when the likelihood of a tail event increases, banks with the highest exposure to such risk should contract credit supply the most. Consequently they also experience the largest increase in expected returns[37]. A panel regression confirms that a one 1% increase in the quarterly credit growth rate at the individual bank level implies a 10.91% (annualized) increase in contemporaneous excess returns and a 4.34% (annualized) decrease in future excess returns.

Historically, the probability of a tail event increases in a recession, therefore this mechanism explains the observed correlation between variation in aggregate bank credit level and business conditions. Economists have put forth a number of explanations for this stylized fact regarding bank credit. However, most explanations rely on market frictions and the supporting empirical evidence has been less than convincing. My explanation does not invoke any market friction, fits within the framework of a standard neoclassical asset pricing model, and provides a clear testable empirical implication. My empirical tests rely on straightforward predictive regressions standard

[37] Ivashina and Scharfstein (2009) show that banks with more short-term debt cut credit the most during the Credit Crisis of 2007.

in much of asset pricing literature. In this sense, the results in this paper are analogous to the documented ability of dividend-yields to predict market returns due to time-variation in expected returns.

To my knowledge, this is the first paper that empirically analyzes the effect of variation in aggregate bank credit level on the valuation of banks. This variation should also impact the bank's bond investors. I focus on bank stock returns since widespread market data on bank bond returns is simply not readily available. The panel regression results in this paper provide one of the few empirical tests of the impact of tail-risk in the cross-section. Usually, a stock's exposure to tail risk is not readily measurable. In this case, actions by banks themselves indicate their exposure to tail events.

This paper builds on three main strands of the literature. First, a large literature beginning with Sprague (1910), Mill (1965), and Wojnilower (1980) has shown that bank credit level varies with business conditions. Several economists such as Bernanke and Gertler (1987), Rajan (1994), Kiyotaki and Moore (1997) among others present rational explanations for this. However, most empirical work focuses on the impact of this variation on borrower firms' valuation and output. A non-exhaustive list includes papers by Kashyap, Stein and Wilcox (1993), Peek and Rosengren (2000), Leary (2009), and Chava and Purnanandam (2011).

Second, Campbell and Shiller (1988), Fama and French (1989), Cochrane and Piazzesi (2005), Philippon (2009), among others show that expected returns vary over time. There is ample empirical evidence of time-varying expected returns in the market for common stocks, government bonds, currencies, real estate, and even commodities. While time-variation in expected returns may reflect the rational response of agents to time-variation in real risk, which real macroeconomic risks vary is still an interesting and open question. One solution is to observe a firm's investment and production decisions and study its link to expected returns to infer which real risk varies.

Such an exercise has been attempted for nonfinancial firms by Jermann (1998), Tallarini. (2000), and Gourio (2009). In this paper, I take the first step towards extending such an analysis to the cross-section, and examining banks in particular.

Finally, this paper extends the disaster framework developed in Rietz (1988), Barro (2006), Wachter (2008), and Gabaix (2011) to financial intermediaries. Gandhi and Lustig (2010) were the first to apply the disaster framework to explain size anomalies in bank stock returns and link it to the implicit government guarantee provided to large banks. In this paper, I use this framework to analyze the empirical linkage between bank credit level and its expected returns and derive testable predictions.

The rest of the paper is organized as follows: I describe the data and present summary statistics in section 3.2; Section 3.3 presents key empirical results; In section 3.4, I present a simple extension of the standard disaster asset pricing model; Section 3.5 concludes.

3.2 Data and summary statistics

In this section, I first describe the data and present summary statistics for bank stock returns. I then describe how I construct the time-series for credit growth for all banks in the U.S. and present its statistical properties.

3.2.1 Bank stock returns

To assess the relationship between credit growth and bank stock returns, I form an index of all publicly listed banks in the U.S. In section 3.3, I also test if credit growth affects stocks returns of investment banks. For this, I require an index of all publicly listed investment banks (financial trading firms).

I collect data on market capitalization and returns over 1960 - 2009 from the Center for Research

Table 25: Stock return series

Notes: This table presents a brief description of each type of financial intermediary. Column 1 indicates the mnemonic used to reference each type. The industry definitions are from Kenneth French's web-site and are presented in column 3. Column 4 describes the kind of business each type of financial intermediary is engaged in.

Mnemonic	Type	SIC code	Description
BN	Banks	6000 - 6199	Deposit banking, related functions, and fiduciary services. Also includes firms that extend credit but do not provide deposit banking services.
FT	Financial trading	6200 - 6299 & 6700 - 6799	Trade securities. Also includes exchanges, clearinghouses, and other allied services.

on Security Prices (CRSP) for banks and financial trading firms. In CRSP, banks are identified by a Standard Industrial Classification (SIC) code between 6000 - 6199. Financial trading firms are identified by an SIC code between 6200 - 6299 and 6700 - 6799[38]. Henceforth, I refer to these 2 types of intermediaries by the mnemonics BN and FT respectively. Table 25 presents a brief description of the intermediaries.

I compute a value-weighted index for each kind of financial intermediary. Table 26 presents the summary statistics. The first panel excludes the data for the crisis years (2006 - 2009) and the second panel shows the results over the full sample (1960 - 2009). The first row in each panel presents the results for the BN index. The table lists the monthly mean, standard deviation, minimum, median, and maximum return expressed in percentages. The last column presents the

[38]These definitions are from Ken French's website. Source: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 26: Summary statistics for financial intermediary index returns

Notes: This table shows the summary statistics for returns of the value-weighted index for each type of financial intermediary. The first and second panel present results for 1960 - 2005 and 1960 - 2009 respectively. Column 1 indicates the type of financial intermediary. Column 2 - 6 present the mean, standard deviation, minimum, median, and the maximum return. Column 7 lists the average number of firms in any given month for which returns are available in CRSP. All statistics are monthly and are expressed in percentages. Monthly data, 1960 - 2009.

Index	Mean	σ	Min	Median	Max	N
			1960 - 2005			
BN	1.54	5.74	-23.18	1.52	26.99	269
FT	1.61	5.05	-20.73	1.69	19.59	474
$CRSP-VW$	0.92	4.39	-22.54	1.25	16.56	5293
			1960 - 2009			
BN	1.43	6.08	-23.18	1.51	26.99	292
FT	1.54	5.28	-21.16	1.69	23.48	486
$CRSP-VW$	0.86	4.48	-22.54	1.25	16.56	5388

average number of firms for each type of intermediary for which returns are available in CRSP in any given month. For reference, I also list the statistics for the CRSP value-weighted index. As expected, returns of financial firms have a higher mean and variance as compared to the CRSP value-weighted index. The annual mean and standard deviation for bank stock returns is 17.16% and 21.06 respectively.

Later, for robustness tests, I also require size-sorted portfolio of banks and financial trading firms. I compute the value-weighted returns of 5 size-sorted portfolios for each type of intermediary by employing the standard portfolio formation strategy of Fama and French (1993). In December of each year, I allocate all firms for each type of financial intermediary to 5 portfolios based on market capitalization. I calculate the value-weighted return of each portfolio for each month over the next year. This results in a monthly time-series from 1960 - 2009 for each size-sorted portfolio.

Table 27 shows the summary statistics. The first and second panels show the results for BN and FT respectively. In each panel, the first column indicates the type of intermediary. In column 2, portfolio '1' refers to the smallest size-sorted portfolio by market capitalization. Columns 3 - 7 of the table show the summary statistics for 1960 - 2005 and columns 8 - 12 show the statistics for the full sample. The statistics are monthly and are expressed in percentages. Since the properties of size-sorted portfolios of financial firms are well-established, I do not discuss them in detail[39].

CRSP data is available from 1926, however, my analysis begins only in 1960. This start date reflects the fact that there are not enough publicly listed banks for which data is available in CRSP to allocate to 5 size-sorted portfolios prior to this date. I check that my results for the BN index are robust to the start date. However, for consistency, all tables in section 3.3 report results starting in 1960. I next describe my estimate of credit growth.

3.2.2 Aggregate bank credit growth

To estimate aggregate bank credit level for all publicly listed commercial banks in the U.S., I measure aggregate bank credit growth (henceforth credit growth or the variable g_t^c). I estimate credit growth by using data from the monthly report on the 'Assets and Liabilities of Commercial Banks in the U.S.' (statistical release $H.8$) issued by the Board of Governors of the Federal Reserve System (FED). Data from the release is available at `http://www.federalreserve.gov/releases/h8/current/default.htm`.

I use non-seasonally-adjusted data for *bank credit* (item code H8/H8/B1001NCBA, column 1 of the $H.8$ release) to compute g_t^c. Bank credit is the total credit extended by all commercial banks

[39]See Gandhi and Lustig (2010) for a detailed analysis of size-sorted portfolios of financial firms.

Table 27: Summary statistics for financial intermediary size-sorted portfolio returns

Notes: This table shows the summary statistics for returns of size-sorted portfolios for each type of financial intermediary. Columns 3 - 8 present results for 1960 - 2005 and columns 9 - 14 present results for 1960 - 2009. Column 1 indicates the type of financial intermediary. In column 2, '1' refers to the smallest portfolio by market capitalization. Columns 3 - 7 and 9 - 13 present the mean, standard deviation, minimum, median, and the maximum return for each size-sorted portfolio. Columns 8 and 14 indicate the average number of firms in each size-sorted portfolio for which returns are available in CRSP. All statistics are monthly and are expressed in percentages. Monthly data, 1960 - 2009.

Index	Portfolio	Mean	σ	Min	Median	Max	N	Mean	σ	Min	Median	Max	N
		1960 - 2005						1960 - 2009					
	1	1.54	6.15	-17.98	1.00	41.31	54	1.31	6.11	-17.98	0.82	41.31	58
	2	1.17	5.32	-19.20	0.98	37.70	54	0.96	5.30	-19.20	0.84	37.70	59
BN	3	1.15	4.99	-19.30	0.99	22.84	54	0.95	5.04	-19.30	0.74	22.84	59
	4	1.10	5.48	-20.32	1.21	24.99	54	0.93	5.75	-24.25	1.12	24.99	59
	5	1.15	5.70	-23.76	1.07	29.33	55	1.01	6.11	-23.91	0.98	29.33	59
		1960 - 2005						1960 - 2009					
	1	1.26	5.07	-19.67	0.96	34.29	94	1.21	5.07	-19.67	0.96	34.29	97
	2	1.14	5.00	-21.41	1.13	34.11	95	1.09	5.04	-21.41	1.11	34.11	97
FT	3	1.04	4.43	-18.05	1.04	26.96	95	0.98	4.49	-18.05	1.04	26.96	97
	4	1.07	4.14	-20.76	1.19	21.92	95	0.99	4.32	-20.76	1.14	21.92	97
	5	1.09	5.17	-21.60	1.11	17.40	95	0.98	5.45	-23.51	1.13	22.43	98

in the U.S. to non-financial entities. It includes commercial and industrial loans, real estate loans, and consumer loans, but excludes interbank loans, repurchase agreements, Federal Funds holdings, derivative positions, and unearned income on loans. Table 47 in the appendix provides details of the loan composition. On average, traditional loans (commercial, real estate, and consumer) comprise nearly 73% of bank credit in any given month, and this ratio never falls below 60%.

Credit growth is the year-on-year growth rate of bank credit for each month from 1960 - 2009. Further, I assume that data for g_t^c is unavailable to investors for another 3 months. This is because data for the $H.8$ report is collected from a sample of 875 banks on a voluntary basis. With voluntary participation, it is plausible that a weak bank may choose not to file a report, rendering the $H.8$ data inaccurate. In order to guard against this, the FED benchmarks the $H.8$ data against the mandatory quarterly 'Report of Condition and Income' (hereafter the Call Report) required to be filed accurately by all FDIC-insured banks. This verification also ensures that the data submitted by participating banks is accurate. Since this benchmarking occurs quarterly, the 3-month lag addresses any concerns regarding the small sample size of banks and the voluntary nature of the $H.8$ report. Again, I confirm that my results are robust to variation in the number of lag months.

I focus on bank credit and not any of its subcomponents, such as commercial and industrial, real estate, or consumer loans, because by definition bank credit is the appropriate measure of aggregate credit extended by all banks in the BN index. A valid question to ask is if my analysis can be extended to each subcomponent of bank credit. Unfortunately, this is not possible using this data because the FED periodically modifies the definitions of data-items in the $H.8$ release. These mandated changes in definitions necessitate moving loan items from one category to another, rendering the choice of any subcomponent problematic. This may also lead to the selection of a time-series for a subcomponent for which the inter-temporal definition is simply inconsistent[40].

[40] Kashyap and Stein (2000) also document the issue of inconsistent time-series for the Call Report Data

Table 28: Summary statistics for credit growth

Notes: This table shows the summary statistics for credit growth for all banks in the U.S. Column 1 indicates the years over which the statistics are computed. Column 2 - 6 present the mean, standard deviation, minimum, median, and the maximum values respectively. All statistics are monthly and are expressed in percentages. Monthly data, 1960 - 2009.

Years	Mean	σ	Min	Median	Max
1960 – 2005	8.22	3.08	1.23	8.30	17.39
1960 – 2009	8.21	3.08	-0.99	8.35	17.39
1960 – 1970	7.44	2.69	1.23	8.30	11.26
1970 – 1980	10.27	4.08	1.57	11.64	17.39
1980 – 1990	8.74	1.73	5.68	8.75	13.77
1990 – 2000	6.26	2.04	2.61	5.88	11.32
2000 – 2009	7.82	2.86	-0.99	8.75	12.36

Is bank credit an appropriate proxy for the total loans issued by all banks in the BN index? The answer is yes, even though over the full sample, the maximum number of publicly listed banks for which returns data is available in CRSP is 818 compared to the nearly 6,911 FDIC-insured banks that operate in the U.S. in September 2010. Thus, only a small fraction of commercial banks that operate in the U.S. are publicly listed. Data from H.8 is still an appropriate proxy as the largest 508 banks, by asset size, control nearly 90% of all bank assets ($10,916.20 B of the total $12,130.30 B bank assets in the U.S)[41]. Thus, if the small banks that are not publicly listed are very different from those that are, my results, only for small banks, need to be qualified.

Bank balance sheet data is also available from COMPUSTAT or from the Call Report. I use H.8 data because it is available at a higher frequency - monthly - and does not have any missing

to which the H.8 release is bench-marked.

[41] See http://www2.fdic.gov/qbp/2010sep/qbp.pdf.

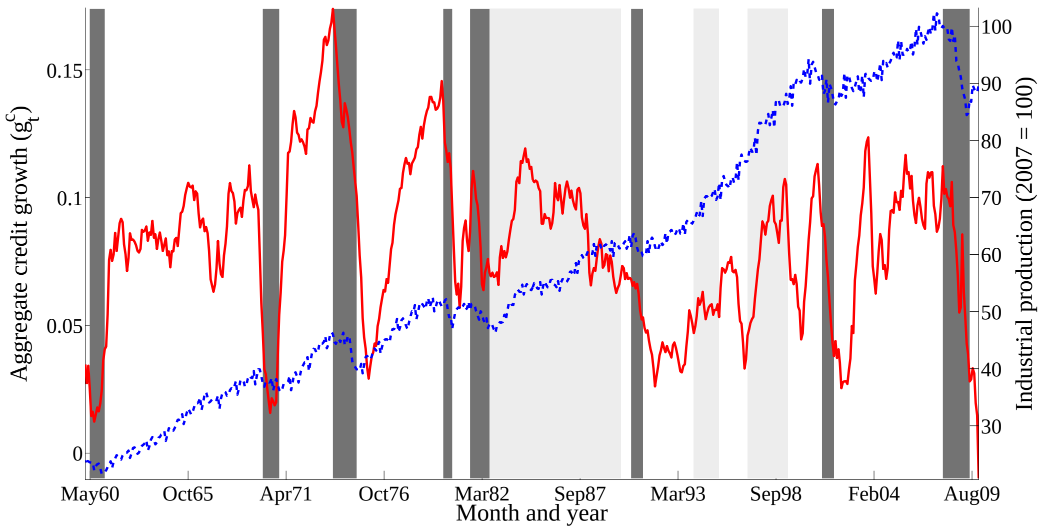

Figure 5: Time-series plot for credit growth

The solid line plots credit growth for all banks in the U.S. The dashed line represents the level of the index of industrial production. The dates are indicated on the x-axis. The left-axis references aggregate bank g_t^c and the right-axis references the index of industrial production. The dark shaded regions represent NBER recessions and the three light shaded regions represent the Less-Developed-Country debt crisis of 1982, the Mexico Peso crisis of 1994, and the Long-Term-Capital-Management crisis of 1998 respectively. Monthly data, 1960 - 2009.

observations, a problem that plagues these other sources. In section 3.3, I use these alternative data sources for robustness tests.

