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Priyank Gandhi
Hanno Lustig

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ABSTRACT

We use bank stock returns to develop an ex-ante measure of the distortion created by the implicit collective guarantee extended to large U.S. financial institutions. The average return on a stock portfolio that goes long in the largest U.S. commercial banks and short in the smallest banks is nearly minus 8% compared to a portfolio of non-bank stocks and bonds with the same exposure to standard risk factors. We provide evidence that 6.35 % of this spread is a subsidy that reflects the government's implicit guarantee of large banks, but not of small banks, when a financial disaster occurs. As predicted by theory, this long-short portfolio of bank stocks rallies during recessions, when the probability of a financial disaster increases, while the benchmark portfolio of non-banks stocks and bonds does not. This 6.35% spread can be decomposed into a 3.1% implicit subsidy to the largest commercial banks and a 3.25% tax on the smallest banks. The annual subsidy to the largest commercial banks is $4.71 billion per bank in 2005 dollars.

Priyank Gandhi
UCLA
110 Westwood Plaza
Los Angeles, Ca 90095
gandhip@ucla.edu

Hanno Lustig
UCLA Anderson School of Management
110 Westwood Plaza, Suite C413
Los Angeles, CA 90095-1481
and NBER
hlustig@anderson.ucla.edu

1 Introduction

We use bank stock returns to develop an ex-ante measure of the distortion created by the implicit collective guarantee extended to large U.S. financial institutions. The events 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. Moreover, even if regulators were 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.

The ex-ante cost of these guarantees can be measured by examining the rate of return required by shareholders for holding different size-sorted bank stock portfolios. We find that a long position in the stock portfolio of largest U.S. commercial banks 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 7.78 percent per annum over the last 39 years. The average risk-adjusted returns decrease monotonically in ten portfolios of commercial banks sorted by market cap. We compute an implicit subsidy of 3.1% to the cost of equity capital for the largest U.S. commercial banks, and a 3.25% tax on the smallest banks. In a model that is calibrated to match the equity premium, we back out a difference in the financial disaster recovery rate of dividends between the largest and smallest banks of 35 cents on the dollar.

Small banks differ from large banks in many ways, but, if markets are reasonably efficient, these differences should not lead to differences in average risk-adjusted returns on bank portfolios unless there is bank-specific risk that is priced by markets but not spanned by the traded returns on other stocks. The critical difference between banks and other non-financial corporations is the phenomenon of bank runs during banking crises, not just runs by depositors but also by other creditors (see Gorton and Metrick, 2009). This leads us to consider banking panics as a potential explanation: rare events that are priced into expected returns on portfolios of banks, but not spanned by the returns on other assets. To model the asset pricing impact of these rare events, we use a version of the Barro (2006); Rietz (1988) asset pricing model with a time-varying probability of rare events, developed by Gabaix (2008); Wachter (2008); Gourio (2008), with two sources of priced risk: normal risk and financial disaster risk.

There is direct evidence for this mechanism. Historically, the probability of a financial disaster increases during recessions. Because of the size-contingent nature of the implicit guarantee extended by the government, the recovery rate for bank stockholders in case of a financial disaster realization depends on the size of the banks in the portfolio. As a result, the variation in the probability of a financial disaster generates a common factor in the normal-risk-adjusted returns of size-sorted bank stock portfolios. This is a size factor because the loadings of bank stock returns on this size factor are determined by the recovery rates and hence by size. The size factor is a measure of the probability of a financial disaster. We find that there is a size factor in that part of the returns on size-sorted portfolios of bank stocks that is orthogonal with respect to standard risk factors in the data, and it is closely tied to to the business cycle.

This size factor is the second principal component of the risk-adjusted returns of size-sorted portfolios of bank stocks. The size factor amounts to a long position in small bank stocks and a short position in large bank stocks. After controlling for exposure to this size factor, the monotonically decreasing size pattern in average risk-adjusted returns disappears. Hence, the covariance between the returns on size portfolios of banks stocks and the size factor explains the size pattern in average risk-adjusted returns. In this specific case, the characteristic –size– determines the covariance, because of the market's participants expectations about the government's actions in case of a banking crisis. This size factor in bank stocks is highly pro-cyclical, even though it is orthogonal to standard risk factors. During NBER recessions, this factor drops by an average of 5.06% per month or 60.83% per annum. This is not the case in other industries. Another explanation for the cyclical variation in the size factor would be counter-cyclical variance of idiosyncratic shocks for smaller banks. While smaller banks are more exposed to idiosyncratic risk, we do not see large increases in this type of risk during recessions.

The average return of this size factor is the price of (government-provided) financial disaster insurance, and the subsidy can be measured as the loading on this factor times this risk price.

In the financial disaster model, the average normal-risk-adjusted return on the long position in the largest banks and the short position in the smallest banks is a disaster insurance premium priced into large bank stocks. Without the government-induced asymmetry in recovery rates, this premium would be zero. At least 635 of the 778 basis points can be directly attributed to covariation with the size factor. We can decompose this further into a 3.1% per annum implicit subsidy to the largest banks and a 3.25% tax on the smallest banks. The largest banks have an average market cap of $ 152 bn in 2005 dollars.[1] For the largest commercial banks, this amounts to an annual subsidy of $4.71 bn per bank.

While we do not have direct evidence linking the implied differences in disaster recovery rates to the government, there is indirect evidence of this linkage. Over the entire sample, the estimated subsidy for all commercial banks is 2.32% and 1.95% for the GSE's. These institutions benefit from special provisions: deposit insurance[2], 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 GSE's. We find that the GSE's benefited from an equity cost of capital subsidy that is as large as those of the largest commercial banks, even though the GSE's are considerably smaller. Moreover, this subsidy was growing over time. For example, the Fannie Mae subsidy tripled to 6.57% in 2000-2005. Furthermore, the estimated subsidy for investment and foreign banks and hedge funds, which do not benefit from these special provisions in the U.S., are much smaller and statistically insignificant.

A general equilibrium version of the model calibrated to match the equity premium can match the average normal-risk-adjusted returns if the shareholders of the largest bank lose 35 cents less per dollar of pre-disaster cash flows than stockholders of the smallest banks, but only if the stock market itself is not too exposed to financial disaster risk. If it is, the spread in the risk premia between small and large banks is absorbed by the spread in β's, not the α's.

The key to activating the collective bailout clause is common variation in bank payoffs. Our paper quantifies this common variation by building portfolios of commercial bank stocks sorted

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

[2] The Federal Deposit Insurance Corporation Improvement Act of 1991 limits the protection of creditors, but it provides a systemic risk exception.

by market capitalization. Our measure of the subsidy is determined by the firm's loading on the common factor, which gauges its systemic risk exposure. As far as we know, our measure is the first to make this connection.

We find large across-the-board increases in the size of the subsidy for large commercial, investment banks and GSE's in the 2000-2005 subsample, after the repeal of the Glass-Steagall Banking Act. These can be interpreted as systemic risk increases. 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 (see Brunnermeier and Sannikov, 2008, for a clear description of this effect of securitization). Because we record the largest loadings on the size factor for 'smaller' firms like Lehman and Fannie Mae with huge systemic risk, we conclude that these loadings on the size factor truly measure the systemic impact of financial institutions. In that sense, our paper contributes to the emerging literature on systemic risk measurement for financial institutions (see Adrian and Brunnermeier, 2008).

Why look at bank stocks? Clearly, the US government and regulators are willing to let small banks fail, not so for large banks. The FDIC reports that 256 banks have failed in the last two years since the failure of IndyMac. All of these banks are small by most standards. By looking at equity, we can compare the exposure of small and large banks to different sources of aggregate risk. This would not be possible if we focused on debt issued by banks or derivatives for bank debt, simply because this data is not available for small banks. The bank stock returns data also allows for a broader historical perspective. Of course, ex ante, one could have expected that the government would wipe out shareholders of large financial institutions in case of a bailout. Our evidence suggests that this is not what market participants expected. This is not surprising. O'Hara and Shaw (1990) document large positive wealth effects for shareholders of banks who were declared too big too fail by the Comptroller of the Currency in 1984, and negative wealth effects for those banks that were not included.[3]

[3]A number of events have been important in creating and sustaining the too-big-too fail perception in the market. Among these are the FDIC'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 LTCM. While the FDICIA limits the protection of creditors,it provides a systemic risk exception.

In more recent work, Acharya, Bharathb, and Srinivasan (2007) find that recovery rates for bondholders actually increase for financials when the industry is in distress; this is not the case for any other industry. This seems consistent with our findings for large financial institutions. Our evidence is consistent with the findings of Gatev, Schuermann, and Strahan (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. Finally, 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. They also document the poor performance of large banks, as measured by ratios of net loan charge-offs and net income to assets, as compared to that of small and medium sized banks.

The key to activating the collective bailout clause is common variation. In a recent paper, 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. Our paper quantifies common variation in stock returns of small versus large banks by building portfolios of commercial bank stocks sorted by market capitalization.

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 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.Veronesi and Zingales (2010)'s main focus is computing the ex post cost of the bailout plan. However, they also use a version of Merton (1974) model to check the ex ante costs.

The rest of this paper is organized as follows. In Section 2 we construct portfolios of bank stocks sorted by size and we measure the financial disaster risk premium. Section 3 develops a simple asset pricing model with time-varying probabilities of a financial disaster that we subsequently use to measure the distortion caused by the government's guarantee. Section 4 establishes that there is a pro-cyclical size factor in the normal-risk-adjusted returns of these portfolios, as predicted by the theory. In section 5 we check that these findings are specific to the banking industry. We use a calibrated version of the model to back out the implied differences in recovery rates in section 6. Section 7 concludes.

2 Size Anomalies in Bank Stock Returns

Section 2.1 describes the data. Section 2.2 computes the average normal-risk-adjusted returns on 10 size-sorted portfolios of banks stocks in the data. We find that there is a size pattern in these α's. The average value of this normal-risk-adjusted return is minus 7.78% per annum when short in the first size decile and long in the last size decile of banks.

2.1 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. Firms with these SIC codes are defined as commercial banks, non-depository credit institutions, and investment banks respectively. Henceforth, we refer to commercial banks, i.e. firms listed under SIC code 60, simply as banks and refer to commercial banks, credit institutions, and investment banks, i.e. firms listed under SIC codes 60, 61, and 62, collectively as financial firms. We exclude data for all financial firms that are inactive and/or not incorporated in the United States. We exclude financial firms not incorporated in the United States 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 United States ensures that all firms in our analysis are subject to a uniform regulatory regime.

