Asset pricing with a bank risk factor *

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Abstract

This paper studies how the state of the banking sector influences stock returns of nonfinancial firms. We consider a two-factor pricing model, where the first factor is the traditional market excess return and the second factor is the change in the average distance to default of commercial banks. We find that this bank factor is priced in the cross-section of U.S. nonfinancial firms. Controlling for market beta, the expected excess return for a stock in the top quintile of bank risk exposure is on average 2.83% higher than for a stock in the bottom quintile.

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1 Introduction

> The jitters began in March 1792. The BUS [Bank of the United States, ...] cut the supply of credit almost as quickly as it had expanded it, with loans down by 25% between the end of January and March. As credit tightened, Duer and his cabal, who often took on new debts in order to repay old ones, started to feel the pinch. Rumours of Duers troubles, combined with the tightening of credit by the BUS, sent America's markets into sharp descent. Prices of government debt, BUS shares and the stocks of the handful of other traded companies plunged by almost 25% in two weeks.
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> — Financial Crisis, *The Economist*, April 12, 2014.

Several financial crises since 1792 show how the health of the financial sector influences the performance of other sectors of an economy. In the crisis of 2008, many banks faced funding difficulties and reduced the credit supplied to other companies. Commercial and industrial firms faced tighter credit standards and higher spreads, which contributed to poorer profitability and an increased number of bankruptcies.

We test whether the state of the banking sector is a relevant risk factor for pricing U.S. nonfinancial firms. We propose a linear factor pricing model that adds a bank risk factor to the standard market risk factor. The aggregate bank risk factor is defined as the change in the average distance to default across all banks. The distance to default (DD) is based on Merton's (1974) model. The underlying assumption is that as banks' distance to default narrows (which means that the probability of default increases), banks find it harder and more expensive to obtain funds. They will then restrict and make more expensive the credit supplied to customers.

The bank risk factor is estimated using data on commercial banks trading on the NYSE, AMEX, or Nasdaq, over 1963–2012. Standard cross-sectional asset pricing tests show that we cannot reject the two-factor model and that both factors are priced and statistically significant. The cross-sectional estimate of the market risk premium is 6.24% per year. More important, the estimate of the bank risk premium is 2.88% per year. The results thus show that average excess returns increase with both bank and market betas. For example, controlling for market beta, the expected excess return for a stock in the top quintile of bank risk exposure is on average 2.83% higher than for a stock in the bottom quintile. Furthermore, the t-ratio on the bank risk premium is 3.45, which is higher than the cutoff of 3.0 recommended by Harvey, Liu, and Zhu (2013) for new factors. Hence, bank risk exposure commands an economically important premium.

These results are intuitive. The loading of each firm on the bank risk factor measures the sensitivity of the firm's stock return to the risk of the financial sector. Firms that have a higher covariance with this risk factor are firms that pay off when the risk of the banking sector drops (DD is high). These firms pay off in good times, in the sense that there are fewer bankruptcies and the overall portfolio of the investor is doing well. Therefore, firms with high bank betas should have higher expected returns in equilibrium. In other words, the bank risk factor should command a positive risk premium. We also find that higher bank betas are associated with higher leverage. This correlation suggests that firms whose stock returns covary more with the bank factor are firms that are likely to have more credit in need of renewal and are thus more dependent on the state of the banking sector.

Given that our bank factor is not traded, our benchmark testing procedure is the standard two-pass cross-sectional test, to which we add several alternative testing procedures. First, we use the Fama and MacBeth (1973) procedure to allow for time variation in betas. We find that the risk premium estimates are robust to time-varying betas. Second, we write an equivalent stochastic discount factor (SDF) representation and estimate it by the generalized method of moments (GMM). One important advantage of the GMM/SDF approach for our study is that it allows us to control for correlation between the new candidate factor and other factors (see, e.g., Cochrane (2005)). GMM/SDF results indicate that the bank factor helps to price assets and should thus be added to the market factor. Finally, some authors (e.g., Balduzzi and Robotti (2008)) advocate replacing a nontraded factor with its mimicking portfolio and performing standard time-series tests. Using this approach, we find that the two-factor bank model substantially reduces the pricing errors of the single-factor CAPM, and the Gibbons, Ross, and Shanken (1989) test does not reject the bank model.