Table 28 presents the mean, median, standard deviation, minimum, and maximum values of g_t^c. All results are monthly and are expressed in percentages. Over the full sample, the average value of g_t^c is 8.21% and its standard deviation is nearly 3%. Dickey-Fuller tests and augmented Dickey-Fuller tests with lags of 4, 8, 10, and 12, and an inclusion of a constant or a time-trend, always reject the unit-root hypothesis that g_t^c is non-stationary at a 10% or higher confidence level.

Figure 5 plots the time-series of g_t^c. Here, the solid line represents g_t^c and the dashed line represents the index of industrial production. The dark regions in the graph represent NBER recessions and the three light shaded regions represent the three crises related to the Less-Developed-

Country debt crisis of 1982, the Mexico Peso crisis of 1994, and the Long-Term-Capital-Management crisis of 1998 respectively. The NBER recession dates are published by the NBER Business Cycle Dating Committee and are available at http://www.nber.org/cycles.html. Kho, Lee and Stulz (2000) provide the dates for the Mexico and the LTCM crisis. The dates for the Less-Developed-Country debt crisis are from FDIC.

From the figure it is clear that credit growth is extremely sensitive to recessions and is strongly correlated with changes in the index of industrial production. To further quantify this sensitivity, I regress g_t^c on a set of dummy variable, one for each month the economy is in a recession. Table 29 presents the results. The dependent variable is g_t^c and the independent variable is a $T \times 12$ matrix of dummy variables. Dummy variable D_1 equals 1 if a month is the 1st month in an NBER dated recession and zero otherwise. As the average length of a recession in the post-war period is 12 months, I restrict the number of dummy variables to 12. The unconditional mean of g_t^c over the full sample is given by α. During the initial months of a recession the economic and statistical significance of the loadings on the dummy variables is small. This may be on account of the fact that initially banks face a run on committed credit lines. However, as the time spent in an economic contraction increases, g_t^c falls, so that by the 8^{th} month of a recession g_t^c falls to nearly 6.18%.

Table 30 presents the correlation between g_t^c and several business cycle variables. In table 30, CPI represents the year-on-year change in the consumer price index, IPG the year-on-year growth rate of industrial production, TS the term spread that equals the difference in the yields of the 10-year Treasury bond and the 3-month Treasury bill, and DS the default spread that equals the difference in the yields of BAA-rated and AAA-rated U.S. industrial corporate bonds. Data is from Global Financial Data (GFD)[42].

[42] See http://globalfinancialdata.com. On GFD consumer price index is identified by $CPUSAM$, industrial production by $USINDPROM$, 10-year Treasury bond yield by $IGUSA10D$, 3-month Treasury

Table 29: Loading on recession dummies for credit growth

Notes: This table shows the estimated coefficients for the regression:

$$g_t^c = \alpha + \sum_{i=1}^{i=12} \beta^i D_t^i + \epsilon_t^i$$

Here D^i is a dummy variable that takes a value 1 for the i^{th} month in an NBER dated recession and zero otherwise. g_t^c is credit growth for all banks in the U.S. at time t. Coefficients are multiplied by 100 and are expressed in percentages. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. Monthly data, 1960 - 2009.

α	β^1	β^2	β^3	β^4	β^5	β^6	β^7	β^8	β^9	β^{10}	β^{11}	β^{12}
8.30***	0.95	0.40	0.33	-0.18	-0.41	-0.82	-1.22	-2.12*	-2.24*	-1.63	-1.30	-0.57

As expected, g_t^c has a statistically significant correlation with CPI ($p < 0.01$), IPG ($p < 0.01$), and TS ($p < 0.01$). The numbers in parenthesis are the p-values. While the correlation with CPI and IPG is positive, the correlation with TS is negative. The positive correlation with IPG, which is pro-cyclical, and the negative correlation with TS, which is counter-cyclical, confirms that g_t^c is indeed pro-cyclical. All other correlations in table 30 are statistically insignificant and none of the correlations have an economically large magnitude. Having described my measure of g_t^c and having demonstrated that it is indeed highly pro-cyclical, I turn to my empirical results.

3.3 Empirical results

In this section, I test if there exists a relationship between g_t^c and the expected returns of an index of all publicly listed banks in the U.S. The advantage of carrying out an analysis at the index level is that it dampens any idiosyncratic noise and makes it easier to identify the empirical relationships.

bill yield by $ITUSA3D$, AAA rated corporate bonds yield by $MOCAAAD$, and BAA rated corporate bonds yield by $MOCBAAD$.

Table 30: Correlation matrix for credit growth

Notes: This table shows the correlation of credit growth for all banks in the U.S. with business cycle variables. CPI is the year-on-year change in the consumer price index, IPG is the year-on-year growth rate of industrial production, TS is the term spread that equals the difference in the yields of the 10-year Treasury bond and the the 3-month Treasury bill, DS is the default spread that equals the difference in the yields of BAA rated corporate bonds and AAA rated corporate bonds. Monthly data, 1960 - 2009.

Series	g_t^c	CPI	IPG	TS	DS
g_t^c	1.00				
CPI	0.16***	1.00			
IPG	0.28***	-0.22***	1.00		
TS	-0.40***	-0.08**	-0.14***	1.00	
DS	-0.03	0.30***	-0.56***	0.30***	1.00

3.3.1 Is there a relationship between credit growth and bank stock returns?

I begin by plotting the cross-autocorrelation between the stock returns of the BN index and g_t^c for various lags. The first panel in figure 6 shows the results for nominal returns and the second panel shows the results for the real returns of the BN index. Lag $= 0$ refers to the contemporaneous cross-autocorrelation and Lag $= 5$ refers to the correlation between returns at time $t + 5$ and g_t^c at time t. The height of the bars represents the magnitude of the cross-autocorrelation and the dashed horizontal lines represent significance at the 5% level.

The leading cross-autocorrelation between returns of the BN index and g_t^c is positive, switches sign and the subsequent correlations are reliably negative. This suggests that g_t^c and expected returns of bank stocks are negatively correlated. That is, if g_t^c increases at time t, expected returns of bank stocks decrease. If expected returns at time t fall, prices at time t increase or time t realized returns are high. However, future realized returns are lower as expected and required by

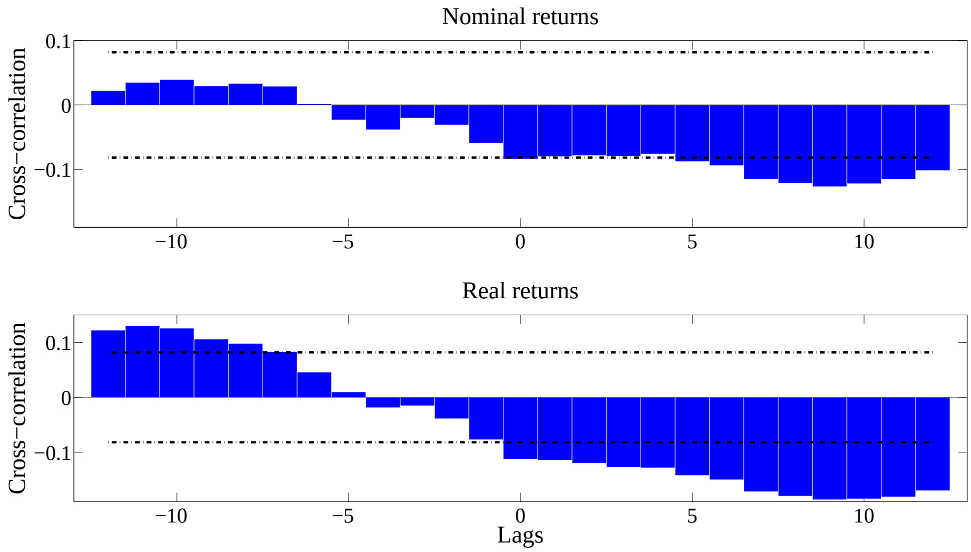

Figure 6: Cross-correlation function

Each panel plots the cross-correlation function between the stock returns of the BN index and credit growth for all banks in the U.S. for various lags. The first panel plots the cross-correlation function between the nominal excess stock returns of the BN index and g_t^c. The second panel plots the cross-correlation function between the real stock returns of the BN index and g_t^c. The height of the bars represents the magnitude of the cross-correlation and the dashed horizontal lines represent significance at the 5% level. In each panel, Lag $= 0$ plots the contemporaneous cross-correlation and Lag $= 5$ refers to the correlation between returns at time $t+5$ and g_t^c at time t.

the market.

The negative correlation between g_t^c and the expected returns of bank stocks is confirmed in table 31 that shows the results of a forecasting regression that uses g_t^c as a predictive variable. The exact specification for the regression is:

$$\sum_{j=1}^{j=H} \log(1 + r_{BN,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \alpha_H + \beta_H^{g^c} \log(1 + g_t^c) + \epsilon_{t+H} \tag{22}$$

Here, the dependent variable is the H-period log excess return of the BN index and is computed as $\log(1+r_{BN,t+1})-\log(1+r_{f,t+1})+...+\log(1+r_{BN,t+H})-\log(1+r_{f,t+H})$. The independent variable is $\log(1+g_t^c)$. Table 31 shows the values of the estimated coefficients, statistical significance, and the adjusted-R^2 over horizons spanning 1 - 12 months. The horizon value is indicated by H. The first row shows the estimated intercept, the second row presents the estimated β on g_t^c, and the third row presents the value of the adjusted-R^2 for each horizon. Statistical significance of the coefficients is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, autocorrelation, and overlapping data using Hansen-Hodrick with 12 lags.

Over a 12-month horizon, a 1% increase in g_t^c implies a 2.94% fall in excess returns of the BN index. The coefficients on g_t^c are statistically different from zero at the 10% level or better at all horizons. Credit growth explains nearly 14% of the variation in excess returns of the BN index over a 12-month horizon.The value of the adjusted-R^2 peaks at 20.98% at the 35-month horizon (not reported in the table).

This predictive relationship between credit growth and bank stock returns is economically significant for several reasons. First, unlike other forecasting relationships, g_t^c tracks excess returns of the BN index over the business cycle rather than over the very long-run. Second, the predictive power of g_t^c for returns of bank stocks is large compared to that of dividend-yield for returns of the value-weighted stock market index. Cochrane (2008) shows that over 1926 - 2004, a 1% increase in dividend yield implies that returns of the value-weighted stock market index over the next year are higher by 3.83%, with an adjusted-R2 of 7.4%. Third, over 1960 - 2009, the standard deviation of predicted returns is 8.37% and the unconditional equity premium of bank stocks in this sample is 9.67%. Hence, the expected return of bank stocks vary as much as its unconditional mean.

Finally, table 32 documents the results of a similar regression for non-financial firms. Non-financial firms generally do not issue credit. However, if I interpret credit as the total investment by banks, I can compare the predictive power of credit growth for bank stock returns to the predictive power of aggregate domestic corporate sector investment growth for stock returns of

Table 31: Forecasting regression for excess returns of banks

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + r_{BN,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \alpha_H + \beta_H^{g^c} \log(1 + g_t^c) + \epsilon_{t+H}$$

Here $r_{BN,t+j}$ is the return of the BN index at time $t + j$, $r_{f,t+j}$ is the return of the risk-free asset at time $t + j$, and g_t^c is credit growth for all banks in the U.S. at time t. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 12 lags. Monthly data, 1960 - 2009.

$H =$	1	2	3	4	5	6	7	8	9	10	11	12
α	0.02***	0.05***	0.07***	0.10***	0.14***	0.17***	0.20***	0.23***	0.26***	0.28***	0.30***	0.33***
β^{g^c}	-0.18*	-0.40**	-0.63**	-0.91***	-1.22***	-1.52***	-1.80***	-2.08***	-2.34***	-2.55***	-2.74***	-2.94***
R^2-adj (%)	0.56	1.33	2.21	3.55	5.11	6.57	7.98	9.44	10.78	11.88	12.94	13.97

non-financial firms.

In the first panel of table 32, the dependent variable is the H-period log excess returns of an index of all non-financial stocks. To form this index I take returns for all firms for which data is available in CRSP, but exclude firms with an SIC code between 6000 - 6799. The predictive variable is g_t^i, the net quarterly year-on-year growth rate of gross corporate domestic investments. Data for gross domestic investments is from NIPA, table 5.1 Line 24. In the second panel, the dependent variable is the H-period log excess return of an index of each of the 39 industries other than financial firms for which data is available on Kenneth French's website[43]. The predictive variable is the net quarterly year-on-year growth rate of industry level investment as measured by the sum of capital expenditures and changes in inventory for all publicly listed firms within a given industry for which data is available in COMPUSTAT. I run a separate forecasting regression for each of the 39 industry indices and report the average statistics.

For the index of non-financial firms (panel I of table 32), the coefficient on g^i is negative and statistically significant at almost all horizons. However, the magnitude of the coefficient is fairly small as compared to the results in table 31. For the indices of other industries (panel II of table 32), the coefficient on investment growth is never statistically significant. Overall, the beta on investment growth for these other assets never exceeds 0.31 and the adjusted-R^2 never rises above 5.60%. Clearly, the relationship between credit growth and bank stock returns is economically significant, both in itself, and as compared to other similar forecasting relationships.

One should not interpret the results in table 32 as an absolute test of a link between expected returns and a firm's investment and production decisions. Instead it highlights the relative strength

[43]Data is actually available for 45 industries other than financial firms. However, to ensure that the results in table 32 are comparable to those for banks, I exclude all industries for which returns are not available from 1960.

Table 32: Forecasting regression for non-financial firms

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + r_{i,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \alpha_H + \beta_H^{g^i} \log(1 + g_t^i) + \epsilon_{t+H}^i$$

In the first panel of the dependent variable is the H-period log excess returns of an index of all non-financial stocks and the predictive variable is g_t^i, the net quarterly year-on-year growth rate of aggregate gross domestic corporate investments. In the second panel the dependent variable is the H-period log excess return of an index of each of the 39 industries other than financial firms for which data is available on Kenneth French's website. The predictive variable is the net quarterly year-on-year growth rate of industry level investments. I run a separate forecasting regression for each of the 39 industries and panel II reports the average statistics. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 12 lags. Quarterly data, 1960 - 2009.

$H =$	3	6	9	12
	Index of non-financial firms			
α	0.04***	0.07***	0.10***	0.13***
β^{g^i}	-0.14***	-0.26***	-0.31***	-0.22
R^2-adj (%)	3.33	5.60	4.96	1.70
	Other industries			
α	0.05***	0.10***	0.15***	0.19***
β^{g^i}	-0.03	-0.05	-0.08	-0.08
R^2-adj (%)	-0.37	0.37	0.87	1.62

of the relationship between expected returns and investment and production decisions for banks as compared to that for industrial firms. In the next section I test if this relationship is robust.