We start by focussing on portfolios of commercial bank stocks. We employ the standard portfolio formation strategy of Fama and French (1993) for the purpose of analysis. In January of each year, we rank all bank stocks by market capitalization. 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 from January 1970 to December 2008. While the CRSP data are available from 1926, our analysis begins only in 1970 for banks. Only a small fraction of all banks that operate in the US are publicly listed. For instance, for the years 2000 to 2008, data is available on CRSP for approximately 630 banks. This compares to more than 7000 FDIC-insured banks operating in the United States over the same period. This is mainly an issue for small banks. The largest 600 banks control more than 88% of all commercial bank assets in the United States[4]. 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.

Market cap Table I reports the total market capitalization of banks in each size-sorted portfolio as a fraction of the total market capitalization of the banking sector in January of each year. All the numbers are reported in percentages. We also report the standard deviation (σ), the minimum, the maximum fraction of market capitalization, and the average number of banks in the portfolio. The first panel in Table I shows that during 1970 - 1980, the smallest banks (those in portfolio 1) on average represented just 0.36% of the total market capitalization of all commercial banks. This compares to 49.78% represented by the largest banks (those in portfolio 10). During any year between 1970 and 1980, banks in portfolio 1 at most accounted for 0.57% of the total market cap of the commercial banking sector and at the minimum accounted for 0.25%. Table I clearly shows the increasing concentration of the U.S commercial banking sector. The top 10% banks account for nearly 50% of the total sector market capitalization in the 70s while they account for more than 90% during the last decade; nearly 84% of this accounted for by the largest 1/2 in this group.

[4] As per FDIC Bank Statistics and Data available at
http://www.fdic.gov/bak/statistical/stats/index.html

Table I: Market capitalization of size-sorted portfolios of commercial banks

Notes: This table presents the total market capitalization of firms in each size-sorted portfolio as a percentage of total market capitalization for the entire banking sector. The market values are measured in January of each year. Mean represents the average value of this percentage over the years specified. σ captures the variation in this proportion. Minimum and Maximum values indicate the range of this ratio for each portfolio. N is the average number of banks in each portfolio over the same period.

	1	2	3	4	5	6	7	8	9	10A	10	10B	10B - 1
						1970-1980							
Mean	0.36	0.92	1.50	1.95	3.50	4.67	7.61	11.51	18.21	13.77	49.78	36.01	35.66
σ	0.10	0.28	0.32	0.38	0.89	1.26	2.10	3.11	2.21	5.08	6.84	6.45	6.34
Min	0.25	0.41	1.21	1.05	2.83	3.47	5.84	8.82	15.49	0.00	36.04	22.20	21.94
Max	0.57	1.61	2.39	2.56	5.60	8.21	11.30	19.79	22.67	17.95	56.49	44.77	44.20
N	8.00	9.00	9.00	9.00	9.00	8.00	9.00	9.00	9.00	4.00	9.00	5.00	
						1980-1990							
Mean	0.33	0.72	1.10	1.66	2.39	3.61	5.71	8.84	17.28	17.97	58.34	40.38	40.05
σ	0.08	0.22	0.29	0.43	0.62	0.94	1.53	1.97	2.60	1.65	7.88	8.90	8.82
Min	0.21	0.42	0.68	1.03	1.45	2.19	3.35	5.37	12.67	15.31	49.55	30.87	30.65
Max	0.45	1.05	1.59	2.23	3.11	4.87	7.31	11.03	21.20	20.41	72.63	57.19	56.75
N	26.00	27.00	26.00	27.00	27.00	26.00	27.00	26.00	26.00	13.00	27.00	14.00	
						1990-2000							
Mean	0.17	0.34	0.52	0.76	1.10	1.56	2.32	3.99	8.52	12.37	80.71	68.34	68.18
σ	0.04	0.07	0.11	0.16	0.24	0.37	0.55	0.97	2.46	4.21	4.75	8.52	8.48
Min	0.11	0.22	0.32	0.46	0.65	0.88	1.29	2.21	4.09	5.21	72.63	57.19	57.08
Max	0.21	0.44	0.68	1.03	1.45	2.19	3.35	5.37	12.67	17.37	89.74	84.53	84.32
N	57.00	57.00	57.00	57.00	57.00	57.00	57.00	57.00	57.00	28.00	57.00	29.00	
						2000-2009							
Mean	0.13	0.24	0.35	0.50	0.68	0.95	1.42	2.33	4.62	4.98	88.78	83.80	83.67
σ	0.02	0.05	0.07	0.09	0.12	0.18	0.29	0.47	0.97	0.82	2.20	2.80	2.78
Min	0.08	0.14	0.21	0.30	0.44	0.61	0.88	1.47	3.21	4.44	85.30	78.00	77.92
Max	0.17	0.31	0.45	0.62	0.85	1.21	1.80	3.15	6.62	7.31	92.66	88.22	88.05
N	62.00	62.00	62.00	62.00	62.00	62.00	62.00	62.00	62.00	31.00	63.00	31.00	

In any given year between 1970 and 1980, on average, we have at least 9 banks per size-sorted portfolio and this increases to 62 banks for any year between 2000 and 2009.

Returns on bank stock portfolios Table II provides mean returns for the size-sorted portfolios of banks over the 1970-2005 sample. 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 the 10^{th} and the 1^{st} portfolio. 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. For 2000-2005, the annual loss on this portfolio is 9.64% per annum.

This relationship between bank size and equity returns may seem consistent with the general size effect documented for non-financial firms[5], but we will show that it is actually quite different. Fama and French (1996) document that the size anomaly for non-financials disappears when one

[5](see Banz, 1981; Basu, 1983; Lakonishok, Shleifer, and Vishny, 1993)

Table II: Average returns on size-sorted bank portfolios

Notes: This table presents the mean returns for each size-sorted portfolio of banks. 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	10A	10	10B	10B - 1
1970 – 2005	17.47	16.73	16.15	15.96	16.05	17.03	15.89	14.37	13.77	14.24	13.26	13.01	-4.47
1980 – 2005	19.81	19.18	18.09	17.84	18.31	19.94	19.38	17.15	16.31	16.77	16.17	15.96	-3.85
1990 – 2005	19.61	20.90	18.24	17.67	20.32	19.15	18.69	17.34	16.62	17.00	16.90	16.97	-2.64
2000 – 2005	19.98	22.36	20.43	20.09	21.51	21.17	20.85	18.40	15.76	15.91	10.61	10.34	-9.64

allows for multiple priced factors; Fama and French (1993) implement a three-factor model that includes the market, a size factor (SMB) and a value factor (HML). If the same holds true for commercial banks, then a portfolio of large banks should not earn lower normal-risk-adjusted returns after accounting for exposure to the size factor SMB as compared to a portfolio of small banks. This is not what we find. In fact, we find that the size effect for banks becomes larger when we adjust for exposure to standard risk factors.

2.2 Measuring Normal Risk Compensation

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 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.

Banks manage a portfolio of bonds of varying maturities and credit risk.[6] Therefore we also include two bond risk factors in addition to three stock risk factors. The vector of normal risk factors

$$\boldsymbol{f}_t = \begin{bmatrix} MKT & SMB & HML & LTG & CRD \end{bmatrix}$$

is 5×1. MKT, 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. MKT is the value-weight return on all

[6] In a recent paper Longstaff and Myers (2009) also show that banks can be treated as active managers of fixed income portfolios.

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. The identifier is $TRUSG10M$. 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. We use the one-month risk-free rate[7]. The Dow Jones Corporate Bond Return Index (CRD) is downloadable from Global Financial Data. The identifier is $DJCBTD$.

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 $\boldsymbol{\beta}_i$:

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

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 the estimated normal-risk-adjusted returns $\widehat{R}^i_{t+1}$. The estimated intercept α is the average disaster risk premium, i.e. the residual risk premium after taking out the compensation for normal risk.

Table III provides the results of the regression specified in equation (1). The table reports the regression coefficients for each size-sorted portfolio along with their statistical significance and the adjusted R^2.

Table III excludes the recent crisis.[8] The estimated intercepts decrease nearly monotonically with bank size from 5.45% for the first portfolio to -2.66% for the last portfolio ($10B$). The implicit risk prices for the factors are given by: $\boldsymbol{\lambda}_t = \begin{bmatrix} 5.80 & 0.88 & 6.62 & 2.92 & 4.01 \end{bmatrix}$.

[7]Data for the risk-free rate and the Fama-French factors was collected from Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[8]According to proposition 1 in the next section, we need to exclude the realization of the banking crisis from the sample to measure disaster risk premia.

Table III: Measuring normal and disaster risk compensation in bank stock portfolios

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. MKT, 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 α's 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	10A	10	10B
α	5.45**	4.11*	3.25	2.05	1.75	2.11	0.64	-0.70	-2.51	-1.94	-2.53	-2.66
MKT	0.36***	0.44***	0.49***	0.55***	0.59***	0.63***	0.69***	0.71***	0.87***	0.97***	1.07***	1.07***
SMB	0.39***	0.44***	0.41***	0.47***	0.50***	0.47***	0.47***	0.44***	0.43***	0.18**	-0.03	-0.06
HML	0.32***	0.38***	0.39***	0.50***	0.52***	0.53***	0.54***	0.55***	0.57***	0.51***	0.42***	0.41***
LTG	-0.16	-0.11	-0.05	0.10	0.15	0.12	0.07	0.12	0.26**	0.10	0.15	0.23**
CRD	0.51***	0.41***	0.35**	0.21	0.17	0.29*	0.30**	0.18	0.11	0.21	0.13	0.07
R^2	29.12	40.47	42.80	53.16	53.56	55.36	61.49	62.99	65.09	61.85	63.62	59.16
								8 - 3	9 - 2	10A - 1	10 - 1	10B - 1
α								-3.95**	-6.62***	-7.38***	-7.97***	-8.10***
MKT								0.23***	0.43***	0.61***	0.71***	0.71***
SMB								0.02	-0.01	-0.21**	-0.42***	-0.45***
HML								0.15**	0.19*	0.19	0.09	0.09
LTG								0.17	0.37***	0.25	0.30*	0.39**
CRD								-0.17	-0.30*	-0.30	-0.38*	-0.44*
R^2								6.21	18.83	20.68	27.91	26.74

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 8.10% 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.

Equity Risk Compensation The second row of Table III reports the coefficient on excess market return, MKT, 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 may be partly due to differences in leverage. By 1990-2009, large bank stocks were nearly 4.0 times more exposed to market risk than small banks. Thus large banks have collectively increased exposure to market risk over time. As a result, the long-short position described above (i.e. long \$1 in large banks and short \$1 in small banks) will be long the market by 71 cents. This net exposure to market risk increases to $1.04 during 1990-2009.

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 0.36 for the 1^{st} portfolio to 0.50 for the 5^{th} portfolio, and then it drops to -0.03 for the 10^{th} portfolio. Clearly, the common variation in banks stock returns 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 1^{st} portfolio to 0.42 for the last portfolio.