There is a long literature proposing new factors to augment the CAPM (Harvey, Liu, and Zhu (2013) provide an extensive list). One strand of the literature has focused on factors related to returns on stock portfolios. Other research suggests factors more exogenous to the stock market and with a deeper macroeconomic motivation. While the first set of factors is typically able to substantially increase the explanatory power of the CAPM, the second set of macro factors provides a more satisfying description of the economic forces that ultimately should determine stock returns.

Our model falls somewhere in between the two extremes of this "exogeneity scale" because the commercial banks that we use to build the bank factor are not included in the portfolios we use to test the model. The contribution of our paper is to show that expected returns of nonfinancial firms depend on their sensitivity to distress in a different sector of the economy — the banking sector.

To justify that the aggregate Distance-to-Default of the banking sector can be an exogenous source of risk for nonfinancial firms, we proceed in several steps. First, we present evidence that a drop in banks' DD is associated with a decline in the credit *supplied* to firms, while a drop in firms' *demand* for credit is almost unrelated to variations in banks' DD. Second, we show that bank distress Granger-causes corporate bankruptcies. Third, we depend on empirical studies that document clear exogenous shocks to the banking sector, followed by financial distress in nonfinancial firms, as well as on theoretical models that formalize this causal relation. Finally, we verify that the bank factor is robust to the inclusion of other typical asset pricing factors, such as small-minus-big (SMB), high-minus-low (HML), momentum, liquidity, VIX, credit spread, and term spread. In particular, we show that the bank factor is robust to and different from a factor that captures financial distress in the whole market (similar to the one in Vassalou and Xing (2004)). This result implies that the bank factor is not simply a mirror of financial distress in the overall economy.

Our main test assets are 25 portfolios of nonfinancial NYSE, AMEX, and Nasdaq firms double-sorted on their covariance with the market factor (market beta) and the bank factor (bank beta). Sorting stocks on the basis of their covariances with the risk factors is consistent with the initial tests of the CAPM (e.g., Black, Jensen, and Scholes (1972), Fama and MacBeth (1973)). In a more recent example, Ang, Hodrick, Xing, and Zhang (2006) use 25 portfolios double-sorted on market and VIX betas to show that aggregate volatility risk is priced.

One can also sort stocks on empirically motivated characteristics, such as size, book-to-market, or momentum. Hence, for robustness we test our model on several alternative portfolios. We find that the bank risk premium is robust to these different test assets. The two-factor bank model improves the explanatory power of the single-factor CAPM and does almost as well as the Fama-French three-factor model in pricing the 25 size and book-to-market portfolios.

Lewellen, Nagel, and Shanken (2010) warn of potential problems in testing new factors on the 25 size and book-to-market portfolios of Fama and French. Given the strong correlation structure of these portfolios (captured by the three Fama-French factors), any new factor that is at least weakly correlated with the SMB or HML factors will seem to have very good explanatory power. Our results are not likely to be driven by this effect because the correlation between the bank factor and SMB or HML is not statistically different from zero. And again, our main tests use market and bank beta sorted portfolios, not size and book-to-market portfolios.

Section 2 details the estimation of the Distance to Default and defines the asset pricing model. Section 3 discusses the interpretation of the bank factor and relates our work to the literature. The remaining sections present several asset pricing tests.

2 Definition and estimation of the bank risk factor

2.1 Definition of the bank risk factor

We use the Merton (1974) model to estimate the default risk for each bank. In Merton's model the capital structure includes equity, with total market capitalization S_t at time t, and a single zero-coupon debt instrument maturing at time T, with face value F. The value of the assets, V_t, follows a geometric Brownian motion, $dV_t/V_t = \mu dt + \sigma dW_t$, where W_t is a standard Brownian motion, $W_t \sim N(0,t)$, and μ and σ^2 are the mean and variance of the instantaneous rate of return on the assets. This process implies that V follows a lognormal distribution, $\ln V_t = \ln V_0 + \left(\mu - \frac{\sigma^2}{2}\right) t + \sigma W_t$. For the maturity date T, we have $\mathrm{E}[\ln V_T] = \ln V_0 + \left(\mu - \frac{\sigma^2}{2}\right) T$ and $\mathrm{Var}[\ln V_T] = \sigma^2 T$.