3.3.2 Are the results robust?

As a first robustness test, I check if this predictability is an artifact of the Credit Crisis of 2007. Table 33 shows the results for the forecasting regression, but excludes data for the crisis years (2006 - 2009). Dropping the data for the crisis years does not significantly effect the key result. As compared to the full sample, the predictive coefficient on g_t^c at the 1-year horizon is lower by only 0.29% (2.65% versus 2.94%) and the adjusted-R^2 at the 12-month horizon drops only slightly from 13.97% to 13.69%.

Since there is ample empirical evidence that returns of the stock market, government bonds, currencies, real estate, and even commodities are predictable by business cycle variables, I next check if g_t^c proxies for one of the variables. In table 34, besides g_t^c, the independent variables are the lagged excess return of the BN index ($\log(1+r_{BN,t})-\log(1+r_{f,t})$), the smoothed dividend-yield of the BN index ($\log D_t - \log P_t$), the term-spread ($y_{10,t} - y_{3,t}$), the log of the 1-month real rate ($\log(1 + r_{r,t})$), the change in the log 1-month nominal rate ($\Delta r_{n,t}$), the relative bill rate defined as the log of the 1-month nominal risk-free rate less its 12-month simple moving average ($r_{rel,t}$), the default-spread ($y_{BAA,t} - y_{AAA,t}$), the year-on-year monthly growth rate of industrial production ($\log(1 + IPG_t)$), and change in leverage (ΔLEV_t). All variables are measured at time t. The exact specification of the regression in table 34 is:

Table 33: Forecasting regression for excess returns of banks excluding crisis years

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + r_{BN,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \alpha_H + \beta_H^{g^c} \log(1 + g_t^c) + \epsilon_{t+H}$$

Here $r_{BN,t+j}$ is the return of the BN index at time $t+j$, $r_{f,t+j}$ is the return of the risk-free asset at time $t+j$, and g_t^c is the credit growth for all banks in the U.S. at time t. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 12 lags. Monthly data, 1960 - 2005.

$H =$	1	2	3	4	5	6	7	8	9	10	11	12
α	0.02***	0.05***	0.07***	0.10***	0.13***	0.16***	0.19***	0.22***	0.24***	0.27***	0.29***	0.32***
β^{g^c}	-0.15*	-0.35*	-0.57**	-0.82**	-1.07**	-1.33***	-1.59***	-1.84***	-2.07***	-2.29***	-2.48***	-2.65***
R^2-adj (%)	0.41	1.21	2.17	3.42	4.81	6.22	7.62	8.97	10.46	11.69	12.71	13.69

$$\sum_{j=1}^{j=H} \log(1 + r_{BN,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) =$$

$$\alpha_H + \beta_H^{g^c} \log(1 + g_t^c) + \beta_H^{LR}(\log(1 + r_{BN,t}) - \log(1 + r_{f,t}))$$

$$+\beta_H^{DP}(\log D_t - \log P_t) + \beta_H^{TS}(y_{10,t} - y_{3,t}) + \beta_H^{r} \log(1 + r_{r,t}) + \beta_H^{n}(\Delta r_{n,t})$$

$$+\beta_H^{rel}(r_{rel,t}) + \beta_H^{DS}(y_{BAA,t} - y_{AAA,t}) + \beta_H^{IPG}(\log(1 + IPG_t)) + \beta_H^{LEV}(\Delta LEV_t) + \epsilon_{t+H}^{i} \tag{23}$$

For clarity, table 34 shows only the results at the 12-month horizon ($H = 12$) over 1960 - 2009. The robustness test also goes through for other horizons ($H = 1, ..., 11$) and also over 1960 - 2005. The first column indicates the predictive variable and each of the remaining columns corresponds to a separate regression. In column 2, I only include g_t^c and the lagged excess return of the BN index as the predictive variables. In column 3, I only include g_t^c and the smoothed dividend-price ratio of the BN index as the predictive variables, and so on. The last column shows the results for the full regression specified in equation (23). The first row shows the estimated intercept and the second row presents the estimated coefficient on g_t^c for each regression. The remaining rows show the estimated coefficients for each of the other predictive variables. The last row presents the value for the adjusted-R^2.

Note that data for aggregate assets and liabilities of banks required to compute leverage is available only from 1973. To compute monthly values of leverage over 1960 - 1972, I use the quarterly data from the U.S. Flow of Funds. Using this data, I first compute the quarterly leverage for all banks in the U.S. over 1960 - 1972, and then use a linear interpolation to compute monthly leverage values.

Credit growth is not a proxy for any other known predictive variable. The magnitude of the predictive coefficients on g_t^c reported in table 34 is comparable to the univariate regression over the

Table 34: Forecasting regression for excess returns of banks including other predictive variables (monthly regressions)

Notes: This table shows the estimated coefficients for the forecasting regression for the monthly robustness tests. Here $r_{BN,t+j}$ is the return of the BN index at time $t+j$, $r_{f,t+j}$ is the return of the risk-free asset at time $t+j$, g_t^c is the credit growth for all banks in the U.S. at time t, LR_t is the lagged log excess return of BN at time t, DP_t is the log dividend-price ratio of BN at time t, TS_t is the term-spread at time t, DS_t is the default spread at time t, IPG_t is the net monthly year-on-year growth rate of the index of industrial production at time t, and LEV is the change in bank leverage at time t. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 12 lags. Monthly data, 1960 - 2009.

Coefficient										
α	0.33***	0.76***	0.22***	0.33***	0.32***	0.32***	0.28***	0.33***	0.36***	0.44*
β^{g^c}	-2.94***	-3.21***	-2.33***	-3.02***	-2.93***	-2.83***	-2.94***	-2.88***	-3.25***	-2.70***
β^{LR}	-0.03									0.14
β^{DP}		0.12*								0.05
β^{TS}			3.90*							5.77*
β^{r}				0.45						1.42
β^{n}					-1.10					-1.62
β^{rel}						-1.22				1.96
β^{DS}							5.33			-4.64
β^{IPG}								-0.13		-0.41
β^{LEV}									0.15	0.16*
R^2-adj (%)	13.83	17.07	17.42	14.09	13.91	14.08	14.71	13.88	17.24	23.10

full sample in table 31. In some cases, the economic significance of the coefficient on g_t^c actually increases, and in all cases g_t^c is still statistically significant at the 1% level.

The only other variables that predict the excess returns of the BN index at the 12-month horizon are the smoothed dividend-yield of the BN index, the term-spread, and the change in leverage. A 1% increase in smoothed dividend-yield results in a 0.12% increase in the excess return of the BN index. The economic magnitude of this coefficient is small as compared to the coefficient on g_t^c. Also, the coefficient is only statistically significant at the 10% level.

The interest rate margin is a crucial measure of profitability for banks and depends on the difference between the long-term and short-term interest rates. Therefore it is not surprising that the term-spread determines the future excess returns of the BN index. A higher term-spread implies higher future profits either through higher interest earnings or through lower cost of funds, or both. A 1% increase in the term spread results in a 3.90% basis point increase in the excess returns of the BN index over the next one year. However, it is statistically significant only at the 10% level and is not significant when I include all the other predictive variables. Also, note that none of the short-term interest rate variables that may affect the bank's cost of funds, predict the future excess returns of the BN index.

Finally, as expected, an increase in leverage implies an increase in expected returns of bank stocks. A 1% increase in bank leverage implies that future bank returns are higher by just 0.16%. This coefficient is not significant by itself but is statistically significant in the full regression. Controlling for leverage is crucial because credit growth's predictive power may arise from its negative correlation with leverage. A negative correlation between credit growth and leverage may exist if both g_t^c and market value of bank stocks drops in each recession. Since a drop in market value of equity effectively increases bank leverage, this may explain the observed negative correlation between credit growth and bank stock returns. However, as is clear from table 34, even after controlling for leverage, the coefficient on g_t^c is statistically significant with a magnitude of -3.25%

Independent of the variables in table 34, Lettau and Ludvigson (2001) and Longstaff and Wang (2008) respectively show that the log consumption-wealth ratio and the size of the credit market also predict returns of the stock market index. Controlling for the size of the credit market is especially important because banks are still one of the largest providers of credit in the U.S. economy[44].

The variables defined in Lettau and Ludvigson and Longstaff and Wang are available only at a quarterly frequency whereas all my previous tests use monthly data. Therefore, I first compute the year-on-year quarterly growth rate in credit using the raw time-series. I also compute the quarterly returns of the BN index by compounding the monthly return series.

Table 35 shows the results. The exact specification of the regression is:

$$\sum_{j=1}^{j=H} \log(1 + r_{BN,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \tag{24}$$

$$\alpha_H + \beta_H^{g^c} \log(1 + g_t^c) + \beta_H^{cay} cay_t + \beta_H^{CR_1} \frac{Int}{Div_t} + \beta_H^{CR_2} \frac{Int}{Assets}_t + \epsilon_{t+H}^i$$

The independent variables are credit growth, cay_t as defined in Lettau and Ludvigson (2001), and the two proxies for the size of the credit market as defined in Longstaff and Wang (2008). Table 35 shows the estimated coefficients, statistical significance, and the adjusted-R^2 1 to 5 quarters ($H = 3$,6 ,9 ,12 ,15) after g_t^c is measured.

In all cases the size of the credit market does not predict the excess returns of the BN index. Cay_t is statistically and economically significant but does not explain away the predictive power

[44] As per U.S. Flow of Funds Accounts (December 2009) commercial banks account for $765.40 B of the total $2,854.20 B lent by the financial sector to the rest of the economy via the credit market. This is second only to the amount lent by issuers of asset backed securities ($799.80 B). Thus banks account for nearly 27% of the funds lent in the credit market.

of g_t^c. Its predictive direction is also not the same as that of g_t^c. While a 1% increase in cay_t implies that log excess returns of the BN index will be higher by 3.94% over the next one year, the corresponding value for g_t^c is -1.69% basis points.

As a final robustness test, I check if the predictive relationship arises due to movements in the short-term risk-free rate (r_f) which may either induce a positive or a negative correlation between g_t^c and the expected stock returns of the BN index. As an example, let r_f increase due to exogenous reasons. If the equity premium of the BN index is constant, this increases the expected return of the BN index. Since banks borrow in the short-term market and lend for the long-term, a high r_f may simultaneously lower the supply for credit. Therefore movement in r_f may induce a positive correlation between the future returns of the BN index and g_t^c. While this particular scenario is not too much of a concern (it biases the estimated coefficients downwards), one can imagine alternate scenarios that induce a negative correlation between g_t^c and the stock returns of the BN index. This negative correlation may arise easily if the risk-premium of bank stocks also varies and if the long-term risk-free rate also changes along with r_f.

Table 36 presents the results for the forecasting regression where the dependent variable is the H-period log real returns of the BN index. The results for real returns are, if anything, stronger. Over the full sample, a 1% increase in g_t^c implies that the real returns of the BN index are lower by 4.62% over a 1-year horizon. All the other results documented in table 31 also go through. This test confirms that the predictability does not arise due to variations in r_f and that the negative correlation between g_t^c and bank stock returns is fairly robust.

To summarize my results so far, g_t^c predicts lower returns for bank stocks and this effect is robust to the exclusion of data from the crisis years and to the inclusion of other variables known to predict returns. In the rest of this paper, I investigate if this predictive variation in bank stock returns arises due to some inefficiency in financial markets or if it simply reflects the rational response of

Table 35: Forecasting regression for excess returns of banks including other predictive variables (quarterly regressions)

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + r_{BN,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \alpha_H + \beta_H^{g^c} \log(1 + g_t^c) + \beta_H^{cay} cay_t + \beta_H^{CR_1} \frac{Int}{Div_t} + \beta_H^{CR_2} \frac{Int}{Assets}_t + \epsilon_{t+H}^i$$

Here $r_{BN,t+H}$ is the quarterly return of the BN index at time $t+H$, $r_{f,t+H}$ is the return of the risk-free asset at time $t+H$, and g_t^c is credit growth for all banks in the U.S. at time t, cay_t is Lettau and Ludvigson (2001) measure of trend deviation in the log consumption-wealth ratio, Int/Div_t is the ratio of total interest received to total dividends received at time t, and $Int/Assets_t$ is the total interest received to total household assets. The data for total interest and total dividends received is from BEA National Income and Product Accounts table 2.1 line 14 and line 15. The data for total household assets is from the Federal Flow of Funds Account table B.100 Line 1. These definitions are consistent with Longstaff and Wang (2008). Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 4 lags. Quarterly data, 1960 - 2009.

$H =$	3	6	9	12	15
α	0.03	0.06	0.12	0.17	0.18
β^{g^c}	-0.19	-0.42	-1.11*	-1.69**	-1.88**
β^{cay}	1.37**	2.58**	3.25*	3.94*	4.64*
β^{CR_1}	-0.01	-0.02	-0.02	-0.02	-0.04
β^{CR_2}	0.25	1.01	1.25	1.35	2.52
R^2-adj (%)	2.79	7.70	13.83	19.82	24.07

Table 36: Forecasting regression for real returns of banks

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + r_{BN,t+j}) = \alpha_H + \beta_H^{g^c} \log(1 + g_t^c) + \epsilon_{t+H}$$

Here $r_{BN,t+j}$ is the real return of the BN index at time $t+j$ and g_t^c is the credit growth for all banks in the U.S. at time t. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 12 lags. Monthly data, 1960 - 2009.

$H =$	1	2	3	4	5	6	7	8	9	10	11	12
α	0.00	0.00	0.01	0.02	0.03	0.04	0.05	0.06	0.06	0.07	0.07	0.07
β^{g^c}	-0.30***	-0.65***	-1.02***	-1.45***	-1.90***	-2.34***	-2.76***	-3.18***	-3.57***	-3.94***	-4.26***	-4.62***
R^2-adj (%)	1.53	2.87	4.14	5.67	7.14	8.35	9.40	10.42	11.28	11.97	12.59	13.27

economic agents to time-variation in real risk.

3.3.3 Are investors making systematic errors?

One may attribute the predictive variation in bank stock returns to investor overreaction or to bank management's rational response to time-variation in expected returns. Investor overreaction can explain my results if optimistic investors first overestimate the impact of new loans on future bank cash flows and drive up the current price of bank stocks (higher initial returns), and then subsequently correct their beliefs, so that future bank stock prices fall (lower future returns). Arguably, investors should learn and not make such systematic errors over time so that these effects would not persist.

Table 37 shows the results for the forecasting regression for nominal excess returns and real returns of bank stocks over 1990 - 2009. Now, a 1% increase in g_t^c implies a 4.31% fall in nominal excess returns of the BN index over the next one year. This is 1.5 times the estimated coefficient over the full sample. Variation in g_t^c explains nearly 20% of the variation in returns of the BN index over the next one year and the adjusted-R^2 peaks at 34.33% at a horizon of 50 months. A similar result is obtained for real returns.

Another reason that the predictive variation in bank stock returns cannot be attributed to investor overreaction is that the predictive power, as measured by the absolute value of the coefficient and the adjusted-R^2 at the 1-year horizon, increases monotonically in leverage and the proportion of short-term debt employed by the bank[45]. Investor errors can co-vary negatively with size if better financial information is available for large banks or if investors pay more attention to large banks. However, it is not clear why investor errors should also increase in leverage or short-term debt. I explore this in further detail in sub-section 3.3.6.

[45] See section 35.