Bond Risk Compensation 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 not only results in a net exposure of 30 cents to long-term government bonds over the entire sample, but this exposure also increases to 89 cents over 1990-2009. Thus large bank stocks relatively out-perform small bank stocks when excess returns on long term government bonds are high.

Credit Risk Compensation On the other hand, the loadings on the credit risk factor, CRD, are negative 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 over 1970-2005 and a positive exposure of 30 cents to bond markets.

2.3 Other Asset Pricing Factors

Overall, because of the exposure to government bond and credit markets, the portfolio that goes long in large and short in small banks offers insurance to investors against large, adverse shocks to the US economy. This is the direct recession insurance effect that is captured by the standard factors. However, the pattern in the average normal-risk-adjusted returns suggest we may be missing factors. Including other factors like the Pastor and Stambaugh (2003) aggregate liquidity factor or the VIX volatility index in the vector of normal risk factors does not change these average returns significantly. Panel I in Table IV shows the effects of including aggregate liquidity as a priced factor. If anything, the spread in α's in the sample excluding the current financial crisis is larger. This is to be expected because large banks are commonly viewed as supplying liquidity when aggregate liquidity is low; Gatev, Schuermann, and Strahan (2007)document a 'reverse bank-run phenomenon' for large deposit-taking institutions in periods of tight aggregate liquidity.

The prevailing view is that momentum returns reflect the profitability of a dynamic trading strategies that buys winners and sells loser stocks rather than a priced risk factor. Nevertheless, we want to check the exposure of our banking portfolios to the momentum factor. Panel II in Table IV shows the effects of including momentum as a priced factor. Including momentum as a priced factor does reduce the difference in average normal-risk-adjusted returns by at least 200 basis points, because large banks have negative loadings on the momentum factor while small banks have positive loadings. This presumably happens not because banks are pursuing momentum trading strategies, i.e., large banks are actually short in momentum strategies, and small banks are long in momentum. If anything, one would have expected the opposite. However, large banks load negatively on the momentum risk factor because momentum is tied to aggregate shocks (e.g., the growth rate of industrial production growth), as first pointed out by Liu and Zhang (2008), and to banking panics: 1$ invested in momentum in August 1929 was worth 77 cents in March 1933. Furthermore, 1$ invested in momentum in December 2007 was worth 59 cents in December 2009. The relevance of this will become clear in the next section. We show that the normal-risk-adjusted returns on banking portfolios are closely tied to industrial production growth. Finally, in Table A in the appendix, we exclude HML and SMB from the regression to guard against the possibility that these are not truly risk factors. The spread in α is only slightly smaller.

Table IV: Adding liquidity and momentum as normal risk factors: Differences

Notes: This table presents the estimates from OLS regression of monthly excess returns of the difference portfolios of banks on Fama-French, bond risk factors, liquidity and momentum. LIQ_{t+1} is the aggregate liquidity factor of Pastor and Stambaugh (2003). MOM is Kenneth French's momentum factor. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. α's 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	10B - 1	10 - 1	10A - 1	9 - 2	8 - 3
			Panel I: Adding a Liquidity Factor		
α	-8.83***	-8.64***	-7.75***	-6.92***	-4.16**
MKT	0.70***	0.71***	0.61***	0.43***	0.23***
SMB	-0.44***	-0.41***	-0.20**	-0.01	0.03
HML	0.06	0.07	0.17	0.18*	0.14**
LTG	0.42**	0.34**	0.27	0.38***	0.18
CRD	-0.47**	-0.41*	-0.31	-0.31*	-0.18
LIQ	0.18**	0.17**	0.09	0.08	0.05
R^2	27.58	28.64	20.81	18.98	6.23
			Panel II: Adding a Momentum Factor		
α	-3.93	-3.83	-4.43	-6.92***	-3.90*
MKT	0.70***	0.71***	0.61***	0.43***	0.23***
SMB	-0.44***	-0.40***	-0.20**	-0.01	0.03
HML	0.06	0.07	0.17	0.19*	0.15**
LTG	0.46***	0.38**	0.30*	0.37***	0.17
CRD	-0.51**	-0.45**	-0.35	-0.29*	-0.17
MOM	-0.27***	-0.27***	-0.19***	0.02	-0.00
R^2	29.97	31.36	22.57	18.68	5.99

3 Asset Pricing Model

To help us interpret our empirical findings, we use a stylized dynamic asset pricing model with time-varying probability of banking panics. In section 6, we develop a general equilibrium version of this model.

Financial Crises and Recessions The U.S. government and the Federal Reserve , as well as other governments, and central banks around the world, stand ready to collectively bail out large financial institutions in the case of rare, large, adverse shocks to the real economy or the financial system (or both), like the 'Great' recession of 2007-2008, that are perceived as a threat to the stability of the financial system. Banking panics are not uncommon even in developed economies. Since 1800, the U.K., the U.S. and France have experienced 12,13 and 15 banking panics respectively. According to Reinhart and Rogoff (2009). Table V lists 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

Table V: 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

of the banking panics were taken from Gorton (1988, p.223) and Wicker (1996, p.155). Banks are different in this respect from non-financials: Giesecke, Longstaff, Schaefer, and Strebulaev (2010) examine 150 years of U.S. corporate history and they document a weak relation between the business cycle and corporate bond defaults. Overall, the U.S. has spent 13% of the time since 1800 in a banking panic, compared to 9.2% for the U.K. and 11.5% for France (see Reinhart and Rogoff, 2009, chapter 10 for more details). The number of banking crises since 1800 is 13 for the U.S.

We set up a stylized model in which the probability of this rare event (disaster) varies over time, and we think of recessions and financial crises as periods during which this probability is elevated. The model serves two purposes. First, it shows how to measure the disaster risk premia in the data using stock returns on bank portfolios. To derive these analytical results, we need strong assumption. We relax these assumptions in the general equilibrium model developed in section 6, and we show that the qualitative results survive. Second, it yields a key testable prediction: a size factor in normal-risk-adjusted returns tied to the U.S. business cycle.

3.1 Normal and Financial Disaster Risk

We adopt a version of the models with time-varying probabilities of disasters proposed by Gabaix (2008) and Wachter (2008). These are extensions of the rare event models developed by Barro

(2006); Rietz (1988). In our model, the stochastic discount factor has two components: a standard normal component and a disaster component:

$$
\begin{aligned}
M_{t+1} &= M_{t+1}^{G} \times 1 \textit{ in states without banking crisis} \\
M_{t+1} &= M_{t+1}^{G} \times M_{t+1}^{D} \textit{ in states with banking crisis.}
\end{aligned}
\tag{2}
$$

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 CCAPM-version of his model, Gabaix (2008) defines $\Delta \log C_{t+1} = g_C + \sigma\varepsilon_{t+1}$ as the growth rate of consumption in normal times, and $\Delta \log C_{t+1} = g_C + \sigma\varepsilon_{t+1} + \log F_t^C$ in the financial disaster state, where $F_t^C > 0$. ε_{t+1} is Gaussian white noise.

In the absence of a financial disaster, the IMRS is completely determined by normal risk, i.e. risk that is not related to the disaster. Henceforth, we refer to these risk factors simply as normal risk factors, to distinguish these from the disaster risk. The normal risk factors are denoted $\boldsymbol{f}_{t+1}$. To derive analytical expressions, we impose some restrictive, simplifying assumptions.

Assumption 1. *The projection of the Gaussian component of the stochastic discount factor on the space of traded payoffs is linear in the normal risk factors:*

$$
Proj(M_{t+1}^G | X) = \boldsymbol{b}'\boldsymbol{f}_{t+1}.
$$

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.

Assumption 2. *The conditional distribution of the normal risk factors $\boldsymbol{f}_t$ is independent of the disaster realization. Moreover, 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. Finally, we assume there is a connection between the business cycle and the incidence of banking panics.

Assumption 3. *The probability of a banking crisis p_t increases during recessions.*

In section 6, we relax these assumptions and we develop a general equilibrium version of this model in which the probability of a banking panic increases in a recession.

3.2 Measuring Financial Disaster Risk Premia

We do not model how and why banks are different from other corporations (see Diamond and Dybvig, 1983; Diamond and Rajan, 2001; Calomiris and Kahn, 1991, for models of banking panics). Instead we simply focus on what transpires in the event of a banking crisis. In case of a banking crisis, the government and the monetary authorities stand ready to intervene. We consider the following simple specification for the (disaster component of) dividend process of a portfolio of bank stocks of size i:

$$\begin{aligned} \Delta \log D^i_{t+1} &= g_D + \sigma^i \varepsilon^i_{t+1} \textit{ in states without banking crisis} \\ \Delta \log D^i_{t+1} &= g_D + \sigma^i \varepsilon^i_{t+1} + \log F^i_t \textit{ in states with banking crisis} \end{aligned}$$

ε^i_{t+1} is standard Gaussian white noise. F^i_t 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; Barro, 2006). This recovery rate will vary across banks depending on size, because the realization of this rare event can trigger a collective bailout of larger banks, but not necessarily of smaller banks. To obtain a simple characterization of the disaster risk premium in banks stocks, we make the following assumption.The resilience of banks is defined as $H^i_t = p_t E_t \left[F^{-\gamma}_{t+1} F^i - 1\right]$. As the US economy enters into a recession, p_t, the probability of a large adverse shock to the economy starts to increase, and the resilience of large banks H^B_t increases relative to small banks H^S_t if $F^B_{t+1} > F^S_{t+1}$. In fact, we assume that the recovery rate $F^n_t > F^{n-1}_t$ increases monotonically in size. 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.

To derive a simple expression for risk premia, we abstract from variation in normal betas and risk prices.

Assumption 4. *The conditional beta* $\boldsymbol{\beta}_t$ *and the conditional risk prices* $\boldsymbol{\lambda}_t$ *are constant.*

Proposition 1. *The expected return on asset* i*, conditional on no disaster realization, after adjusting for normal risk exposure, becomes* $E_t[\widehat{R}^i_{t+1}] = \exp(r - h^i_t)$*, where* $E_t[\widehat{R}^i_{t+1}] = E_t[R^i_{t+1}] - \boldsymbol{\beta^i}\boldsymbol{\lambda}$*, and* r *denotes* $\log R$*, and* h^i_t *denotes* $\log(1 + H^i_t)$.

The proof is in Appendix A.

Corollary 1. *In a sample without a disaster realization, the average return (in population) will be given by:* $E[\widehat{R}^i_{t+1}] = exp(\overline{r} - \overline{h}^i)$*, where* $\overline{h}^i = E[\log(1 + H^i_t)]$.

Differences in Resilience The difference in α's reported in Table III in a regression of returns of the bank stock portfolios on the normal risk factors in a sample without a rare event realization reveal the differences in average resilience: $\log \alpha^B - \log \alpha^S = \overline{h}^S - \overline{h}^B$. We refer to this as the disaster risk discount on small bank stock prices or premium in large bank stock prices. Hence, if this model is the right one, we can interpret the 8% 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. However, we will compute a more conservative measure by only imputing that part of these differences in average normal-risk-adjusted returns that can directly be attributed to the covariation with the size factor in section 4.

Monotonic Pattern in Average Normal Risk-adjusted Returns 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: $\Pi[\{D^A\}] + \Pi[\{D^B\}] \geq \Pi[\{D^{A+B}\}]$. 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 $\Pi[\{D^A\}] + \Pi[\{D^B\}] \geq \Pi[\{D^{A+B}\}] - C[A, B]$ 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.

This is what happened in the U.S. banking sector over the last decades. There was a large amount of concentration in the banking sector in the last decades. Table I reported an increase from 50% (in the 70's) to 90 % (in the last decade) in the share of total market cap 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 monotonically decreasing pattern in the α's that we have found in the data.

Table VI: Measuring normal risk exposure in bank stock portfolios: Excluding NBER recessions

Notes: This table presents the estimates from OLS regression of monthly excess returns of each size-sorted portfolio of banks on Fama-French and bond risk factors only for those months in which the U.S. economy was (not) in a recession. Statistical significance is indicated by *, **, and *** at the 10%, 5% and 1% levels respectively. α's 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.

	1	2	3	4	5	6	7	8	9	10A	10	10B
Panel A: Financial Disaster Risk Premia with Estimated Loadings Excluding Recessions												
α^1	5.75	4.96	3.55	2.56	2.35	3.06	1.25	-0.16	-1.48	-1.16	-1.79	-1.91
α^2	3.11	2.48	1.08	-0.43	0.01	0.46	-1.00	-1.59	-3.04	-2.27	-3.16	-3.24
Panel B: Estimated Loadings Excluding NBER Recessions - 1970-2009												
MKT	0.30***	0.37***	0.45***	0.50***	0.50***	0.54***	0.64***	0.66***	0.78***	0.87***	1.03***	1.04***
SMB	0.35***	0.42***	0.40***	0.42***	0.42***	0.41***	0.47***	0.40***	0.37***	0.16**	-0.12	-0.17
HML	0.35***	0.36***	0.39***	0.47***	0.46***	0.46***	0.52***	0.50***	0.51***	0.49***	0.39***	0.37***
LTG	-0.14	-0.05	-0.03	0.07	-0.05	-0.05	-0.02	-0.00	0.15	0.01	0.05	0.12
CRD	0.47**	0.28	0.33**	0.25*	0.42**	0.43***	0.32**	0.30**	0.19	0.26	0.16	0.10
Panel C: Estimated Loadings Excluding NBER Expansions - 1970-2009												
MKT	0.54***	0.56***	0.45***	0.60***	0.68***	0.75***	0.89***	0.89***	0.99***	1.11***	1.44***	1.42***
SMB	0.34*	0.39***	0.45***	0.53***	0.55***	0.51***	0.48***	0.61***	0.73***	0.37*	0.20	0.22
HML	0.27**	0.37***	0.23***	0.44***	0.46***	0.63***	0.88***	0.98***	0.87***	0.70***	1.25***	1.33***
LTG	-0.19	-0.07	-0.00	0.26**	0.50***	0.53***	0.68***	0.86***	1.02***	0.89***	0.83**	0.87***
CRD	0.33	0.21	0.14	-0.16	-0.43**	-0.27	-0.55*	-0.86***	-0.80**	-0.79**	-0.92*	-0.92*

3.3 Covariation between p_t and normal risk factors

Obviously, the independence of risk factors and p_t (see assumption (2)) that we need to derive simple, analytical characterizations of the risk-adjusted returns is very restrictive. In section 6, we develop a general equilibrium version of this model, in which these restrictions do not hold. However, we show there is a qualitatively similar relation in this general equilibrium version of the model between the average risk-adjusted returns and the financial disaster recovery rates provided that the market itself is not very exposed to financial disaster risk.

In the data, the probability of a disaster will co-vary with the standard risk factors, which violates assumption (2). We try to guard against this by recomputing the loadings excluding recession data.

The loadings on the credit risk factor, CRD, are negative 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 73 cents over 1970-2009 and a positive exposure of 53 cents to bond markets. These coefficients imply that a 1% fall in excess returns on an index of investment-grade bonds results in a 0.73% increase in excess equity returns for a portfolio of long-large-banks-short-small-banks over 1970-2009. This is puzzling. Why should large banks load negatively or not-at-all on proxies for credit risk? One can argue that better access to markets for securitization allows large banks to more effectively manage exposure to credit risk. This does not, however, explain the negative or statistically insignificant coefficients on proxies of credit risk, especially considering the fact that the securitization process requires these banks typically hold some portion of the first-loss tranche. In any case, because of the credit risk exposure, the long in big, short in small banks portfolio outperforms during US recessions.

When we exclude the recent crisis, this number decreases from 73 cents to 38 cents. The negative credit exposures in the long-short positions are much smaller: the 10-minus-one loading on the credit risk factor drops by 30 basis points in absolute value. This is not surprising. The normal risk factors in the data are correlated with p_t, the probability of a rare event realization. As the probability of a banking crisis increased during the recent crisis, credit spreads increases and large banks outperformed small banks as a result. In the model, we assumed that p_t is orthogonal to $\boldsymbol{f}_t$, but this assumption is obviously violated in the data. This implies that our estimates of the disaster risk premium in small bank stocks is likely to be biased downwards, because part of the effect of variation in p_t is absorbed by the 'normal' risk factors themselves. This is the likely explanation for the anomalous negative loadings of large bank returns on the credit factor and the large positive loadings on the long bond return.

In fact, these negative credit loadings largely disappear when we exclude NBER recessions when p_t starts to vary from our sample. These results are reported in Table VI. The first line in Panel A reports the α computed using the loadings estimated on the 1970-2005 sample without recessions. The second line in Panel A reports the α computed using the loadings estimated on the 1970-2009 sample without recessions. We used the same risk prices: the averages of the factor computed using the entire sample. Panel B reports the estimated factor loadings excluding NBER recessions. These are a better measure of normal risk exposure. If we use these factor loadings estimates instead of the ones estimated over the entire sample, but we keep the same risk prices, the estimated spread in α's between portfolio 1 and 10 is 7.54%, with the risk price estimates from the 1970-2005 sample.

4 Size Factor in the Risk-Adjusted Returns of Bank Stocks

Next we look for direct evidence of this mechanism. As is clear from eq. (1), 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. The loadings on this common factor are proportional to $F^i - 1$. To see why, note that $\log(1 + H_t^i) \approx p_t E_t \left[F_{t+1}^{-\gamma} F^i - 1\right]$. 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 simple expression: $\log E_t \left[\widehat{R}_{t+1}^B\right] - \log E_t \left[\widehat{R}_{t+1}^S\right] = h_{t+1}^S - h_{t+1}^B$. As p_t increases during recessions and banking crisis, the risk premium on this long-short portfolio becomes more negative. The size factor tracks the variation in p_t.

In this section, we show that the second principal component of normal-risk-adjusted returns $\widehat{R}_i$ has loadings that depend monotonically on size. We interpret this slope factor in normal-risk-adjusted returns as the common factor in returns imputed by time variation in the probability of a disaster. In the model, this disaster risk premium increases in recessions if the probability of a disaster p_t increases in recessions. This is what we find in the data. As dictated by the model, we look at the time-series properties of the normal-risk-adjusted returns –the residuals of the time series regression in equation (1) in the data. We find that there is a size factor in the time series of the normal-risk-adjusted-returns that explains the pattern in average normal-risk-adjusted returns. We compute the residuals from the time series regression of returns of each size-sorted portfolio of banks on the equity and bond risk factor in 1. We extract the loadings for the principal components $(\boldsymbol{w}_1, \boldsymbol{w}_2)$ of these regression residuals and we report the results in Table VII. This table only shows the loadings for the first two principal components.

The first principal component is a banking industry ('level') factor with roughly equal weights on

Table VII: Principal components of size-sorted 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 1. The last row indicates the % explained by each principal component.

	1970 - 2009		1980 - 2009		1990 - 2009		2000 - 2009	
Portfolio	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$
1	0.31	0.42	0.34	0.37	0.34	0.36	0.25	0.32
2	0.29	0.35	0.33	0.29	0.34	0.34	0.27	0.41
3	0.28	0.31	0.30	0.27	0.27	0.27	0.19	0.32
4	0.28	0.26	0.30	0.21	0.28	0.21	0.22	0.34
5	0.33	0.16	0.33	0.17	0.33	0.21	0.26	0.30
6	0.34	0.00	0.35	0.03	0.34	0.04	0.31	0.17
7	0.35	-0.21	0.33	-0.20	0.34	-0.20	0.39	-0.17
8	0.32	-0.26	0.29	-0.28	0.30	-0.29	0.37	-0.26
9	0.32	-0.37	0.26	-0.35	0.26	-0.37	0.30	-0.36
10	0.33	-0.51	0.31	-0.63	0.35	-0.58	0.49	-0.40
%	47.63	18.37	53.79	19.67	56.55	21.06	57.55	21.26

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 line up with the average normal-risk-adjusted returns that we want to explain. Together, these two principal components explain 66% of the residual variation over the entire sample and this fraction increases steadily to nearly 79% of the residual variation during 2000-2009.

Next, we take our $(T \times 10)$ matrix of estimated residuals, $\boldsymbol{\epsilon}_t$, formed above and multiply it by the (10×10) loadings of the principal components, to construct the asset pricing factors. The weights $(\boldsymbol{w}_1, \boldsymbol{w}_2)$ are re-normalized to $(\widehat{\boldsymbol{w}}_1, \widehat{\boldsymbol{w}}_2)$ so that they sum to 1.[9] 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 $PC_t^2 = \widehat{\boldsymbol{w}}'_2 \boldsymbol{\epsilon}_t$. Thus for each month, the residuals of each of the 10 portfolios from the above regression are multiplied by their corresponding re-normalized weights in the second principal component and added together.

PC^2 is the normal-risk-adjusted return on a portfolio that is long small banks and short large banks. We refer to PC^2 as a size factor. The weights of the portfolio are given by the second

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

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

.

principal component. Figure 1 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 grey-shaded regions in the graph represent NBER recessions and the light-shaded regions represent banking crisis. The NBER recession dates are published by the NBER Business Cycle Dating Committee at http://www.nber.org/cycles.html. The dates for the Mexico and LTCM crisis were obtained from Kho, Lee, and Stulz (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, as predicted by the model. 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 red line seems to drop a couple of months after the start of the NBER recessions. The red line also tends to increase before the end of the NBER recession. There are two exceptions. One is the double-dip recession in the early 80's. 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 LTCM 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 i.p.). On average, during recessions, this normal-risk-adjusted return drops by an average of 3.30% per month or 39.57% per annum.