Table 37: Forecasting regression for excess returns of banks

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + r_{BN,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \alpha_H + \beta_H^{g^c} \log(1 + g_t^c) + \epsilon_{t+H}$$

Here $r_{BN,t+j}$ is the return of the BN index at time $t+j$, $r_{f,t+j}$ is the return of the risk-free asset at time $t+j$, and g_t^c is the credit growth for all banks in the U.S. at time t. The first panel shows the result for nominal excess returns and the second panel shows the results for real returns. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 12 lags. Monthly data, 1990 - 2009.

$H =$	1	2	3	4	5	6	7	8	9	10	11	12
	Nominal excess returns											
α	0.03**	0.05**	0.08**	0.12***	0.16***	0.20***	0.24***	0.28***	0.32***	0.35***	0.39***	0.43***
β^{g^c}	-0.21	-0.45	-0.68	-1.05*	-1.49*	-1.92*	-2.32*	-2.75*	-3.16*	-3.51*	-3.89**	-4.31**
R^2-adj (%)	0.16	0.74	1.24	2.47	4.15	5.83	7.57	9.76	11.97	14.13	16.98	19.56
	Real returns											
α	0.01	0.02	0.03	0.04	0.06	0.07	0.08	0.09	0.10	0.10	0.10	0.11
β^{g^c}	-0.55***	-1.14**	-1.70**	-2.36**	-3.05**	-3.69**	-4.27**	-4.85**	-5.39**	-5.86**	-6.33**	-6.93**
R^2-adj (%)	2.98	5.13	6.62	8.66	10.63	12.12	13.40	14.97	16.45	18.04	20.19	22.67

3.3.4 Do managers respond rationally to time-variation in expected returns?

Alternatively, one may also attribute the predictive variation in bank stock returns to bank management's rational response to time-variation in expected returns. If the negative correlation between g_t^c and bank stock returns is due to time-variation in expected returns linked to standard risk factors, then g_t^c should be correlated with the loadings of bank stock returns on these standard risk factors, or with changes in aggregate risk-premium, or both.

To check credit growth's correlation with the conditional loadings of bank stock returns on systematic risk factors, I compute 5-year rolling betas of bank stock returns on the three Fama-French factors - MKT, SMB, and HML - and two bond market factors - the excess return of an index of long-term government bonds (LTG) and the excess return of an index of investment-grade corporate bonds (CRD). A negative correlation with these factor loadings implies that a higher credit growth lowers the exposure of banks stock returns to standard risk factors and hence the expected return required by the average investor to hold bank stock falls. The drop in expected returns equals the change in loadings times the risk premium of these risk factors.

Figure 7 plots the results. In each panel, the solid line plots g_t^c and the dashed line corresponds to one of the five risk factors mentioned above. The left panel in the top row depicts the correlation between g_t^c and the 5-year rolling beta on MKT. Each of the remaining panels show the 5-year rolling betas of bank stocks on SMB, HML, LTG and CRD respectively. To avoid detecting spurious correlations, I exclude data from the crisis years (2006 - 2009).

Over the full sample g_t^c has a statistically significant correlation with MKT (-0.11, $p < 0.01$), HML (0.11, $p < 0.01$), and LTG (0.18, $p < 0.01$). It's correlation with SMB (-0.02, $p = 0.60$) and CRD (0.04, $p = 0.30$) is statistically not significant. The annual risk price for these factors in the sample expressed in percentages is respectively:

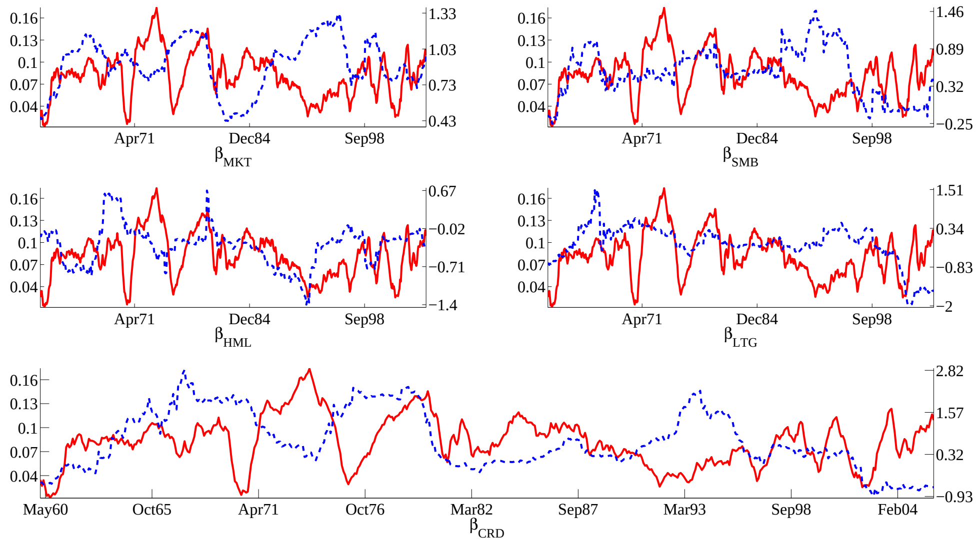

Figure 7: Correlation between 5-year rolling factor betas and credit growth

In each panel the solid line plots the net monthly year-on-year credit growth for all banks in the U.S and the dashed line represents the 5-year rolling beta on one of the standard risk factors. The left panel in the first row shows the 5-year rolling beta for $MKTT$. Each of the other panels correspond to the loadings on SMB, HML, LTG, and CRD. The dates are indicated on the x-axis. The left-axis references g_t^c and the right-axis references the 5-year rolling betas. Monthly data, 1960 - 2005.

$$[6.25 \ 1.66 \ 5.49 \ 1.57 \ 2.59]$$

This implies that a 1% increase in credit growth results in an increase of nearly 6% in the expected returns of bank stock as measured by the loadings on the standard risk factors mentioned above. This 6% increase reflects the correlation between g_t^c and rolling betas times the risk price divided by the variance of credit growth. These results are robust to the window over which the rolling betas are estimated and to sub-sample selection.

These results should be interpreted carefully as the loadings of bank stock returns on the standard risk factors may not have the same interpretation as that for industrial firms. This is because unlike industrial firms, high leverage for banks does not necessarily imply distress. Further, changes in loadings of bank stock returns on MKT may simply be related to changes in leverage and may not imply a change in exposure to systematic risk. However, variation in exposure to standard risk factors is still unlikely to explain the predictive variation of bank stock returns given that g_t^c predicts returns even after I control for the change in leverage.

While g_t^c is uncorrelated with loadings of bank stock returns on standard risk factors, it could still be correlated with changes in the aggregate price of risk. Indeed, the aggregate price of risk varies over the business cycle. In section 3.2 I have already established that g_t^c is correlated with business cycle variables. If predictive variation in bank stock returns arises entirely due to credit growth's correlation with changes in the aggregate price of risk, I should find that credit growth's predictive power for other assets, as measured by the absolute magnitude of the coefficient on credit growth and the adjusted-R^2 at the the 1-year horizon, should be comparable to that for banks.

The results in 34 reassure us that the predictive variation in bank stock returns does not arise solely from g_t^c's correlation with business cycle variables (hence with aggregate price of risk). Still, in order to estimate what proportion of the predictive variation in bank stock returns may arise from this correlation, I use credit growth to predict returns of a control set of assets other than banks. Table 38 presents the results. Each column in table 38 refers to a separate forecasting regression for a distinct asset class. In the first column, titled TB, the dependent variable is the log excess return for an index of treasury bonds, CB is the log excess return of an index of investment-grade corporate bonds, and OI is the log excess return of an index of other industries. Table 38 shows the results only for $H = 12$, although results at other horizons are similar. In each case I also control for all other business cycle variables shown in table 34. Data for government and corporate bonds is from GFD[46]. To obtain estimates for the forecasting regression OI, I again run

[46]On Global Financial Data (GFD) these assets are identified by the item codes TRUSG2M and

Table 38: Forecasting regression for excess returns of other asset classes

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + r_{i,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \alpha_H^i + \beta_H^{g^c} \log(1 + g_t^c) + \epsilon_{t+H}^i$$

Here $r_{i,t+j}$ is the return of the index of treasury bonds, corporate bonds, and an index of 39 other industries at time $t + j$, $r_{f,t+j}$ is the return of the risk-free asset at time $t + j$, and g_t^c is the credit growth for all banks in the U.S. at time t. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 12 lags. Monthly data, 1960 - 2009.

$i =$	TB	CB	OI
α	0.01	0.03	0.12
β^{g^c}	-0.23**	-0.51*	-1.06
BC vars	Yes	Yes	Yes
R^2-adj (%)	12.14	31.45	9.28

the forecasting regression for each of the 39 industries other than financial intermediaries for which data is available on Kenneth French's website. The figures in the column are average statistics for all 39 industry indices.

The coefficient on g_t^c at the 12-month horizon is statistically significant only for treasury bonds and corporate bonds. In these cases the coefficient is at most 0.50 or one-sixth of its value for bank stock returns. The average coefficient at the 12-month horizon for the 39 other industries is only -1.08% and is not statistically significant. Of the 39 individual coefficients on g_t^c at the 12-month horizon, only 3 are statistically significant at the 5% level or better. In fact, 6 of the coefficients are positive. Thus the relationship between g_t^c and the stock returns of intermediaries is not mechanical, and is indeed special for bank stock returns. A similar regression over 1990 -

TRUSACOM respectively.

2009, for these asset classes shows that the coefficients on g_t^c are not economically or statistically significant at any horizon and the values of the adjusted-R^2's are small. Note that in table 38 for corporate bonds, the high adjusted-R^2 of 31% reflects the fact that I include the term-spread and the default spread as predictor variables.

In table 39 I check if g_t^c predicts returns for an index of non-financial stocks or an index of non-financial stocks sorted by various characteristics. For the results in this table the dependent variables are the $H-$period log excess returns of a value-weighted index of non-financial stocks (MKT), a value-weighted index of non-financial stocks sorted by size ($MKT - SM$), a value-weighted index of non-financial stocks sorted by leverage ($MKT - HL$), and a value-weighted index of non-financial stocks sorted by short-term debt ($MKT - ST$). I have already described the construction of MKT in section 3.3.1 above. To form $MKT - SM$, I sort non-financial firms into 5 portfolios by market capitalization and analyze the returns for the smallest firms. To form $MKT - HL$, I sort all non-financial firms into 2 portfolios by assets and leverage, and analyze firms with highest leverage and smallest market capitalization. Finally, table 39 also presents the results for an index of non-financial stocks sorted by the proportion of short-term debt. Again, I restrict myself to the portfolio of non-financial firms with the highest proportion of short-term debt and the smallest market capitalization. In all cases the coefficient on g_t^c is small and not statistically significant. Credit growth has no predictive power for an index of non-financial stocks and the adjusted-R^2 for any regression is also low. Thus, g_t^c does not appear to have an independent predictive power, outside of its correlation with other business cycle variables, to predict the returns of the control group of assets.

Finally, I check if predictive variation in returns arises due to variation in some risk that is specific to financial intermediaries and the kind of projects they fund. I test if g_t^c predicts the returns of a value-weighted index of bank-dependent firms and a value-weighted index of financial

Table 39: Forecasting regression for excess returns of non-financial market index

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + r_{i,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \alpha_H^i + \beta_H^{g^c} \log(1 + g_t^c) + \epsilon_{t+H}^i$$

Here $r_{i,t+j}$ is the return of non-financial stocks (MKT), non-financial stocks with small market capitalization ($MKT - SM$), with high leverage ($MKT - HL$), and with high short-term debt ($MKT - ST$) respectively at time $t + j$, $r_{f,t+j}$ is the return of the risk-free asset at time $t + j$, and g_t^c is the credit growth rate for all banks in the U.S. at time t. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 12 lags. Monthly data, 1960 - 2009.

$i =$	MKT	$MKT - SM$	$MKT - HL$	$MKT - ST$
α	0.14	0.06	0.06	0.15**
β^{g^c}	-1.42	-1.46	-1.46	-0.82
BC vars	Yes	Yes	Yes	Yes
R^2-adj (%)	9.53	8.25	11.44	7.62

Table 40: Forecasting regression for excess returns of bank-dependent firms and financial trading firms

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + r_{i,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \alpha_H + \beta_H^{g^c} \log(1 + g_t^c) + \epsilon_{t+H}$$

Here $r_{i,t+j}$ is the return of bank-dependent firms (BD), bank-dependent firms with small market capitalization ($BD - SM$), with highest leverage ($BD - HL$), with high short-term debt ($BD - ST$), and financial trading firms at time $t + j$, $r_{f,t+j}$ is the return of the risk-free asset at time $t + j$, and g_t^c is the credit growth rate for all banks in the U.S. at time t. As in Kashyap, Lamont and Stein (1994) bank-dependent firms are identified by an absence of a public debt rating and presence of interest expenses in the income statement. Financial trading firms are defined in section 3.2 above. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 12 lags. For bank-dependent firms data with short-term debt, data is monthly over 1980 - 2009. For other columns, data is monthly over 1960 - 2009.

$i =$	BD	$BD - SM$	$BD - HL$	$BD - ST$	FT
α	0.21*	0.09	0.30	-0.28**	1.02***
β^{g^c}	-1.07	-2.17*	-2.24	-1.09	-1.79**
BC vars	Yes	Yes	Yes	Yes	Yes
R^2-adj (%)	3.31	14.10	4.28	31.24	21.83

trading firms (investment banks). As in Kashyap, Lamont and Stein (1994), I use the absence of a public-debt rating as the proxy for bank-dependence. Data for public-debt rating is available from COMPUSTAT only from 1980, so regression results for this index are reported for 1980 - 2009. I have already described the construction of the index of financial trading firms, FT, in section 3.2 above. The results for financial trading firms is over the full sample, 1960 - 2009.

Each column in table 40 represents a separate forecasting regression for a distinct index. In the first column the dependent variable is an index of all bank-dependent firms and in the second column the dependent variable is index of bank-dependent firms with the smallest market capitalization. The third and fourth column present the results for bank-dependent firms sorted by leverage and the proportion of short-term debt. For analysis of portfolios sorted by leverage and short-term debt, as above, I restrict myself to portfolios with the highest leverage or short-term debt and the smallest market capitalization. The last column presents the results for financial trading firms. To ensure that the results are comparable to those presented earlier, in each case I control for other business cycle variables.

While credit growth does not predict returns for all bank-dependent firms or for bank dependent firms sorted by leverage or short-term debt, it does predicts returns for bank-dependent firms with small market capitalization. In fact, for small bank-dependent firms the coefficient is almost as large as that for banks, and the value of the adjusted-R^2 exceeds 14%. Credit growth also predicts returns of financial intermediaries other than banks. Over a 12-month horizon, a 1% increase in g_t^c predicts a 1.79% fall in excess returns of FT and the adjusted-R^2 is 10%. The coefficients and the adjusted-R^2 are smaller as compared to those for BN. This may be due to the fact that g_t^c is constructed using only data from banks and does not include any balance sheet data from financial trading firms. Credit growth also predicts the excess stock returns of size-sorted portfolios of FT and all other robustness tests performed for BN also go through for FT.