The long-in-small-short-in-large-banks is pro-cyclical and leads unemployment and non-farm payroll data by 12 months, both lagging business cycle indicators, while it has a smaller lead for industrial production growth. The 12-month moving average ($t-11$ to t) of the normal-risk-adjusted returns on PC^2 has a correlation of -.30 with the year-over-year change in the unemployment rate, .25 with year-over-year non-farm payroll growth, and finally a correlation of .36 with year-over-year industrial production growth. The 24-month moving average ($t-23$ to t) of the normal-risk-adjusted returns on PC^2 has a correlation of -.49 with year-over-year non-farm payroll growth, .45 with non-farm payroll growth, and finally a correlation of .46 with year-over-year

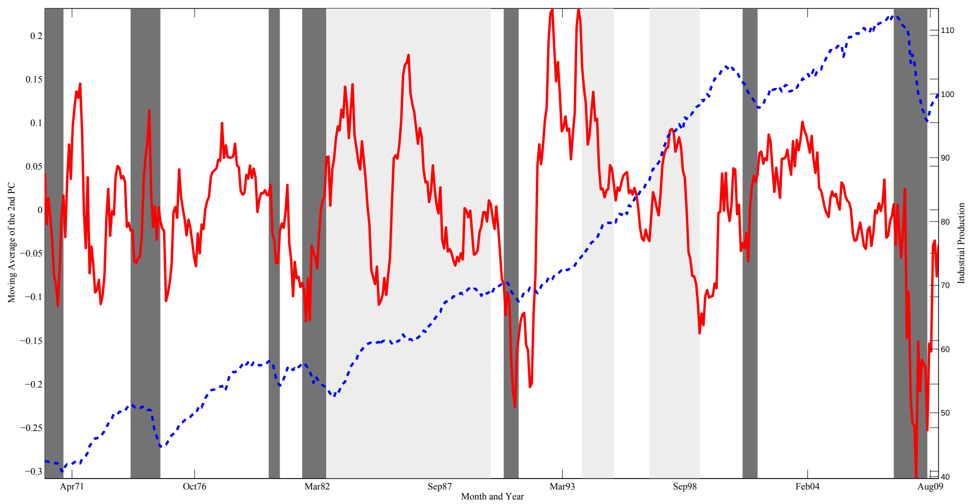


Figure 1: Size factor in normal risk-adjusted returns

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 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. 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.

industrial production growth.

Panel A in Table VIII 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 third column reports the dollar value without risk-adjustment; the second 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 can be thought of as the performance on a portfolio that is hedged to have zero betas with respect to the standard risk factors. On average, the unhedged slope 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 more than \$ 60 per recession. If we start the 2001 recession in November 2000 instead of March 2001, when the decline in industrial output starts, the normal-risk-adjusted return value of the portfolio is \$ 101 at the end of the recession. As is clear from the bottom panel, the largest losses are concentrated in the first 6 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 LDC and the LTCM crises. Panel B in Table VIII shows the average value of the portfolio n months into a recession. The hedged portfolio gradually drops more in value. 12 months after the peak it hast lost almost \$63 dollars of its value.

Table B in the appendix reports the same returns, but after excluding the first portfolio with the smallest banks. After adjusting for normal risk exposure, this hedged long-short portfolio loses about \$ 34 per recession. Most of these losses are concentrated in the first 6 months.

Covariances line up with Average Returns The size factor not only has an appealing macroeconomic interpretation, but it also is a natural candidate for explaining the size pattern in normal-risk-adjusted returns, because the variation in average normal-risk-adjusted returns lines up nicely with the variation in 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,

Table VIII: Cumulative return on 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. An asterisk indicates non-NBER dating. 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 I: 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
Financial Crises			
08: 1982	12: 1989	69.71	64.45
01: 1994	06: 1995	161.19	125.16
01: 1997	04: 1999	6.70	37.45
Panel II: 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

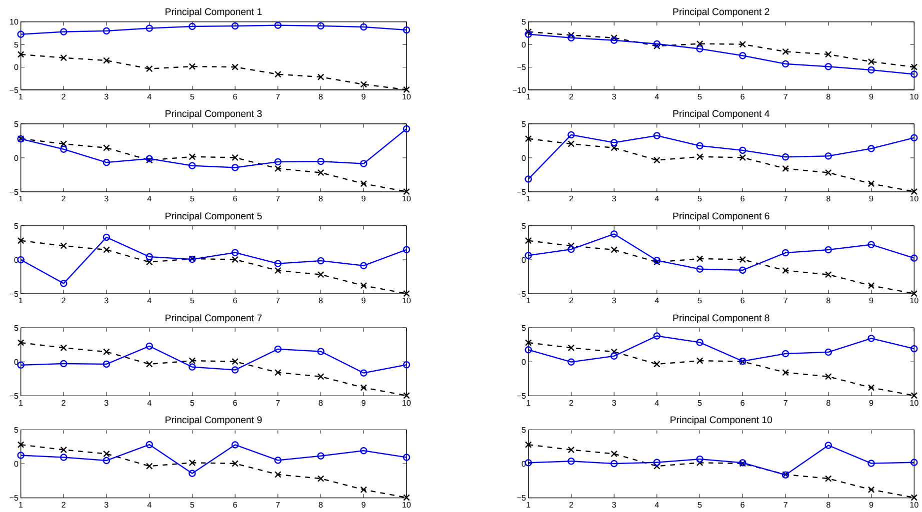


Figure 2: Covariances between risk adjusted returns and principal components

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.

as is clear from figure 2. 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 2nd PC is the only one for which the covariances line up with the average excess returns, and they do, which suggests 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 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 $R[PC_2]$:

$$R^i_{t+1} - R^f_{t+1} = \alpha^i + \boldsymbol{\beta}^{i,\prime} \boldsymbol{f}_{t+1} + \beta^i_{PC,2} R[PC_2]_{t+1} + \varepsilon^i_{t+1}. \tag{3}$$

The disaster-and-normal-risk-adjusted returns or α's from this regression are presented in Table IX. The risk-adjusted returns on all portfolios are smaller than 250 basis points over the entire sample. The average risk-adjusted return on the long-short position is reduced to -27 basis points. Remarkably, not only does the magnitude of the α's change, but all of them are statistically insignificant. In addition, there is no discernible size-related pattern in these normal-risk-adjusted returns. The size factor explains the size effect in normal-risk-adjusted returns of bank portfolios.

4.1 Sorting on Total Balance Sheet

We also sort commercial banks into portfolios by total assets instead of market capitalization. Total assets may seem like the more relevant characteristic when it comes to the government guarantee. While our results in the main paper were based on 15,536 bank-years, the results here are based on only 12,556 bank-years. The reduction in the number of banks is primarily on account of missing balance sheet data in the CRSP-Compustat merged data-set. These results are very close to the ones obtained by sorting on market cap. The separate appendix provides a detailed description. We find essentially the same size anomaly in average normal-risk-adjusted returns and we find a similar size factor.

4.2 Measuring the Subsidy

The average return of this size factor, $\widehat{E}\left[R[PC_2]\right]$ is 3.24% per month or 38.93% annualized. This can be interpreted as the price of the government insurance against banking panics. We can use

Table IX: Implicit tax 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. α's 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.

	Average Normal-and-Disaster-risk-adjusted returns											
Year	1	2	3	4	5	6	7	8	9	10A	10	10B
1970 - 2005	0.78	0.60	0.26	-0.41	0.56	2.28	1.77	0.87	0.27	0.98	1.66	1.84
								8 - 3	9 - 2	10A - 1	10 - 1	10B - 1
1970 - 2005								0.61	-0.33	0.88	0.20	1.06

	Loading on 2nd PC											
	1	2	3	4	5	6	7	8	9	10A	10	10B
1970 - 2005	0.08***	0.06***	0.05***	0.04***	0.02**	0.00	-0.02**	-0.03***	-0.05***	-0.05***	-0.07***	-0.08***
	Tax											
	1	2	3	4	5	6	7	8	9	10A	10	10B
1970 – 2005	3.25	2.44	2.08	1.71	0.83	-0.12	-0.79	-1.10	-1.94	-2.03	-2.92	-3.13

this risk price to infer the implicit subsidy to some of the largest commercial banks as this risk price times the loading on PC_2:

$$\tau^i = \beta^i_{PC_2} \widehat{E}\left[R[PC_2]\right].$$

This is an alternative to using the estimated α's as the measure of the implicit tax. It is a more conservative measure because it only imputes that part which can be attributed directly to covariance with the size factor. The last line in Table IX reports this tax rate on an annualized basis. To compute the ex ante cost, we should use the sample ending in 2005. The implicit tax ranges from minus 3.25% for the smallest banks to minus 3.13% for the largest banks.

Evidence for Investment Banks, Foreign Banks and GSE's We also compare the estimated tax to commercial banks to the tax for investment banks and foreign banks listed in the U.S. stock markets. Table X compares the results for a value-weighted index of commercial banks, investment banks, foreign banks and GSE's. The first line reports the value-weighted average market-cap for each index. For foreign banks, this only includes the market capitalization of U.S. listed shares.

Investment and foreign banks do not benefit from the subsidy to commercial banks, but the GSE's (Fanny Mae and Freddie Mac) clearly do. Over the entire sample, the subsidy to commercial banks is 2.32% and the subsidy to GSE's is 1.95%. The loadings on $R[PC_2]$ are much smaller (investment banks) or positive (foreign banks) and not statistically significant. We also computed the loading on $R[PC_2]$ for an index of hedge fund returns [10]. Over the entire sample (from 1991 - 2005) the loading for hedge fund returns on $R[PC2]$ is 0.02 (t-stat of 2.66) and this reduces to 0.01 (t-stat of 0.91) over 2000 - 2005. These results lend support to our interpretation of the size factor. Commercial banks benefit from deposit insurance and have access to the discount window at the Federal reserve and other special lending facilities. GSE's are smaller than the commercial banks, but we find that they benefit as much from the subsidy. This is sensible because GSE's benefit from explicit government guarantees.[11]

After 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. The repeal effectively allowed large commercial banks to originate and trade collateralized debt obligations. Our measure indicates a marked increase in systemic risk. After 2000, the subsidy to commercial banks more than doubled to 4.78%, and the subsidy to GSE's more than tripled to 6%. These numbers were computed 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.

Individual Banks In Table X, we show the same results for the largest commercial, investment banks and GSE's. Panel A shows the results for the entire sample excluding the crisis. The implicit subsidy are largest for the large commercial banks. For BoA (1973-2009), we estimate a subsidy of 3.12% per annum, for and Wells Fargo (1970-2009) 3.27% per annum, for Citibank (1986-2009) 1.94 % per annum. Overall, these effects are much smaller for investment banks than for commercial

[10] The total returns for an index of hedge funds is from Datastream and is identified by HFRIFWC(TOTR)
[11] The GSE's and foreign banks were suggested to us by Martin Bodenstein.

Table X: Implicit subsidy for investment banks, foreign banks and GSE's.

Notes: This table presents the estimates from OLS regression of monthly excess returns on an value-weighted index of commercial banks, investment banks, and GSE's 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 parenthesis 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. α's 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).

	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 I: Full Sample							
MKT	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***
subsidy	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 II: 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***
subsidy	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***
subsidy	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

banks and not statistically significant. Lehman is the only exception.

The second panel looks at different subsamples. The loadings for the largest commercial banks increased dramatically in the last decade. The BoA subsidy increased from 2.37% to 3.56% in 2000-2005, while the Citi subsidy increased from 3.12% to 4.53%. 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 5.37% in 2000-2005, compared to 4.06% in the 1990-2005 sample. The largest subsidy is collected by Fannie Mae (6.57%), in spite of its smaller size. Lehman also collects a large subsidy in this subsample. Both Lehman and Fannie Mae obviously were building up substantial exposure to the subprime mortgage market during this sub-sample. Note that there is no mechanical connection between our size factor and the subprime exposure, since we exclude the crisis from the sample. Exposure to the size factor seems a good yardstick of systemic risk exposure.

Size and the Subsidy Even in the highest decile, there is strong negative relation between the market cap of individual firms and the loading on the size factor. In Figure 3, we plot the loadings for these firms, computed over 5-year windows following time t, against the log of the market cap/GDP ratio at time t. As individual firms grow larger over time relative to GDP, their loadings on this size factor clearly tend to increase. The slope coefficient in the regression line is **0.018**, meaning that a 100% increase in the size of market cap relative to GDP raises the loading by **0.018** in absolute value or, equivalently, it increases the subsidy by 68 bps per annum.

4.3 Business Cycle Variation in Common and Idiosyncratic Risk

There are other factors that could explain the cyclicality in the size factor. Large common and 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 XI 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

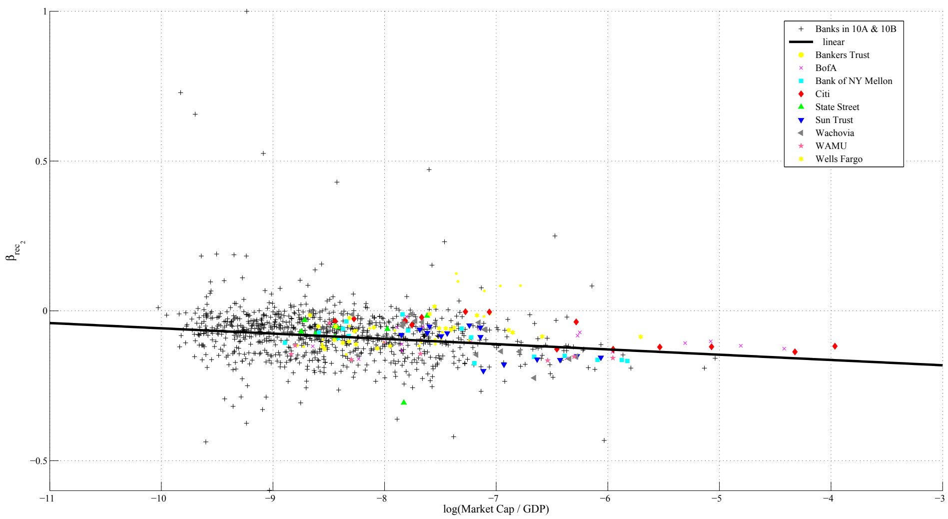


Figure 3: Size factor loading and market cap/GDP in portfolio 10

Notes: This graph shows the scatter-plot for the log of market capitalization/GDP of banks in portfolios 10 (x-axis) against the loadings on β_{REC_2} (y-axis). The black solid line shows the fitted trend line. We chose banks that were in portfolio 10 in each year from 1970 - 2000 and then computed the loadings on PC_2 over the subsequent 5-year window. Desc:

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. This suggests that large bank stocks are more exposed to uncertainty about the nature of government intervention during these recessions. This type of uncertainty is modeled and its effect on asset prices is analyzed in Pastor and Veronesi (2010).

As expected, smaller banks are 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.

Table XI: 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 multiply 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

4.4 Ex-post Evidence: Size Factor during the Crisis

Another plausibility check concerns the behavior of the size factor during the crisis. We focus on three key events: the failure of two major financial institutions (Bear Stearns and Lehman) and one smaller financial institution (IndyMac). All of these events trigger huge losses on the size portfolio even though this portfolio has a negative market beta of -3.18! Figure 4 plots the cumulative return at daily frequencies on the size portfolio after these events. We invest \$ 100 at the announcement date. The Bear Stearns event triggers a 5 σ negative daily return. The Lehman event triggers a 10 σ negative daily return. This is surprising because Lehman and Bear Stearns are large investment banks that are more similar in risk exposure to large commercial banks, while IndyMac qualifies as medium-sized to large (\$32 bn in assets). However, if we assume these events increase the probability of a collective bailout for large commercial banks, that is exactly what the model predicts.

4.5 Extending the Sample

Finally, we also checked our results on the longest sample that starts in 1925. Figure 5 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 over a longer sample starting in 1927. In this extended sample, the second principal component is not a size factor. Moreover, there is no size anomaly. We used the

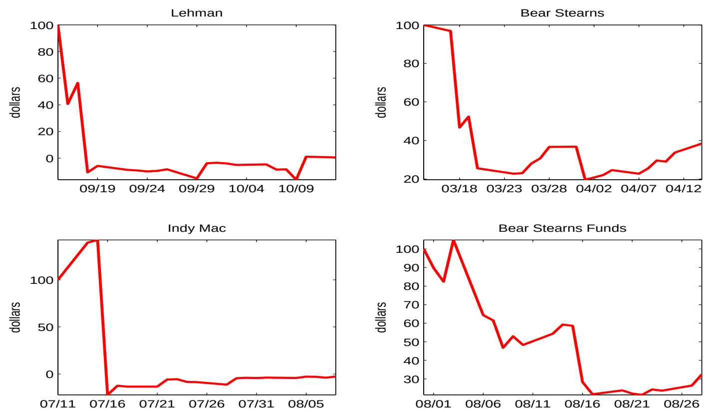


Figure 4: Size portfolio during crisis

Notes: The solid line plots the cumulative return on the size factor at daily frequencies starting with \$100 invested in this portfolio at the event. This is the cumulative return on the portfolio of size-sorted bank portfolios with weights $\boldsymbol{w}_2$. These are the unhedged returns. The portfolio is long in small banks and short in large banks. The events considered are the failure of the Bear Stearns hedge fund, the rescue of Bear Stearns, the liquidation of IndyMac and the bankruptcy of Lehman. A one standard deviation daily return on the size factor is 9.18%.

same principal component loadings as in figure 1. To increase the number of banks, we included investment banks when actually computing the banking portfolio returns. The cyclical pattern is present throughout the sample but is most pronounced in the early part of the sample, and after 1970.

5 Other industries

This section shows that the facts we have documented for banks are in fact bank-specific. First, we look at size portfolios of all stocks. Second, we also construct size-sorted portfolios at the industry level.

Macro level Panel I in Table XII measures normal risk compensation in 10 size-sorted portfolios of all stocks on NYSE-AMEX-NASDAQ. We use the longest available sample. The average normal-risk-adjusted returns on the smallest stocks is 5.23% per annum. All the others are smaller and most are not statistically significantly different from zero.

Figure 6 plots all of the principal components against the average risk-adjusted returns. The

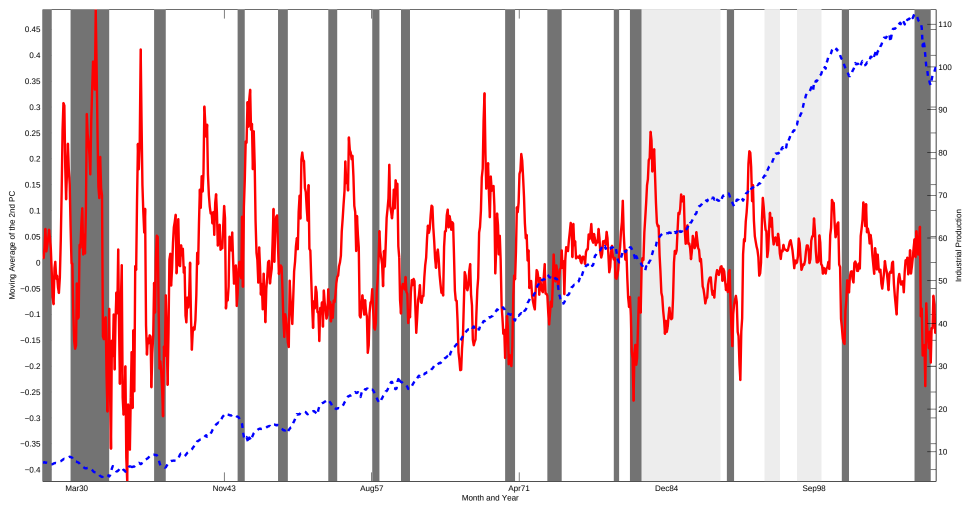


Figure 5: Size factor in normal risk-adjusted returns: Longer sample

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 financial firms on the Fama-French and bond risk factors. The weights are given by the second principal component and sum to 1. The second principal component loadings were computed using the ten size-sorted portfolio of banks over the sample period 1970 - 2009. The weights were applied to the residuals from the regression of each of the ten size-sorted portfolios of financial firms over the sample period 1927 - 2009. The dashed line represents the growth of index of industrial production. The left-axis refers to the moving average of the residuals (the units are monthly returns) 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.