Figure 8 suggests the possible source of the predictive power of g_t^c for the returns of the FT index. The figure plots the growth rates of credit market assets held by banks and financial trading firms. Data is from the U.S. Flow of Funds Accounts, table $L.1$, Lines 33-57. I use quarterly, non-seasonally adjusted data over 1960-2005. I exclude 2006 - 2009 to avoid detecting any spurious correlations. Banks include data for commercial banks (line 35), savings institutions (line 40), and credit unions (line 41) and financial trading firms include data for ABS issuers (line 53), finance companies (line 54), REITS (line 55), brokers and dealers (line 56), and funding corporations (line

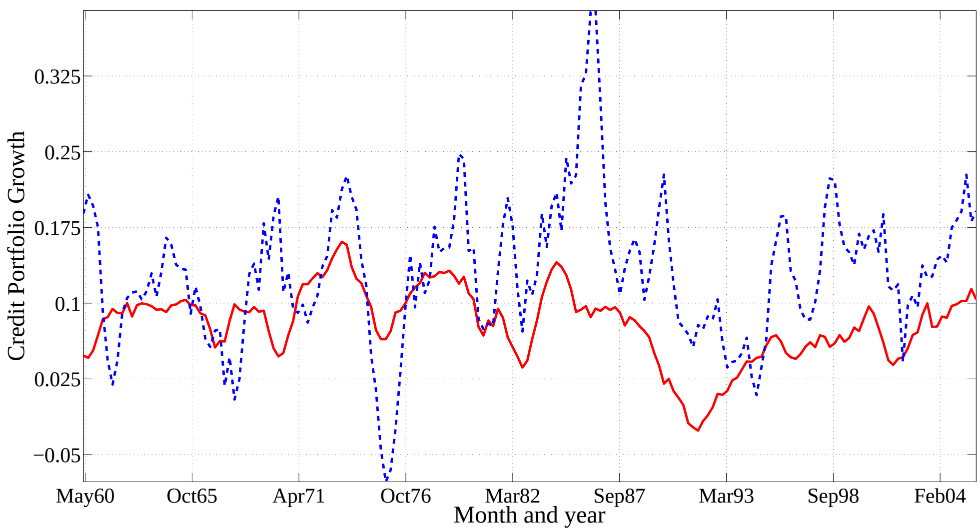

Figure 8: Correlation between growth rate of credit portfolios of banks and financial trading firms

Notes: This figure shows the growth rates of credit market assets held by various financial intermediaries. The solid line plots the growth rate of credit market assets held by banks and the dashed line plots the growth rate of credit market assets held by financial trading firms. Data is from the U.S. Flow of Funds Accounts, table $L.1$, lines 33-57. I use quarterly, non-seasonally adjusted data over 1960-2005. I exclude 2006 - 2009 to avoid detecting any spurious correlations. Banks include data for commercial banks (line 35), savings institutions (line 40), and credit unions (line 41); Financial trading firms include data for ABS issuers (line 53), finance companies (line 54), REITS (line 55), brokers and dealers (line 56), and funding corporations (line 57).

57).

The solid and dashed lines plot the quarterly year-on-year growth rate of credit market assets of banks and financial trading firms. Over 1960 - 2005, the correlation between the credit market asset growth rates is 34.48% ($p < 0.01$). Over 2000 - 2005, the correlation increases to 71.10% ($p < 0.01$). This suggests a possible reason why g_t^c also predicts the stock returns of financial trading firms: factors that cause banks to vary the supply of credit may also be at work in financial trading firms.

This evidence that g_t^c predicts returns of banks, financial trading firms, and bank-dependent firms but does not have an independent effect, outside of its correlation with business cycle variables, on the returns of an index of treasury bonds, investment-grade corporate bonds, non-financial stocks, and non-financial stocks with highest leverage, suggests that the predictive variation in bank stock returns arises due to investor's rational response to time-variation in risk that is specific to the assets typically funded by intermediaries. However, the exact nature of this risk is not entirely clear. I next turn my attention to this question.

3.3.5 So what is the exact nature of the risk?

In this section I argue that the predictive variation in returns reflects the representative agent's rational response to a small time-varying probability of a tail event. The nature of the tail event is such that its realization results in a large loss of cash flows from projects typically funded by bank loans. However, it may not impact other projects in the economy. Examples of such events (included in the sample) are the Less Developed Country Debt crisis of 1982, the Mexico crisis of 1994, the East Asian crisis of 1997, and the Long-Term-Capital-Management crisis of 1998. Each of these events resulted in large losses of cash flows from projects funded by banks and a significant drop in the profitability and valuation of banks in the U.S. However, there was no measurable effect on the performance of other projects in the economy. These crises were not accompanied by recessions, and other important asset markets such as the stock and housing market, were also relatively unaffected.

Bank management is very sensitive to changes in the probability of a tail event. This high sensitivity arises from the balance sheet characteristics of banks. Table 41 compares balance sheet characteristics of publicly listed financial and non-financial firms. Data is from COMPUSTAT over 1960 - 2009. Note that an average financial firm employs nearly 700% more leverage than

Table 41: Characteristics of financial firms and non-financial firms

Notes: This table compares the characteristics of publicly listed financial and non-financial firms. Data is from COMPUSTAT. In COMPUSTAT financial firms are identified by an SIC code between 6000 - 6799. For each firm equity is measured as the difference between total assets (item code at) and total debt. Total debt is computed as a sum of notes payable (NP) and long-term debt due in 1-year ($DD1$). Short-term debt equals notes payable (NP). Finally, tangible assets equal gross property, plant, and equipment ($PPEGT$). Quarterly data, 1960 - 2009.

Statistic	$Financial$	$Others$
$\frac{\text{Assets}}{\text{Equity}}$	13	2
$\frac{\text{Tangible assets}}{\text{Assets}}$	0.02	0.81
$\frac{\text{ST debt}}{\text{LT Debt}}$	16	4
Subject to a run	Yes	No
Fix market value of assets	$Diff$	$Easy$

an average non-financial firm and has only 2% of its book value in tangible assets. The market value of the remaining 98% of assets, typically invested in loans, is difficult to compute. Also a financial firm relies nearly 400% more on short-term debt than the average non-financial firm. Finally, financial firms can be subject to runs by both depositors and creditors. Regulators believe that these characteristics combined with the very possibility of a tail event provide the justification for the special treatment and close regulation of banks and other financial intermediaries.

That financial firms are more sensitive to tail events is clear from figure 9. This figure plots the monthly rate at which firms 'delist' from the CRSP data-set by counting the number of delistings in each month as a fraction of total firms for which returns are available on the CRSP data-set at the beginning of the year. Only delistings due to liquidation (delisting code = 400) are included in the count. A separate delisting rate is computed for financial and non-financial firms.

The solid line plots the delisting rate for financial firms and the dashed line plots the delisting rate for non-financial firms. Note that the delisting rate for financial firms increases in almost all recessions and financial crises while the delisting rate for non-financial firms mostly remains flat or in some cases actually falls. The baseline rate at which financial firms delist due to liquidation is also nearly 4 times higher than the delisting rate for non-financial firms. Figure 9 may actually underreport the 'true' liquidation rate for financial firms but not so for non-financial firms. This is because regulators often do not allow large, troubled, financial firms to liquidate, but oversee their acquisition. For example, FDIC reports that 256 banks have failed in the recent crisis since the failure of IndyMac. All of these banks are small by most standards. Including such 'mergers' actually increases the 'liquidation rate' for financial firms.

Since banks are more sensitive to the probability of a tail event, an increase in the likelihood of a large loss of cash flows implies that projects with lower expected cash flows are not approved for bank funding. This effectively raises the discount rate used by the bank to evaluate projects, thereby contracting the supply of credit. Simultaneously, the discount rate used by the bank's customers (the project manager) to evaluate projects also increases in the probability of a tail event. In fact many projects with low expected cash flows that would customarily be taken to the bank for evaluation, may be rejected at the outset by the project manager herself. This contracts the demand for credit. My mechanism does not require that I distinguish supply from demand contraction, only that both supply and demand of credit be negatively correlated with the probability of a tail event - a reasonable assumption. The actual fall in credit level attributed to supply or demand contraction may differ in each business cycle and may depend on the financial condition of the bank, the balance sheet strength of the project manager, and the exact nature of the tail event.

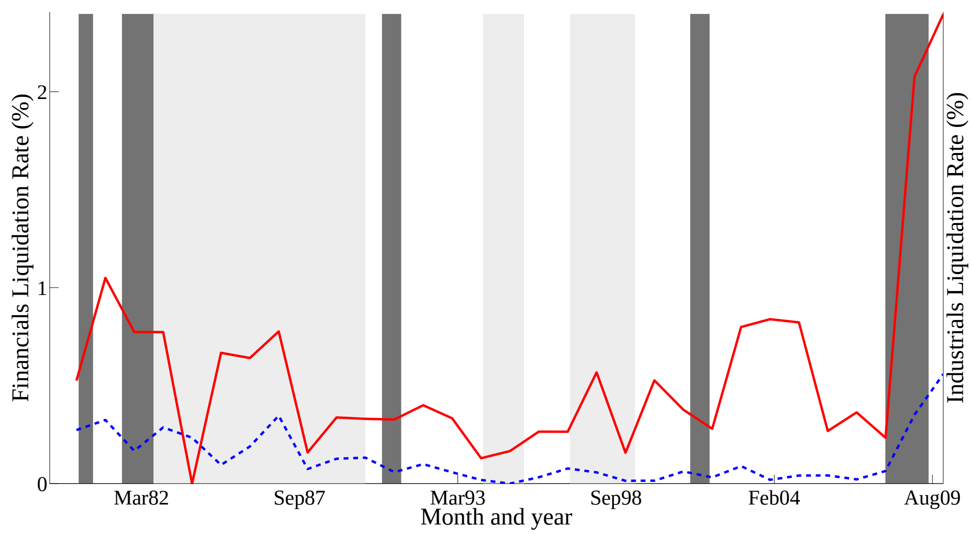

Figure 9: Delisting rates

Notes: This figure shows the monthly rate at which firms delist from the CRSP data-set. The solid line plots the delisting rate for financial firms and the dashed line plots the delisting rate for non-financial firms. The delisting rate is measured by counting the number of delistings in each year as a fraction of number of firms for which data is available in CRSP at the beginning of that year. Only delistings due to liquidations (delisting code = 400) are included in the count. A separate delisting rate is computed for financial and non-financial firms. Financial firms are identified by an SIC code between 6000 - 6799.

The standard disaster-risk asset pricing framework also implies that the expected returns required by the average investor to hold bank stocks and any stock in the projects themselves increase in the probability of the tail risk. This explains the observed negative correlation between credit growth and expected returns of bank stocks and between credit growth and expected returns of bank-dependent firms and financial trading firms.

Note that the predictive power of g_t^c, measured by the absolute value of the predictive coefficient and the adjusted-R^2 at the 12-month horizon, is stronger for banks than for bank-dependent firms as banks are more exposed to tail risk given their balance sheet characteristics. Further, the negative correlation between g_t^c and returns of projects typically funded by banks may be difficult to empirically detect in the data. This is because in a typical bank's loan portfolio, projects with most exposure to tail risk include firms that are informationally-difficult, illiquid, and with no alternative sources of funds. It is unlikely that this subset includes many publicly listed firms, if at all. However, publicly listed firms are the only kind for which any stock return data is available. As Kashyap, Stein and Wilcox (1993) and Chava and Purnanandam (2011) show, it is easy for publicly listed bank-dependent firms to replace bank credit with alternate sources of credit at times of aggregate economic shock. So the results in table 40 may actually understate the impact of g_t^c on bank-dependent firms and bank-funded projects.

One implication of this hypothesis is that banks actively fund projects with higher exposure to tail risk. Measuring the exact loadings of a typical bank's loan portfolio to tail risk is difficult to assess without loan-level cash-flow data. Still, I argue that not only do banks actively fund projects with higher exposure to tail risk, but also that the proportion of such funding has been increasing over time.

First, several papers, beginning with (Diamond, 1984, 1991), Ramakrishnan and Thakor (1984), Fama (1985), and Boyd and Prescott (1986), develop theoretical models for banks. A common theme is that banks specialize in extending credit to illiquid, informationally opaque borrowers that cannot (or will not) access public financial markets. In these models a bank is the only economic entity that possesses the experience to lend and periodically monitor to such borrowers. It is reasonable to argue that such illiquid, informationally dense borrowers are more exposed to tail risk. The fact that the market value of these loans is difficult to compute, as shown in O'Hara (1993), Berger, King and O'Brien (1991), Lucas and McDonald (1987), and Pennacchi (1988) lends further support to this hypothesis.

Second, Boyd and Gertler (1993) show that banks actively seek exposure to projects with tail risk due to competition from foreign banks, growth of non-bank intermediation, and asset markets (commercial paper market and securitization). This has forced banks to move into riskier, less-liquid assets over time. McCauley and Seth (1992), Berger, Klapper and Udell (2001), and Berger, Klapper, Martinez Peria and Zaidi (2008) analyze the impact of foreign banks on bank lending. They find that, in many cases, foreign banks are subject to lower reserve requirements and can offer better terms of credit. This mainly attracts larger, better rated, transparent, and older firms away from domestic banks who replace these customers with even more informationally opaque firms. A similar mechanism is at work due to competition from non-bank intermediaries and the commercial paper market. Thus, it is reasonable to conclude that the U.S. banks loan portfolios are more sensitive to tail risk.

Boyd and Gertler (1993) also show that securitization has moved high-quality assets off the bank's balance sheet. This is true in their sample (1954 - 1990). They argue that securitization, without recourse to the bank's balance sheet, succeeds only if loans that are securitized are liquid enough to be sold on the secondary market. Over 1954 - 1990, at most 30% of a bank's loan portfolio was securitized. This implies that most of the loans on a bank's balance sheet were not sufficiently liquid to be sold on the secondary market and the risk of such assets was retained by the bank[47].

Finally, regulators certainly believe that exposure of a bank's balance sheet to such tail risk is not merely hypothetical. Regulators contend that opaqueness in a bank's balance sheet assets justifies the special treatment of banks. Regulators believe that in the event of a fire sale, a bank may not realize the full value of its portfolio due its illiquidity and opaqueness. This justifies deposit insurance schemes, operation of a discount window, and the role of lenders of last resort - policies deemed essential to provide comfort to market participants and avoid bank runs in case a tail event is realized.

Having proposed an entirely plausible driver of the predictive variation in returns, the next section presents actual evidence that links the predictive variation in returns to tail risk.

3.3.6 Is predictive variation in returns actually linked to time-variation in tail risk?

If variation in the probability of a tail event causes the negative correlation between g_t^c and the expected returns of bank stocks then the predictive power should depend systematically on variables known to regulate a bank's exposure to tail risk. Here, predictive power is measured by the absolute magnitude of the coefficient on g_t^c and the adjusted-R^2 at the 12-month horizon.

In this section, I focus on three such variables - size, leverage, and the proportion of short-term debt. A priori, I expect that the predictive power monotonically decreases in size. Large banks should have a lower exposure to tail risk not only because they benefit from an implicit government guarantee but also because they are well-diversified and have more assets. A similar argument applies to banks with a higher leverage or a higher proportion of short-term debt. Banks with

[47]This analysis may not apply to recent run up in bank lending and securitization of sub-prime mortgages. However as I show in section 3.3 above, my results hold even if this period is excluded from the analysis.

higher leverage or short-term debt should be more exposed to tail risk. Hence, predictive power should decrease in size, and increase in leverage and the proportion of short-term debt. This is confirmed in tables 42, 43, and 44.

Each panel in table 42 shows the results for the forecasting regression for each of the 5 size-sorted portfolios of BN. Here size is measured by market capitalization. The number '1' in the first column refers to the smallest size-sorted portfolio. While g_t^c predicts negative excess returns for all size-sorted portfolios of BN, the magnitude of the coefficient and the adjusted-R^2 at the 12-month horizon monotonically decreases in size. A 1% increase in g_t^c predicts a 4.09% decrease in the excess returns of the smallest banks and explains 18% of the variation in excess returns over the next 12 months. The corresponding numbers for the largest banks are 2.92% and 13% respectively.

To form portfolios sorted by other characteristics, such as leverage or the proportion of short-term debt, I require bank-level balance sheet data. The Chicago Fed collects balance sheet data for all bank holding companies (BHC) in the U.S. at a quarterly frequency via the mandatory Call Report required to be filed by all FDIC-insured institutions. The data is available online at http://www.chicagofed.org/webpages/banking/financial_institution_reports/bhc_data.cfm. The data is available from 1986 for approximately 5,396 BHCs over 92 quarters (496,462 observations). The Call Report identifies BHCs using a unique 'Entity Code' that is mapped to the 'Permco' in CRSP for all publicly traded banks. This mapping is available only for BHCs and not for individual banks[48].

I keep data for total balance sheet assets (item BHCK2170), total balance sheet liabilities (item BHCK2948), total short-term debt (BHCK 2309, 2332, and 3298). I delete observations where total assets equal zero or is missing. I eliminate BHCs for which a matching Permco is either

[48] The mapping is available at http://www.newyorkfed.org/research/banking_research/datasets.html and also includes the dates for which the mapping is valid.

Table 42: Forecasting regression for excess returns of bank portfolios sorted by market capitalization

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + r_{i,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \alpha_H^i + \beta_H^{g^c} \log(1 + g_t^c) + \epsilon_{t+H}^i$$

Here $r_{i,t+j}$ is the return of the i^{th} size-sorted portfolio of banks at time $t+j$, $r_{f,t+j}$ is the return of the risk-free asset at time $t+j$, and g_t^c is credit growth for all banks in the U.S. at time t. Column 1 indicates the size-sorted portfolio for which the coefficients are estimated. Portfolio 1 refers to the smallest size-sorted portfolio by market capitalization. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 12 lags. Monthly data, 1960 - 2009.

Size	$H=$	1	2	3	4	5	6	7	8	9	10	11	12
	α	0.03***	0.06***	0.09***	0.12***	0.16***	0.20***	0.24***	0.28***	0.32***	0.35***	0.38***	0.41***
1	g_t^c	-0.25**	-0.54***	-0.85***	-1.21***	-1.61***	-2.01***	-2.40***	-2.79***	-3.16***	-3.49***	-3.79***	-4.09***
	R^2-adj (%)	1.33	2.61	4.13	5.94	7.88	9.93	11.69	13.52	15.30	16.68	17.56	18.34
	α	0.02**	0.04***	0.07***	0.10***	0.13***	0.16***	0.19***	0.23***	0.26***	0.28***	0.31***	0.33***
2	g_t^c	-0.21**	-0.44**	-0.72***	-1.04***	-1.37***	-1.73***	-2.08***	-2.43***	-2.76***	-3.07***	-3.33***	-3.57***
	R^2-adj (%)	1.16	2.09	3.47	5.22	6.97	8.86	10.63	12.17	13.67	14.91	15.72	16.16
	α	0.02**	0.04***	0.06***	0.09***	0.12***	0.15***	0.19***	0.22***	0.25***	0.28***	0.30***	0.33***
3	g_t^c	-0.19**	-0.41**	-0.66***	-0.96***	-1.29***	-1.64***	-1.99***	-2.34***	-2.69***	-3.00***	-3.28***	-3.55***
	R^2-adj (%)	1.02	1.91	3.09	4.69	6.48	8.15	9.67	11.28	12.85	14.10	14.93	15.60
	α	0.02**	0.04**	0.06**	0.08***	0.11***	0.14***	0.17***	0.20***	0.23***	0.25***	0.28***	0.30***
4	g_t^c	-0.17*	-0.36**	-0.58**	-0.87**	-1.18***	-1.51***	-1.84***	-2.17***	-2.49***	-2.79***	-3.05***	-3.31***
	R^2-adj (%)	0.56	1.16	2.11	3.58	5.11	6.68	8.15	9.63	11.11	12.28	13.29	14.15
	α	0.02**	0.04**	0.06**	0.08***	0.11***	0.14***	0.17***	0.19***	0.22***	0.24***	0.25***	0.27***
5	g_t^c	-0.17*	-0.38**	-0.60**	-0.87**	-1.18***	-1.48***	-1.77***	-2.05***	-2.30***	-2.53***	-2.72***	-2.92***
	R^2-adj (%)	0.48	1.12	1.88	3.07	4.51	5.88	7.25	8.66	9.90	10.98	11.99	13.00

not available or for which the observation date lies outside the valid mapping dates. I also delete observations for BHCs that are inactive or for which stock return data is not available for each of the 5 subsequent quarters relative to its observation date in the Call Report. At the end of this exercise, I am left with 20,500 observations (233 BHCs each year). This is typical of studies that use this data-set[49].

To form portfolios, I employ the standard portfolio formation strategy of Fama and French (1993). For example, to construct the portfolios sorted by leverage, in December of each year, I rank all BHCs by leverage and market capitalization. BHCs for which 4^{th} quarter data is missing are simply dropped from the analysis for the subsequent year. A newly-listed BHC is not considered until the following year. I assign the BHCs to 4 portfolios based on leverage and market capitalization and compute the value-weighted return of each portfolio for each month over the next year. I use a double-sort based on the balance sheet characteristic and market capitalization as size, leverage, and the proportion of short-term debt employed by the bank may be correlated. This results in the monthly value-weighted returns of each of the 4 portfolios sorted by leverage from January 1987 to December 2009. Data for BHCs is available from 1986. I reserve one year for lags and hence my data begins only in January 1987.

The results for portfolios sorted by leverage and market capitalization are in table 43. 'Small' and 'large' refer to size as measured by market capitalization and 'low' and 'high' refer to leverage. The figure in parenthesis report average market capitalization (in $ Billions) and leverage for each portfolio over the sample respectively. Thus small-low banks in this sample had an average market capitalization of $ 100 million and an average assets to equity ratio of 6.41.

Table 43 presents the results only for $H = 12$ months. Results at all other horizons are similar. For small banks, fixing market capitalization but increasing leverage increases the absolute

[49]For example Cooper, III and Pattersonc (2003) use data for 213 BHCs over 1986 - 2009.

magnitude of the predictive coefficient on g_t^c at the 12-month horizon, from -5.02 to -6.15. Similarly, for large banks the predictive coefficient on g_t^c increases from -3.41 to -4.81. Keeping leverage constant, but increasing market capitalization decreases the absolute magnitude of the predictive coefficient on g_t^c and the value of the adjusted-R^2 at the 12-month horizon for both banks with low and high leverage. For banks with low leverage the coefficient on g_t^c declines from -5.02 to -3.41. The value of the adjusted-R^2 also declines from 30.41% to 16.07%. Note that the predictive power is the strongest for small banks with high leverage. For these banks g_t^c explains nearly 31% of the variation in excess returns over a 1-year horizon.

Finally, the results for portfolios double-sorted by market capitalization and short-term debt are in table 44. Portfolio 'small-low' refers to banks with the lowest market capitalization and lowest proportion of short-term debt. Portfolio 'large-high' refers to banks with the highest market capitalization and highest proportion of short-term debt. The figure in parenthesis report average market capitalization (in $ Billions) and the ratio of short-term debt to total assets for each portfolio over the sample respectively. Thus small-low banks in this sample had an average market capitalization of $ 50 million and average short-term debt to asset ratio of 0.71.

Table 44 shows the results only for $H = 12$ months. As was the case with leverage, fixing assets and increasing short-term debt increases the coefficient on g_t^c, while keeping short-term debt fixed and increasing assets lowers both the coefficient on g_t^c and the value of the adjusted-R^2. In this case the effect is strongest for banks with low market capitalization and the highest proportion of short-term debt for whom g_t^c explains nearly 30% of the variation in returns over a 1-year horizon.

Thus the predictive power of g_t^c decreases in size, measured by market capitalization, increases in leverage, and increases in the proportion of short-term debt employed by the bank. But are these characteristics really linked to higher proportion of tail risk? To address this, table 45 shows that the higher predictive power of g_t^c for small banks, banks with more leverage, or more short-term

Table 43: Forecasting regression for excess returns of bank portfolios double sorted by market capitalization and leverage

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + r_{i,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \alpha_H^i + \beta_H^{g^c} \log(1 + g_t^c) + \epsilon_{t+H}^i$$

Here $r_{i,t+j}$ is the return of the i^{th} portfolio of BN sorted by market capitalization and leverage at time $t + j$, $r_{f,t+j}$ is the return of the risk-free asset at time $t + j$, and g_t^c is credit growth for all banks in the U.S. at time t. Small and large refer to market capitalization and low and high refer to leverage. The figures in parenthesis along column and row headings show average leverage and market capitalization in $ Billion for each portfolio. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 12 lags. Monthly data, 1987 - 2009.

	Coefficient	Low Leverage (6.41)	High Leverage (14.22)
	α	0.41***	0.51***
Small ($0.10)	g_t^c	-5.02***	-6.15**
	R^2-adj (%)	30.41	24.95
	α	0.30***	0.38**
Large ($43.00)	g_t^c	-3.41*	-4.81*
	R^2-adj (%)	16.07	11.09

Table 44: Forecasting regression for excess returns of bank portfolios double sorted by market capitalization and short-term debt

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + r_{i,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \alpha_H^i + \beta_H^{g^c} \log(1 + g_t^c) + \epsilon_{t+H}^i$$

Here $r_{i,t+j}$ is the return of the i^{th} portfolio of BN sorted by market capitalization and book value of short-term debt at time $t+j$, $r_{f,t+j}$ is the return of the risk-free asset at time $t+j$, and g_t^c is credit growth for all banks in the U.S. at time t. Small and large refer to market capitalization and low and high refer to short-term debt. The figures in parenthesis along column and row headings show average short-term debt as a proportion of total assets and market capitalization in $ Billion for each portfolio. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 12 lags. Monthly data, 1987 - 2009.

	Coefficient	Low ST Debt (0.71)	High ST Debt (7.43)
	α	0.43***	0.51***
Small ($0.05)	g_t^c	-5.29***	-6.13***
	R^2-adj (%)	24.97	29.81
	α	0.37***	0.37***
Large ($33)	g_t^c	-4.24***	-4.69**
	R^2-adj (%)	19.88	14.30

debt, is due to the fact that banks with these characteristics are more exposed to tail risk. Table 45 reports the estimates for the following regression:

$$r_{i,t+j} - r_{f,t+j} = \alpha^i + \beta_1^{VIX} \Delta VIX_{t+j} + \beta_2^{VIX} D_{t+j} \Delta VIX_{t+j} + \epsilon_{t+H}^i \quad (25)$$

Here $r_{i,t+j}$ is the return for size-sorted portfolio of banks and non-financial firms at time $t+j$, $r_{f,t+j}$ is the return of the risk-free asset at time $t+j$, ΔVIX_{t+j} is change in the daily implied volatility of the index options on the S&P500 (VIX) at time t, and D_{t+j} is a dummy variable that equals 1 if a date lies within the start and end dates of a recession or a financial crises and equals zero otherwise. Dates for recessions and financial crisis are same as the ones used in section 3.2.

In this regression, β_1^{VIX} measures the sensitivity of asset i to changes in VIX and β_2^{VIX} measures the increase in this sensitivity in a recession or a financial crisis. The first panel shows the results for the size-sorted portfolios of banks and the second panel shows the results for the size-sorted portfolios of non-financial firms. The last column reports the percentage increase in this coefficient in economic recessions ($\frac{\beta_2^{VIX}}{\beta_1^{VIX}}$).

Note that the absolute magnitude of the coefficient, β_1^{VIX} is higher for large banks and large non-financial firms. This may be simply on account of the fact that the VIX represents the implied volatility of index options on the S&P500 and this would typically include large financial and non-financial firms. One may also attribute the higher coefficient for small non-financial firms to the fact that these firms usually have a lower market capitalization than the smallest banks in my sample. The appropriate benchmark for the increase in sensitivity to tail risk should then be the percentage increase in the coefficient in economic recessions and financial crises.

Note that only the coefficient, β_2^{VIX}, for large and small banks is statistically different from the coefficient, β_1^{VIX}, in economic recessions and crises. For small banks the coefficient on changes in VIX increases nearly by 100% and this difference is statistically significant. The coefficient for large banks also increases, but only by 25% and this difference is statistically significant at only

Table 45: Sensitivity to changes in VIX in economic expansions and recessions

Notes: This table shows the estimated coefficients for the regression:

$$r_{i,t+j} - r_{f,t+j} = \alpha^i + \beta_1^{VIX} \Delta VIX_{t+j} + \beta_2^{VIX} D_{t+j} \Delta VIX_{t+j} + \epsilon_{t+H}^i$$

Here $r_{i,t+j}$ is the return for size-sorted portfolio of banks and non-financial firms at time $t+j$, $r_{f,t+j}$ is the return of the risk-free asset at time $t+j$, and ΔVIX_{t+j} is change in the daily implied volatility of the index options on the S&P500 (VIX) at time t. D_{t+j} is a dummy variable that equals 1 if a date lies within the start and end dates of a recession or a financial crisis and equals zero otherwise. The first panel shows the results for banks and the second panel shows the results for non-financial firms. The last column reports the percentage increase in this coefficient in recessions and financial crisis. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity and auto-correlation using Newey-West with 3 lags. Daily data, 1990 - 2009.

Size	β_1^{VIX}	β_2^{VIX}	% Change
Small banks	-0.84***	-0.72**	85.71
Large banks	-8.28***	-2.16*	26.09
Small firms	-3.00***	-0.12	4.00
Large firms	-7.44***	0.24	4.36

the 10% level. The coefficient for both small and large non-financial firms does not change in times of distress.

A final argument in favor of variation in tail risk explaining the predictive variation in returns is that g_t^c also does not significantly predict the cash flows of the BN index as measured by the dividend growth rates. In a forecasting regression of g_t^c on future dividend growth rates The coefficient is never statistically significant. Its maximum magnitude over a one year horizon is 0.02, the adjusted-R^2 reaches a maximum value of 0.54% in 8-months, and the sign of the coefficient is also not stable. This again argues against the predictive variation in returns arising from variation in sources of risk other than tail risk. This is because standard cash flow risk would show up in the sample and hence I should also be able to predict future cash flow growth in the sample.

3.3.7 Results from the cross-section

The last set of results I present relate to cross-sectional tests using data for individual bank holding companies. Generally, it is difficult to conduct cross-sectional tests of disaster models as a particular firm's exposure to tail risk is not readily measurable. However in this case, actions by banks themselves may indicate their exposure to tail risk. When the likelihood of a disaster decreases, banks with the highest exposure to tail risk increase credit supply the most and consequently experience the largest drop in the expected equity premium.

For this, I again require bank-level balance sheet data from the Chicago FED. In each quarter, I sort BHCs into 5 portfolios based on credit growth at the BHC level. Credit growth is defined as the log change in total loans outstanding over 1 quarter. BHCs with the lowest credit growth are sorted in portfolio 1 and those with the highest credit growth are sorted in portfolio 5. I compute the average return of each portfolio over 1 year from the portfolio formation date.

Recall from the results in section 3.3.1 that banks with the largest drop in today's expected returns should have the highest contemporaneous realized excess return and the lowest subsequent excess returns. That is, the results should be analogous to the cross-correlation diagram in figure 6.

In figure 10, each bar corresponds to the mean return of portfolio 5 relative to the mean return of portfolio 1. The first bar plots this relative mean return one quarter after the portfolios are formed. The statistics are annualized by multiplying by 4 and are expressed in percentages. On the x-axis $Q1 - Q4$ refer to the quarter after portfolios are formed and the figures in parentheses refer to the t-stats.