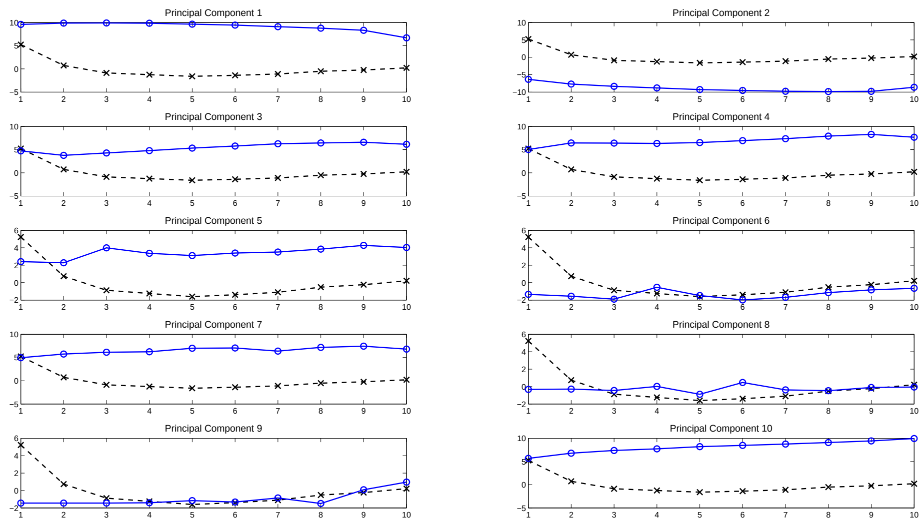


Figure 6: Covariances between risk adjusted returns and principal components

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 all NYSE-AMEX-NASDAQ stocks. 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.

second principal component of the normal-risk-adjusted returns on these size-sorted portfolios comes closest to a size factor:

$$\begin{bmatrix} \text{-0.46} & \text{-0.08} & +0.06 & +0.22 & +0.32 & +0.37 & +0.47 & +0.38 & +0.34 & \text{-0.07} \end{bmatrix}$$

However, there is no cyclical pattern. Figure 7 plots a 12-month moving average of this second principal component. The units (shown on the left axis) are monthly returns. Quantitatively, the variation is an order of magnitude smaller and it is not pro-cyclical.

Industry Level At the industry level, building size-sorted deciles is harder, because in many industries there are not enough firms. We started with the 48 industries in French's industry portfolios, but we dropped all financials and those non-financials with less than 5 firms per size decile. These are all of the non-financial industries in the 48 industry classification used by Fama and French. The total market cap in the commercial banking industry exceeds that for all industries,

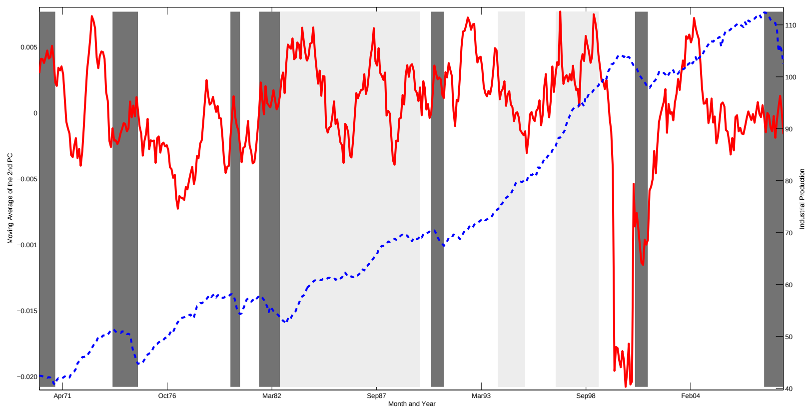


Figure 7: Second pc of normal-risk-adjusted returns: NYSE-Amex-Nasdaq size deciles

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 OLS regression of monthly excess stock returns for ten size-sorted portfolio of NYSE-Amex-NASDAQ stocks over 1927 - 2009. 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 (units are monthly returns) 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.

except for the drugs and the oil industry. The banking industry is very large in terms of market capitalization relative to most other industries.

The average normal-risk-adjusted return on the first portfolio (averaged across 31 different industries) is large and positive (8.92 %), but there is no size pattern in the other average normal-risk-adjusted returns. The 10-minus-1, 9-minus-2, and 8-minus-3 average normal-risk-adjusted returns are negative but statistically not significantly different from zero. Moreover, stock returns in these industries do show the standard pattern in the loadings on SMB; these decrease from .71 to .13. Moreover, the spread in the credit risk exposure is on the 10-minus-one portfolio is still negative but much smaller ($-.38$). We could have made all the same points about the size effect in bank stock returns, while dropping the first portfolio from the sample. In these other industries, the only remaining size effect is in the first portfolio. However, these are stocks with very small market capitalization, 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 cap in the second portfolio is much larger (\$ 65.7 million in 1980).

Table XII: Measuring normal risk compensation for size-sorted portfolio in other industries: Averages

Notes: Panel I reports OLS regression results of monthly excess returns of 10 size-sorted portfolio of all NYSE-AMEX-Nasdaq stocks in CRSP. The sample is 1970-2009. Panel II presents the average estimates from OLS regression of monthly excess returns of each size-sorted portfolio of firms in 31 other industries (different from banks). The definitions for these industries were obtained from Kenneth French's website. We deleted those industries with less than 5 firms per portfolio. We then average the OLS estimates obtained for each of these industries to construct the following table. MKT, 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. α's have been annualized by multiplying by 12 and are expressed in percentages. The last 3 columns indicate the difference between the estimates for the 10^{th}-1^{st}, 9^{th}-2^{nd}, and the 8^{th}-3^{rd} portfolios. The standard errors were adjusted for heteroscedasticity and auto-correlation using Newey-West with 3 lags.

Year	1	2	3	4	5	6	7	8	9	10	10 - 1	9 - 2	8 - 3
Panel I: NYSE-AMEX-Nasdaq (1970-2009)													
α	5.23*	0.73	-0.88	-1.25	-1.61	-1.39	-1.11*	-0.52	-0.24	0.22*	-5.02*	-0.97	0.36
MKT	0.86***	0.91***	0.95***	0.98***	1.02***	1.04***	1.06***	1.05***	1.06***	0.99***	0.12	0.15**	0.11**
SMB	1.13***	1.03***	0.97***	0.93***	0.89***	0.85***	0.75***	0.64***	0.42***	-0.14***	-1.27***	-0.60***	-0.32***
HML	0.43**	0.36***	0.34***	0.36***	0.32***	0.29***	0.24***	0.21***	0.16***	-0.05***	-0.48**	-0.20*	-0.13
LTG	-0.50**	-0.35***	-0.23**	-0.09	-0.07	-0.00	0.02	0.05*	0.02	-0.01*	0.49**	0.38***	0.28***
CRD	0.44	0.27	0.17	0.07	0.06	-0.01	-0.03	-0.03	-0.02	0.01	-0.42	-0.29	-0.20
R^2	56.03	71.28	78.24	82.26	88.25	91.31	92.39	95.12	95.28	99.67	38.27	25.21	16.68
Panel II: 31 industries (1970-2009)													
α	9.50*	1.85	-0.06	-1.61	-2.42	-1.77	-1.47	-2.10	-0.44	-0.43	-9.92*	-2.29	-2.04
MKT	0.71***	0.81***	0.90***	0.94***	0.99***	1.02***	1.05***	1.06***	1.06***	1.00***	0.29**	0.25**	0.16
SMB	0.70***	0.81***	0.82***	0.87***	0.83***	0.81***	0.76***	0.66***	0.47***	0.12	-0.59***	-0.34**	-0.16
HML	0.27	0.33**	0.36**	0.34**	0.36***	0.30**	0.30**	0.25**	0.17*	0.06	-0.21	-0.16	-0.10
LTG	-0.44*	-0.45*	-0.34	-0.30	-0.27	-0.16	-0.10	-0.07	-0.07	-0.02	0.42	0.38	0.27
CRD	0.42	0.47	0.24	0.27	0.29	0.14	0.04	0.01	0.00	-0.01	-0.42	-0.46	-0.23
R^2	19.16	30.69	36.89	44.39	48.14	50.10	53.01	54.79	55.08	52.84	7.53	6.06	3.50

Table XIII: Principal components of normal-risk-adjusted returns on size-sorted portfolios: Averages

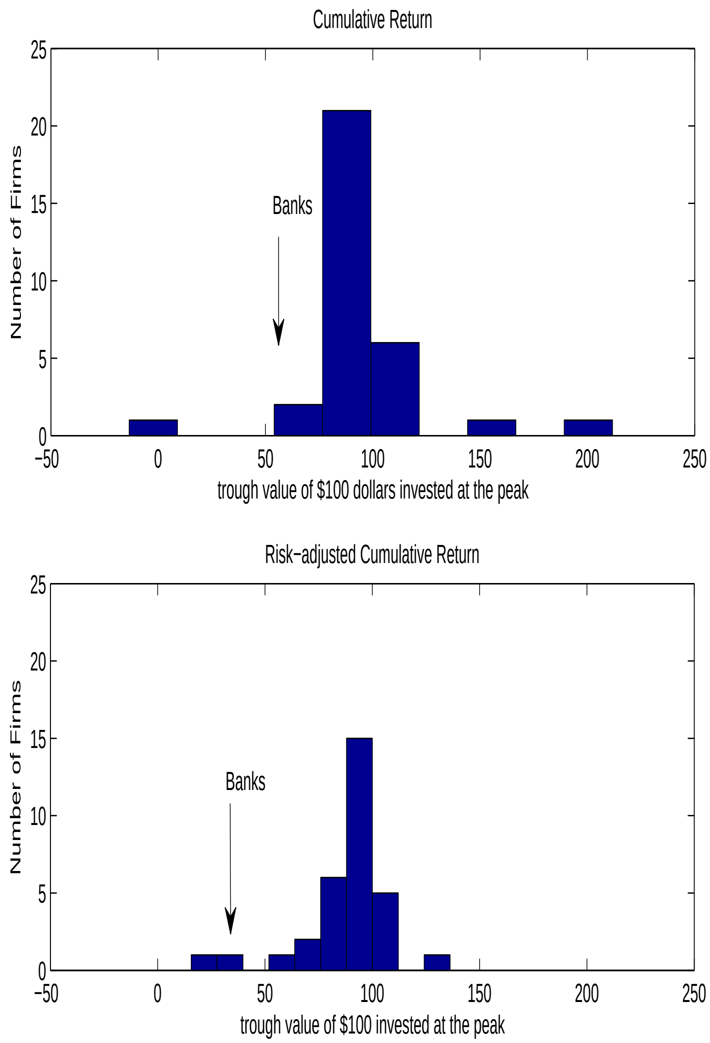
Notes: This table presents the loadings for the first and second principal components ($\boldsymbol{w}_1, \boldsymbol{w}_2$) extracted from the OLS regression of returns of ten size-sorted portfolios for 44 industries other than financials on the Fama-French and bond market factors. The definitions for these industries were obtained from Kenneth French's website. The last row indicates the % explained by each principal component.