Clearly, banks with the highest credit growth initially outperform banks with the lowest credit

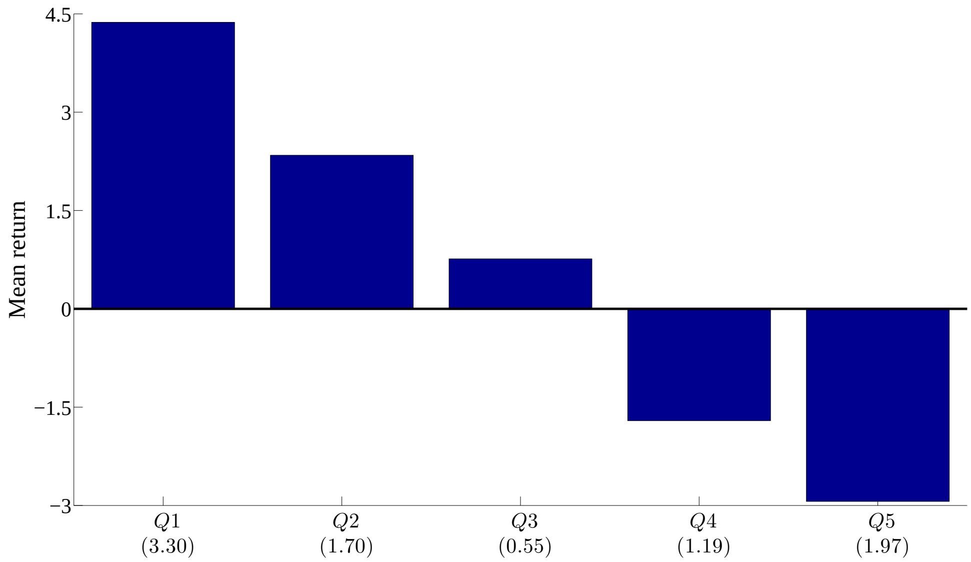

Figure 10: Relative mean returns for individual banks sorted by credit growth

In each quarter individual bank holding companies (BHCs) are sorted into 5 different portfolios based on credit growth. Credit growth is measured by the change in the log of total loans outstanding over 1 quarter at the BHC level. BHCs with the lowest credit growth are sorted into portfolio 1 and BHCs with the highest credit growth are sorted into portfolio 5. Each bar corresponds to the mean return of portfolio 5 relative to the mean return of portfolio 1. The first bar plots this relative mean return one quarter after the portfolios are formed. The statistics are annualized by multiplying by 4 and are expressed in percentages. On the x-axis $Q1 - Q5$ refer to the quarter after portfolios are formed and the figures in parenthesis refer to the t-stats. Quarterly data, 1987 - 2009 growth. The contemporaneous mean return of high credit growth BHCs exceeds that of low credit growth BHCs by 437 basis point. This difference is statistically significant at the 1% level. However, this soon reverses and by quarter 4 high credit growth portfolios underperform low credit growth portfolios by nearly 300 basis points. This difference is significant at the 5% level.

Table 46 formalizes the relationship between credit growth and equity returns of individual banks. The dependent variable is the log excess return of each BHC measured at $t + H$. $H = 0$ refers to the quarter in which credit growth is measured and $H = 1 - 5$ refer to each of the subsequent 5 quarters. The independent variable are the log change in total loans outstanding, log change in book to market, and the log change in leverage over 1 quarter .

In table 46 the first row shows the intercept, and rows two to four present the estimated coefficient on credit growth, leverage change, and book to market change respectively. The intercept and the coefficient are multiplied by 100 and expressed in percentage. The final row presents the value for the adjusted-R^2 for each horizon. The last row shows the number of observations. For each regression I include both quarter and BHC fixed effects. The data is quarterly from 1987 - 2009. The standard errors are adjusted for heteroscedasticity and autocorrelation using Newey-West with 4 lags.

A 1% increase in credit growth at the BHC level implies that contemporaneous returns are higher by 10.91%. The magnitude of the coefficient declines monotonically with lags and eventually reverses so that the coefficient for quarter '5' is -4.34%.

I next develop a simple theoretical framework. A calibration of this framework with reasonable parameters shows that an approximately 1% drop in credit produced results in a nearly 3% increase in the unconditional equity premium from 7% to 10%. This 3% increase in the unconditional equity premium is approximately the same as the 2.94% increase in table 7 when g_t^c decreases by 1%.

Table 46: Forecasting regression for excess returns of individual bank holding companies

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\log(1 + r_{i,t+H}) - \log(1 + r_{f,t+H}) = \alpha_H^i + \beta_H^{g^{c,i}}(\Delta g_t^{c,i}) + \beta_H^{g^{l,i}}(g_t^{l,i}) + \beta_H^{g^{b,i}}(\Delta g_t^{b,i}) + \epsilon_{t+H}^i$$

Here $r_{i,t+j}$ is the quarterly return of the i^{th} individual bank holding company (BHC) at time $t + H$, $r_{f,t+H}$ is the quarterly return of the risk-free asset at time $t + H$, $g_t^{c,i}$ is the quarterly credit growth, $g_t^{l,i}$ is the quarterly change in leverage, and $g_t^{b,i}$ is the quarterly change in book/market ratio of BHC i at time t. I include both time- and BHC-fixed affects. For $H = 0$ the dependent variable is the contemporaneous return of the i^{th} BHC in the quarter that credit growth is measured. For $H = 1-5$, the dependent variable is the return of the i^{th} BHC in quarters $Q1 - Q5$ after credit growth is measured. All coefficients are expressed in percentages. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity and auto-correlation using Newey-West with 4lags. Quarterly data, 1987 - 2009.

$H =$	0	1	2	3	4	5
α	-5.16***	-6.76***	-32.02***	7.59***	-35.64***	-39.83***
$g^{c,i}$	10.91***	0.06	-0.96	-1.46	-2.58**	-4.34***
$g^{l,i}$	0.44	-1.55	-0.90	-2.29**	-0.36	4.20***
$g^{b,i}$	-12.93***	3.58***	0.49	-0.02	-3.21***	-0.10***
R^2-adj (%)	28.06	32.16	33.82	33.42	35.02	35.41
TFE	Yes	Yes	Yes	Yes	Yes	Yes
BFE	Yes	Yes	Yes	Yes	Yes	Yes
N	20,550	20,550	$20,550$	20,550	20,550	20,550

3.4 Theoretical framework

In this section I present a simple extension of Rietz (1988) and Barro (2006) disaster framework that produces the exact same relationship between g_t^c and expected returns of bank stocks that is documented in section 3.3. Section 3.4.1 presents the model. In section 3.4.2, I explore the magnitude of the effect by calibrating the model with reasonable parameter values.

3.4.1 Model

Consider an economy with a risk-averse representative investor, I, and a representative bank, B. The bank is completely equity financed. To avoid extra parameters, I assume that the utility function for both I and B is given by:

$$u(c_t) = e^{-\rho t} \frac{c_t^{1-\gamma} - 1}{1-\gamma}. \tag{26}$$

Here, ρ reflects time preferences and γ is the coefficient of relative risk aversion. In this economy, in each period there is a small chance of a realization of a tail event. The variable c_t represents consumption at time t. In the model banks derive consumption from total cash flows from loans issued. I describe below the effect of the tail event, when it is realized. The tail event follows a Poisson process and at t, its intensity is given by λ_t. For simplicity, I assume that the bank can perfectly observe λ_t at t.

In each period the bank has the opportunity to finance n_t new loans. Each loan references a project managed by an entrepreneur who requires the bank loan to produce cash flows. Throughout this paper I use the terms loans and projects interchangeably. Each loan i promises a perpetual cash flow stream given by $x_{i,t}$ that evolve as:

$$\log(x_{i,t+1}) - \log(x_{i,t}) = \overline{\theta} + \theta_{i,t+1} + \eta_{t+1}. \tag{27}$$

The variable $x_{i,t}$ represents the cash flows from the project promised to the bank. Actual project cash flows may exceed $x_{i,t}$ and are not modeled. The bank can verify the cash flows from the project. Also, the size of the loan and the first cash flow from the project ($x_{i,0}$) are dependent on the size of the project. This ensures that the bank does not unconditionally prefer large projects but makes decisions based on the riskiness of each project.

In equation (27), $\overline{\theta}$ is constant. The variable $\theta_{i,t+1}$ is project dependent and its distribution for the i^{th} project is given by:

$$\theta_{i,t+1} \sim \mathcal{N}\left(\mu_i, \sigma_i^2\right). \tag{28}$$

The mean μ_i is dependent on the type of the project so that μ_i is high for good projects and vice versa. The distribution of the quality of the projects eligible for bank financing in the economy at any instant is described by:

$$\mu_i \sim \mathcal{N}\left(0, 1\right). \tag{29}$$

The distribution of the quality of the projects does not vary over time or with business conditions. Allowing for such time-variation should presumably strengthen my results if the probability of a tail event realization increases and the fraction of projects that are eligible for bank financing contracts in a recession. In this case banks not only increase the performance criteria required to finance projects but also the proportion of good quality projects available in the economy declines.

The bank observes μ_i at time of loan issuance. This is in accordance with the theoretical models of banks in Diamond (1984, 1991), Ramakrishnan and Thakor (1984), Fama (1985), Boyd and Prescott (1986), that suggest banks have a special ability to assess the credit worthiness of informationally difficult borrowers and can access information that is not available to other market participants.

In equation (27), η_{t+1} represents an economic shock that identically affects the cash flows of all loans. When a tail event is realized, a fixed fraction s of the cash flows from each loan is lost and becomes unavailable to the bank's stock investors for consumption. This loss may reflect funds required to restore bank capital or maintain minimum reserve ratios mandated by regulators:

$$\eta_{t+1} = \begin{cases} 0 & \text{with probability } e^{-\lambda_t} \text{ if no crisis is realized,} \\ \log(1-s) & \text{with probability } 1-e^{-\lambda_t} \text{ if crisis is realized.} \end{cases} \tag{30}$$

The bank makes a case-by-case decision to finance new loans and does not consider the correlation of a new loan with loans already on its balance sheet. This is consistent with the stylized fact that banks, especially small ones, specialize in lending by industries. If the loan lasts from t to $t+1$, then the bank agrees to fund the loan if the discounted marginal utility of the cash flow from the loan next period is greater than the marginal utility of the capital required to fund the loan today. Thus, the loan decision is governed by:

$$e^{-\rho}\mathbb{E}_t\left[u'(x_{i,t+1})\right] \geq u'(k). \tag{31}$$

Here k is the initial loan capital. Equation (31) implies that the bank will accept all loans for which μ_i exceeds a threshold ω which is given by:

$$\mu_i \geq \omega = \frac{1}{\gamma}(\frac{1}{2}\gamma^2\sigma_i^2 + \log(e^{-\lambda_t} + (1-e^{-\lambda_t})(1-s)^{-\gamma}) - \gamma\overline{\theta} - \rho). \tag{32}$$

As the likelihood of a tail event increases (λ_t increases), the fraction of loans funded by the bank and hence credit produced by the bank decreases and is described by:

$$l_t = n_t(1 - F(\omega, 0, 1)). \tag{33}$$

In equation (33) 'F' is the CDF of a standard normal distribution. Next,to compute the expected returns of bank stocks I need to model the overall bank cash flows and the process for aggregate consumption. I assume that in the course of its business, the bank incurs expenses such as loan origination costs, loan servicing costs, wages, and overhead expenses. These expenses do not affect the cash flow from individual loans but impact the overall bank cash flows. Hence, cash flows from individual loans do not aggregate to the overall bank cash flows. I do not model the expenses and directly model the overall bank cash flow which is given by:

$$\log(X_{t+1}) - \log(X_t) = \overline{\theta} + \theta_B + \eta_{t+1}. \tag{34}$$

To ensure that the evolution of the cash flows from the individual loans is consistent with the evolution of the overall cash flow of the bank I set:

$$\theta_i \approx a_i \times \theta_B. \tag{35}$$

Here, a_i is a constant that (approximately) equals the fraction of the total bank loan portfolio invested in loan i. Thus the distribution of θ_B is also normal and is given by:

$$\theta_B \sim \mathcal{N}\left(\mu_B, \sigma_B^2\right). \tag{36}$$

At any instant, t, the bank accounts for a fixed fraction, f, of the total economy. Thus, aggregate consumption at t equals $C_t = \frac{1}{f} X_t$. This can of course be generalized to assume that the bank accounts for a stochastic fraction of the overall economy. With stochastic size, the magnitude of the inverse correlation between credit produced and expected returns of bank stocks should increase in the size of the banking sector. Table 36 shows that the predictive power nearly doubles from 1960 - 2009 over 1990 - 2009 and this can be on account of the fact that the size of the banking sector increased by nearly 40% over the same period[50].

As in Barro (2006), there also exists a government bond, G, which can default. On default, a fraction d of the gross return on the bond is lost. The payoff for the government bond is given by Equation (37). Government bond defaults never occur in normal times, default events do not

[50] Table 6.17 of National Income and Product Account (NIPA).

apply to equities, and do not affect bank cash flows:

$$1 + r_{t+1}^G = \begin{cases} 1 + r_t^f & \text{with probability } e^{-\lambda_t} \text{ if no crisis is realized,} \\ (1-d)(1+r_t^f) & \text{with probability } 1 - e^{-\lambda_t} \text{ if crisis is realized.} \end{cases} \tag{37}$$

Given the setup I compute the stock price of a one period claim on bank cash flows as:

$$P_t = X_t e^{-\rho + (1-\gamma)\overline{\theta} + (1-\gamma)\mu_B + 0.5(1-\gamma)^2\sigma_B^2} \left[e^{-\lambda_t} + (1 - e^{-\lambda_t})(1-s)^{1-\gamma} \right] \tag{38}$$

Also, the unconditional and conditional (on no tail events) expected equity premium of bank stocks is given by:

$$\log(\mathbb{E}_t[1 + r_t]) - \log(\mathbb{E}_t[1 + r_t^G]) = \gamma\sigma_B^2 + \lambda_t[(1-s)^{-\gamma} - (1-s)^{1-\gamma} - s] \tag{39}$$

$$\log(\mathbb{E}_t[1 + r_t]) - \log(\mathbb{E}_t[1 + r_t^G])_{|\eta_t = 0} = \gamma\sigma_B^2 + \lambda_t[(1-s)^{-\gamma} - (1-s)^{1-\gamma}]$$

In the next section, I calibrate the model to the actual frequency of financial crisis in OECD countries.

3.4.2 Calibration

To explore the magnitude of the inverse relationship between g_t^c and expected return of bank stocks I calibrate the model using reasonable parameter values. I adopt most of the parameter values from Barro (2006). I set $\rho = 0.05$ and $\gamma = 3$.

I normalize the number of loan applications received by the bank in each period to 100. With $n_t = 100$, the variation in the number of loans approved per period, l_t, directly represents the percentage change in credit levels. Fixing $n_t = 100$ implies that only bank credit supply changes and that there is no impact on demand for credit. Clearly, this is not true and difficult to verify in the data. My mechanism does not require that I distinguish supply from demand contraction, only that both supply and demand of credit be negatively correlated with the probability of a tail event - a reasonable assumption. The actual fall in credit level attributed to supply or demand contraction may differ in each business cycle and will depend on several factors such as the financial condition of the bank, the balance sheet strength of the project manager, and the nature of the tail event.

I calibrate the mean and volatility of θ_B to the mean and volatility of the growth rate of annual log bank profits over 1960 - 2000. Data for annual bank profits is from Table 6.17 of National Income and Product Accounts (NIPA). I set the mean loss of cash flows in a tail event to $s = 22\%$ which represents the average drop in log bank profits in a recession or a financial crisis.

To calibrate the value of λ_t I use data from Laeven and Valencia (2008). Laeven and Valencia list 37 financial crisis for the 34 OECD countries over 1970 - 2007 (27 years). Thus the probability of entering a financial crisis is 2.94% per year. I set the baseline value of λ_t to 2.94%. This also implies that the probability of an intermediary sector specific tail event is considerably higher than the probability of a rare disaster as measured by Barro, which equals 1.76%. All other parameter values follow Barro (2006).

Figure 11 plots key model quantities. The left panel plots the fraction of loans accepted by the bank at time t, l_t, as a function of λ_t. The y-axis presents the fraction of loans accepted by the bank and is expressed in percentage. The right panel plots the unconditional equity premium of bank stocks, $\log(\mathbb{E}_t[1 + r_t]) - \log(\mathbb{E}_t[1 + r_t^G])$ as a function of λ_t. The y-axis presents the equity premium of bank stocks. For the right panel, 0.07 on the y-axis repersents an equity premium of 7%. In each case λ_t is plotted on the x-axis and is allowed to vary from 0 to 0.25.

An increase in λ_t lowers the fraction of loans accepted by the bank and raises the unconditional equity premium of bank stocks. Note that an increase in the tail event intensity, λ_t from 0 to 2.94%, the baseline value, results in approximately 1% drop in the fraction of loans accepted by

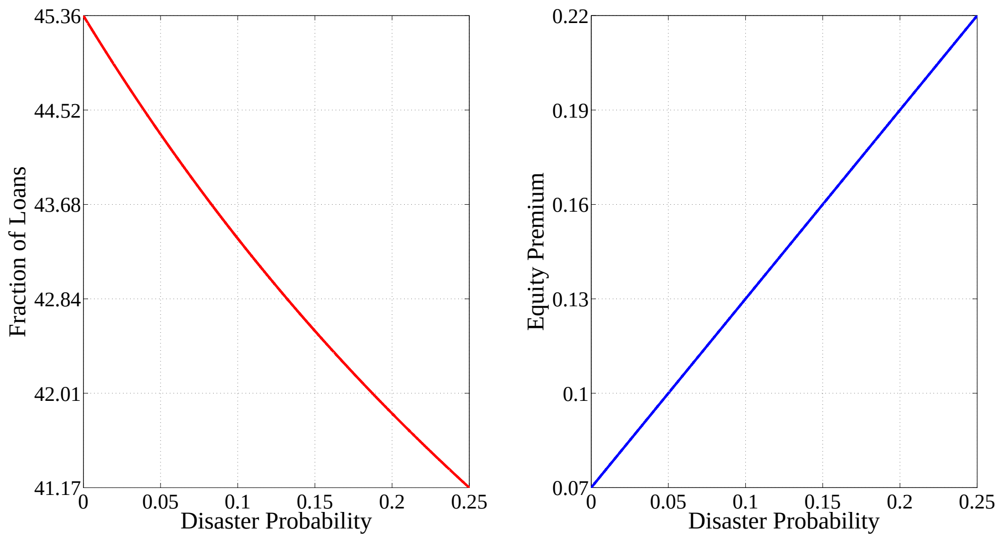

Figure 11: Bank loans and bank equity premium

Figure 11 plots key quantities from the model in section 3.4. The left panel plots the fraction of loans accepted by the bank, l_t, as a function of the intensity of a tail event realization, λ_t. The y-axis presents the fraction of loans accepted by the bank and is expressed in percentage. The right panel plots the unconditional equity premium of bank stocks, $\log(\mathbb{E}_t[1+r_t]) - \log(\mathbb{E}_t[1+r_t^G])$. The y-axis presents the equity premium on bank stocks. For the right panel, 0.07 on the y-axis equals an equity premium of 7%. In each case I allow the tail event intensity to vary from 0 to 0.25.

the bank and also a nearly 3% increase in the unconditional equity premium from 7% to 10%. This 3% increase in the unconditional equity premium is approximately the same as the 2.94% increase in table 31 when g_t^c decreases by 1%.

3.5 Conclusion

In this paper, I study the empirical linkage between the aggregate bank credit growth and the expected returns of bank stocks and document that credit growth and the expected returns of bank stocks are negatively correlated. A 1% increase in credit growth implies that excess returns of bank stocks are lower by nearly 3% over the next year. The annual adjusted-R^2 of this regression is nearly 14%.

Unlike most other variables, credit growth tracks bank stock returns over the short-term to intermediate horizon and its effect is robust to the exclusion of data from the crisis years and to the inclusion of several popular forecasting variables used in the literature. Credit growth also does not predict future cash flows of bank stocks as measured by dividend growth rates. Credit growth has limited predictive power for stock returns of bank-dependent firms but does not predict returns for any other asset class.

A straightforward extension of the Rietz (1988) and Barro (2006) disaster framework produces the exact same negative correlation between credit growth and the expected returns of bank stocks. I show that this predictive variation in returns reflects investors' rational response to a small time-varying probability of a tail event. Realization of a tail event results in a large loss of cash flows from projects funded by bank loans. Bank management is rational, but very sensitive to changes in the probability of a tail event. This high sensitivity arises from higher leverage, shorter debt maturity structure, and lower fraction of tangible assets that characterize the balance sheet of a typical bank.

These characteristics also increase the likelihood that a bank will enter distress upon the realization of a tail event. Hence, as the probability of a tail event increases, projects with lower expected cash flows are rejected by the bank. This effectively raises the discount rate used by the bank to evaluate projects, thereby contracting the supply of credit. In fact, many projects with low expected cash flows that would customarily be taken to the bank for evaluation may be rejected at the outset by the project manager herself, thereby contracting the demand for credit.

The standard disaster-risk asset pricing framework also implies that the expected returns required by the average investor to hold bank stocks increases in the probability of a tail event. This drives the observed negative correlation between credit growth and the expected returns of bank stocks. The disaster-risk framework also explains the fact that credit growth predicts the excess returns of investment banks (financial trading firms). This is because tail events that impact cash flows of bank-funded projects may also affect cash flows of projects funded by other intermediaries.

Consistent with this hypothesis, the predictive power, as measured by the absolute magnitude of the coefficient on credit growth and the adjusted-R^2 at the the 1-year horizon, depends systematically on variables that regulate exposure to tail risk. Predictive power decreases monotonically in size, increases in leverage, and increases in the proportion of short-term debt employed by the bank. This is because small banks, banks with higher leverage, or higher proportion of short-term debt, are more exposed to tail risk. I also rule out that the predictive variation in returns reflects investor overreaction or bank management's rational response to sources of variation in expected returns other than tail risk. Historically, the probability of a tail event increases in a recession, therefore the proposed mechanism also explains the observed correlation between changes in bank credit levels and business conditions.

3.6 Appendix

3.6.1 Composition of aggregate bank credit

Table 47 shows the summary statistics for the various categories of loans that comprise bank credit. In any given month bank credit is computed as the sum of total securities (TS), commercial and industrial loans (IL), real estate loans (RL), consumer loans (CL), and miscellaneous loans (ML). Column 1 of the table indicates the loan category. Columns 2 - 6 present the mean, standard deviation, minimum, median, and maximum for each loan category expressed as a percentage of total bank credit. Over 1960 - 2009, TS accounts for 23.23% of bank credit on average in any given month. The corresponding values for IL, RL, CL, and ML are 22.33%, 25.15%, 13.38%, and 11.90% respectively. Traditional bank loans, computed as a sum of IL, RL, and CL on average account for nearly 73% of total bank credit in any given month. The level of traditional loans never falls below 60% (approx.) of total bank credit. The statistics for traditional loans are reported in the last line of the table.

Table 47: Composition of aggregate bank credit

Notes: This table shows the summary statistics for various categories of loans that comprise aggregate bank credit. In any given month bank credit is computed as the sum of 'total securities (TS)', 'total commercial and industrial loans (IL)', 'total real estate loans (RL)', 'total consumer loans (CL)', and 'total miscellaneous loans (ML)'. Column 1 indicates the loan category. Column 2 - 6 present the mean, standard deviation, minimum, median, and maximum for each loan category as a percentage of total bank credit. All statistics are monthly and are expressed in percentages. Monthly data, 1960 - 2009.

Loan category	Mean	σ	Min	Median	Max
TS	27.23	4.46	21.96	25.67	40.94
IL	22.33	3.72	13.78	23.19	28.35
RL	25.15	8.35	13.86	22.01	42.01
CL	13.38	2.08	8.78	13.96	16.68
ML	11.90	2.21	8.02	11.91	15.97
$Trad.loans$	72.77	4.46	59.06	74.33	78.04

3.6.2 Additional empirical results

Non-overlapping data Table 48 presents the results for non-overlapping data. In table 48 the dependent variable is the log excess return of the BN index at time $t + H$ and the independent variable is $\log(1 + g_t^c)$. Even in this case g_t^c significantly predicts returns of the BN index and thus the results are robust to the use of non-overlapping data.

Excluding credit growth In table 49, I test if variables known to predict the excess stock returns of the stock market index, by themselves, predict the excess stock returns of the BN index.

Table 48: Forecasting regression for excess returns of banks (non-overlapping data)

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\log(1 + r_{BN,t+H}) - \log(1 + r_{f,t+H}) = \alpha_H^i + \beta_H^{g^c} \log(1 + g_t^c) + \epsilon_{t+H}^i$$

Here $r_{BN,t+j}$ is the return of BN at time $t + H$, $r_{f,t+H}$ is the return of the risk-free asset at time $t + H$, and g_t^c is the credit growth all banks in the United States at time t. Coefficients have been annualized by multiplying by 12. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity and auto-correlation using Newey-West with 12 lags. Monthly data, 1960 - 2009.

$H =$	1	2	3	4	5	6	7	8	9	10	11	12
	1960 - 2009											
α	0.27***	0.30***	0.31***	0.36***	0.38***	0.38***	0.37***	0.37***	0.35***	0.33***	0.30***	0.28***
g^c	-2.19**	-2.53***	-2.73***	-3.30***	-3.55***	-3.61***	-3.52***	-3.43***	-3.23***	-2.93***	-2.53**	-2.34**
R^2-adj (%)	0.56	0.80	0.95	1.45	1.69	1.75	1.64	1.54	1.35	1.08	0.76	0.63
	1990 - 2009											
α	0.30**	0.31**	0.32***	0.41***	0.46***	0.48***	0.48***	0.51***	0.53***	0.50***	0.49***	0.45***
g^c	-2.51	-2.72	-2.71	-4.09**	-4.86**	-5.12**	-5.00**	-5.34**	-5.42**	-4.89**	-4.94**	-4.34**
R^2-adj (%)	0.16	0.24	0.23	1.04	1.64	1.84	1.73	2.08	2.20	1.73	1.82	1.30

The predictive variables used in this table are the same as in table 35. All predictive variables are measured at time t. Only the coefficient on the term spread is statistically significant. Recall that in table 35 this variable is only marginally significant, and is not significant once we include g_t^c as a predictive variable.

Total asset growth Table 50 shows the results for the typical forecasting regression with total asset growth of all commercial banks in the U.S. as the predictive variable. In the $H.8$ release, data for total assets is available only from 1973. I reserve one year for lags and hence estimate the coefficients using data from 1974 to 2009. Total asset growth does not have any significant forecasting power for future bank stock returns. At all horizons the coefficients are both economically and statistically insignificant and the adjusted-R^2 never exceeds 0.29%.

I also run predictive regressions with each of the remaining subcomponents of the aggregate bank balance sheet as a predictive variable. I also use the growth rate of aggregate bank assets less the growth rate of aggregate loan portfolio as a predictive variable. In all cases the predictive coefficient at the 12-month horizon never exceeds -81 basis points and is only marginally statistically significant. Also, the value of the adjusted-R^2 over any horizon never exceeds 6%.

3.6.3 Definition of selected variables

This section provides definitions for other predictive variables for the robustness test in equation (23). The first predictive variable other than g_t^c, is simply the lagged value of the dependent variable.

To compute the smoothed dividend-yield, I follow Cochrane (2008). Dollar-dividends for each bank in the BN index is computed as $\frac{R_t^i}{R_{x,t}^i} \times P_t^i$ where R_t^i is the gross cum-dividend return, $R_{x,t}^i$ is the gross ex-dividend return, and P_t^i is the common equity price at t of each bank i in the BN index. The smoothed dividend-price ratio of the BN index is the sum of dividends paid over the

Table 49: Forecasting regression for excess returns of banks excluding credit growth

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\sum_{j=1}^{j=H} \log(1 + r_{BN,t+j}) - \sum_{j=1}^{j=H} \log(1 + r_{f,t+j}) = \alpha_H + \beta_H^{LR}(\log(1 + r_{BN,t}) - \log(1 + r_{f,t})) + \beta_H^{DP}(\log(D_t) - \log(P_t)) + \beta_H^{TS}(y_{10,t} - y_{3,t}) + \beta_H^{DS}(BAA_t - AAA_t) + \beta_H^{IPG}(\log(1 + IPG_t)) + \epsilon_{t+H}^i$$

Here $r_{BN,t+j}$ is the return of BN at time $t+j$, $r_{f,t+j}$ is the return of the risk-free asset at time $t+j$, LR_t is the lagged log excess return of BN at time t, DP_t is the log dividend-price ratio of BN at time t, TS_t is the term-spread at time t, DS_t is the default spread at time t, IPG_t is the net growth rate of the index of industrial production at time t. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity, auto-correlation, and overlapping data using Hansen-Hodrick with 12 lags. Monthly data, 1960 - 2009.

Coefficient									
α	0.09***	0.33	0.01	0.10**	0.09***	0.09***	0.04	0.11***	0.37
LR	0.06								0.05
DP		0.07							0.08
TS			6.05***						7.85***
r_r				-0.19					1.01
Δr_n					-1.92				-1.65
r_{rel}						-3.40			2.00
DS							5.29		-9.67
IPG								-0.62	-1.00
R^2-adj (%)	-0.14	0.92	9.96	-0.12	0.09	2.01	0.70	1.46	12.94

Table 50: Forecasting regression for excess returns of banks and total asset growth

Notes: This table shows the estimated coefficients for the forecasting regression:

$$\log(1 + r_{BN,t+H}) - \log(1 + r_{f,t+H}) = \alpha^i_H + \beta^{AG}_H \log(1 + AG_t) + \epsilon^i_{t+H}$$

Here $r_{BN,t+j}$ is the return of BN at time $t + H$, $r_{f,t+H}$ is the return of the risk-free asset at time $t + H$, and AG_t is credit growth for all banks in the United States at time t. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. The standard errors are adjusted for heteroscedasticity and auto-correlation using Newey-West with 12 lags. Monthly data, 1974 - 2009.

$H =$	1	2	3	4	5	6	7	8	9	10	11	12
	1960 - 2009											
α	-0.01	-0.02	-0.02	-0.03	-0.03	-0.00	0.04	0.10	0.17	0.25	0.34	0.43
AG	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.00	-0.01	-0.01	-0.02	-0.02
R^2-adj (%)	-0.22	-0.20	-0.19	-0.18	-0.18	-0.21	-0.23	-0.23	-0.19	-0.10	0.08	0.29

previous 12 months divided by the current stock price.

Data sources and definitions for the term-spread, default spread, and the growth rate of industrial production are described in section 3.2, table 30.

The short rate equals the 1-month nominal risk-free rate, and is computed using the average of the bid and ask yields, provided by Eugene Fama[51]. The inclusion of short-term interest rate variables ensures that g_t^c does not predict excess returns for the BN index because it is related to movements in the short-term risk-free rate.

I deflate nominal returns using the consumer price index available from Global Financial Data. On Global Financial Data, the consumer price index is identified by the code $CPUSAM$.

[51] Available on Wharton Research Data Services (WRDS). See http://wrds.wharton.upenn.edu/.

4 Chapter 4: References

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