	1970 - 2009		1980 - 2009		1990 - 2009		2000 - 2009	
Portfolio	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$	$\boldsymbol{w}_1$	$\boldsymbol{w}_2$
1	0.55	0.49	0.57	0.51	0.57	0.49	0.50	0.42
2	0.25	-0.24	0.24	-0.21	0.25	-0.19	0.24	-0.08
3	0.25	-0.11	0.25	-0.13	0.24	-0.10	0.26	-0.02
4	0.23	-0.13	0.23	-0.15	0.22	-0.08	0.21	-0.11
5	0.16	-0.09	0.16	-0.11	0.17	-0.09	0.19	-0.11
6	0.15	-0.13	0.14	-0.14	0.13	-0.13	0.14	-0.13
7	0.12	-0.12	0.12	-0.14	0.12	-0.13	0.14	-0.16
8	0.11	-0.13	0.11	-0.15	0.11	-0.14	0.15	-0.18
9	0.09	-0.11	0.09	-0.13	0.09	-0.12	0.12	-0.11
10	0.06	-0.08	0.06	-0.09	0.05	-0.08	0.07	-0.09
%	33.57	16.35	35.96	16.86	37.57	16.80	39.72	16.67

Table XIII reports the principal components obtained for these industries. These loadings are averaged over 44 industries. The first two columns report the estimates for the entire sample. The first factor is mostly a level factor, although the loadings of the first principal component do decrease in size. There is no size factor. The second principal component has a large positive loading on the first portfolio and negative loadings on the others.

The normal-risk-adjusted returns on the second principal component (long in small firms, short in large firms) are only weakly procyclical. For each industry, we compute the second principal component, and normalize these so use them as portfolio weights; we determine the sign of the loadings by checking that we go short in the 10-th portfolio. The histogram in Figure 8 reports how this long-in-small-sort-in-large investment strategy fares in recessions. On average, the investor loses less than \$ 10 during a recession, after hedging out exposure to other risk factors, compared to \$ 61 for banks. So, even though there is a minor recession effect in other industries, it is much smaller. Table Iin the separate appendix reports detailed results.

Figure 8: Histogram of cumulative recession returns on long-short portfolio for 32 industries



Trough Value of a $100 invested at the peak in a portfolio that goes long in small banks and shorts large banks with portfolio weights $\boldsymbol{w}_2$. 31 2-digit SIC Code Industries and commercial banks. The definition of each industry, indicated in column 1, is from Kenneth French's website. We started with 48 2-digit SIC code industries and we dropped all of the industries with fewer than 5 firms in each portfolio. The cross-sectional mean is $95 and $89 for the hedged portfolio.

6 Calibrated GE Asset Pricing Model

We use a fully specified version of our model that is calibrated to match the equity premium to compute the implied recovery rates from the disaster risk premia that we estimated in the data. The restrictive assumptions imposed in section 3 are relaxed: In this model, the normal risk factor (the market) is correlated with the probability of default, and the equity risk premium partly compensated for exposure to financial disaster risk. The average normal-risk-adjusted returns (α's) still reflect financial disaster risk premia provided that the stock market is not too exposed to financial disaster risk.

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

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

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:

$$M_{t+1} = \beta^{\frac{1-\theta}{1-\alpha}} \left(\frac{C_{t+1}}{C_t}\right)^{-\alpha\frac{1-\theta}{1-\alpha}} R_{w,t+1}^{\frac{\alpha-\theta}{1-\alpha}}, \tag{4}$$

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

The process for aggregate consumption growth is given by:

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

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.

6.1 Calibration

We choose σ 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).[12] 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 crisis. The market (equity) is a levered claim to aggregate consumption C^{λ}:

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

Bank Cash Flows Bank cash flows are also a levered claim to aggregate consumption. We assume that small and large banks have the same cash flow properties in normal times. However,

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

small banks will have recovery rates below the $F^S < F^c$, and large banks will have recovery rates in excess of $F^L > F^c$.

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

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

We assume that small and large banks are equally exposed to 'normal' aggregate risk. 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.

Evidence from Dividends First, we turn to the evidence in the dividend growth rates for each of our size-sorted portfolios of banks. We first compute the dollar dividend for each portfolio[13] Since each portfolio does not pay dividends every month, we use a 12-month moving average of the dollar dividends paid on each portfolios. Finally we weight the dollar dividends of each portfolio by its corresponding weight in the second principal component (re-normalized) so that it sums to 1. This produces dollar dividend series of the small minus large banks. Small banks are able to maintain or increase dividends relative to large banks during most recessions and financial crises. On average, a portfolio of small banks is able to increase repurchase-adjusted dividends by 7 cents per dollar during recessions as compared to large banks. Hence, there does not appear to be much empirical evidence to rationalize the under-performance of small banks during recessions.

Evidence from FDIC Reports Our second piece of evidence comes from the Quarterly Banking Reports issued by the Federal Deposit Insurance Corporation[14]. While we classify banks on market capitalization, FDIC classifies banks on balance-sheet size. In 2001, FDIC classified 80

[13] The cum-dividend returns, ex-dividend returns, and the portfolio price are used to compute the dollar dividend amount for each portfolio.

[14] See the Quarterly Banking Profile and Reports issued by the Federal Deposit Insurance Corporation available at http://www2.fdic.gov/qbp/. The reports on the FDIC website are available only since 2001

banks as large with assets above $10 billion. This maps into the 71 banks in our 10^{th} portfolio over the same period. In 2008 FDIC classified 114 banks as large and this maps into the 106 banks in our 10^{th} and 9^{th} portfolios. 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. 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. If anything, we are being conservative in the way we model bank cash flows.

6.2 Results

First, we consider the benchmark case in which the market is exposed to levered normal and disaster risk. Panel I in Table XIV reports the results we obtained 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 ($E[R^{m,e}|no\ disaster]$). 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 α, 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 α's are very close to zero, even though the CAPM does not hold exactly (see equation 4: The log SDF depends on the (unlevered) total wealth return and consumption growth).

The left panel considers the benchmark case of a 5% drop in aggregate consumption. 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 and large banks is 482 basis points; the difference is 10.82 percentage points. However, most of this difference is accounted for by the higher beta. 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. Because the market itself is exposed to financial disaster risk, small banks have much higher loadings on the market than large banks. The right panel 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.

Unlevering Financial Disaster Risk in the Stock Market 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:

$$\Delta \log D_{t+1}^m = g_C + \lambda \varepsilon_{t+1} \sigma, \textit{ in states without financial disaster}$$

$$\Delta \log D_{t+1}^m = g_C + \lambda \varepsilon_{t+1} \sigma + \log F^c, \textit{ in states with financial disaster.}$$

Table XIV: 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 I, θ is 13.25 and α is 0.75. σ is 3% and μ is 2%. In Panel II, 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 I: 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 Ban ks						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 II: 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

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 XIV. The top panel considers the benchmark case of a 5% drop in aggregate consumption. The leverage of the market is 2.5, but leverage only applies to the Gaussian component. 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 average normal risk-adjusted returns (α).

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 α's exceeds 600 basis points, while the β's 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 basis points spread in the β's, and a 642 basis point spread in the α's. The required difference in the recovery rates is 35 cents on the dollar.

Figure 9 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 $\beta's$ of more than 100 bps between portfolio 1-10 observed in the data. However, the spread in α's is only 500 bps.

7 Conclusion

Over the last four decades, the average normal-risk-adjusted return on a stock portfolio that goes long in the largest banks and short in the smallest banks is minus 8 percent. Moreover, this portfolio provides investors with insurance against recessions. We show evidence that this is a

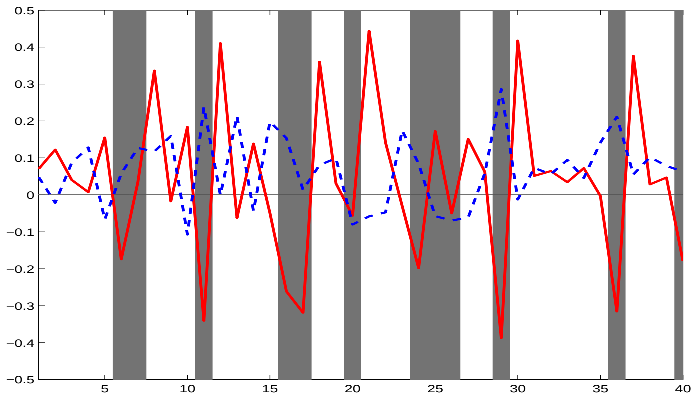


Figure 9: Size factor in bank stocks and recessions

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.

financial disaster risk premium. Using a calibrated version of the model, we backed out an implicit recovery rate of pre-disaster cash flows in disaster states that is 35 cents per dollar higher for the largest banks than for the smallest banks.

If these large differences in the implied recovery rates indeed reflect the market's expectations of the government's asymmetric actions during a disaster, then the disaster risk discount for large banks represents a large subsidy. This obviously presents banks with a huge incentive to bundle the cash flows of small banks and create large banks: Simply by bundling the cash flows, its risk properties change, because of the government's asymmetric guarantee.

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A Proofs

Proof of Proposition 1

Proof. 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 (3). This Euler equation can be decomposed as follows:

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

We assume that the distribution of the Gaussian factors is (conditionally) independent of the realization of the disaster (see assumption 2):

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

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

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

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:

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

which can be stated as follows, in the case of no disaster: $R^{G,i}_{t+1} = \frac{(P_{t+1}/D_{t+1})+1}{P_t/D_t}\exp(g_D)\exp\left(\varepsilon^{D,i}_{t+1}\right)$. In case of a disaster, the return is given by: $R^i_{t+1} = R^{G,i}_{t+1}F^i_{t+1}$, which only reflects the effect of the recovery rate on the dividend growth realization (see assumption 2). Using the definition of resilience $p_t E_t[F^{-\gamma}F^i - 1]$, this yields the following expression:

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

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

$$E_t[M^G_{t+1}]E_t[R^i_{t+1}] + cov_t[M^G_{t+1}, R^{G,i}_{t+1}] = \left(1 + H^i_t\right)^{-1}.$$

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

$$E_t[R^{G,i}_{t+1}] = E_t[M^G_{t+1}]^{-1}\left(1 + H^i_t\right)^{-1} - \frac{cov_t[M^G_{t+1}, R^{G,i}_{t+1}]}{var_t[M^G_{t+1}]}\frac{var_t[M^G_{t+1}]}{E_t[M^G_{t+1}]},$$

or equivalently: $E_t[R^i_{t+1}] - \boldsymbol{\beta^i_t}\boldsymbol{\lambda_t} = R\left(1 + H^i_t\right)^{-1}$, where β^i_t is the vector of multiple regression coefficients in regression of returns on the factors and λ_t is the vector of risk prices. 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 $\boldsymbol{\beta^i_t}$ are constant. In that case, the expected return on asset i, conditional on no disaster realization, after adjusting for Gaussian risk exposure, becomes: $E_t[\widehat{R}^i_{t+1}] = exp(r_t - h^i_t)$, where $E_t[\widehat{R}^i_{t+1}] = E_t[R^{G,i}_{t+1}] - \boldsymbol{\beta^i}\boldsymbol{\lambda}$, and r denotes $\log R$, and h^i_t denotes $\log(1 + H^i_t)$. □