If the value of the assets at the maturity date is below the amount due ($V_T < F$), it is rational for shareholders to default on the debt. A natural risk measure for bank i, denoted Distance to Default, is thus defined as:

$$DD_{i,t} := \frac{\ln V_t + \left(\mu - \frac{\sigma^2}{2}\right)\tau - \ln F}{\sigma\sqrt{\tau}} \tag{1}$$

where $\tau = T - t$. The numerator captures how far from default we expect to be at time T, while the denominator standardizes this distance by the standard deviation of the assets to make DD more comparable across banks.

This DD is very similar to the one used initially by KMV (now part of Moody's Analytics), also described in Dwyer and Qu (2007). Several authors show that DD measures are good descriptors of the health of financial institutions — see, for example, Gropp, Vesala, and Vulpes (2006), Carlson, King, and Lewis (2011), and Eichler, Karmann, Maltritz, and Sobanski (2011). Munves, Smith, and Hamilton (2010) show that Moody's Expected Default Frequency (EDF), which is based on DD, is able to rank-order defaults of financial institutions during the 2007–2010 period.

Our bank factor at time t is the change in the value-weighted average DD across all I banks:

$$\text{BANK}_t := 0.01 \sum_{i=1}^{I} (DD_{i,t} w_{i,t} - DD_{i,t-1} w_{i,t-1}) \tag{2}$$

where $DD_{i,t}$ is the distance to default for bank i at time t, defined in (1), and $w_{i,t}$ is the weight of bank i in the total market capitalization of all banks at time t. Weighting by market capitalization, which we assume to be a good proxy for the amount of business a bank has, makes the average more indicative of the state of the banks that matter to more nonfinancial firms. The arbitrary scaling by 0.01 simply produces bank betas with magnitudes similar to market betas. Pástor and Stambaugh (2003) similarly scale their liquidity factor.

2.2 Asset pricing model

Our benchmark model includes two risk factors: the standard market excess return, and the new bank factor. The expected return in excess of the risk-free rate for each asset i, R_i^e, is given by

$$E(R_i^e) = \beta_{im}\lambda_m + \beta_{ib}\lambda_b \tag{3}$$

The betas for each firm i are defined as the coefficients in the time-series regression

$$R_{it}^e = a_i + \beta_{im}\text{RMRF}_t + \beta_{ib}\text{BANK}_t + \varepsilon_{it}, \quad t = 1, 2, \ldots, T \tag{4}$$

where RMRF_t is the market excess return and BANK_t is the bank factor defined in (2).

This model can be motivated by the Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1973). To address the "fishing license" criticism of using the theoretical ICAPM to justify any ad hoc empirical factor (Fama, 1991), the results in section 3.1.2 show that the banking sector average DD is a plausible state variable for the investment opportunity set because it helps to forecast something relevant for future stock returns: the total number of bankruptcies in the economy. The ICAPM then shows that expected excess returns should be related to the covariance between returns and changes in DD (β_{ib}).

We expect the risk premium for the bank factor, λ_b in (3), to be positive. Intuitively, firms that have high covariance with the bank factor, high β_{ib}, are firms that pay off more (less) when the banks' distance to default increases (declines). These are good (bad) times, in the sense that there are fewer (more) firms that go bankrupt. Hence, firms with high bank beta pay off when marginal utility is low and increase the overall volatility of the investor's consumption. They must therefore provide a higher expected excess return in equilibrium.

2.3 Estimation of the bank factor

To compute the distance to default in (1), we need to estimate the current value of the assets (V_t), and the drift (μ) and volatility (σ) parameters. We follow the iterative procedure in Vassalou and Xing (2004), which is itself similar to the Moody's-KMV estimation procedure (see Dwyer and Qu, 2007).

From Merton (1974), the market value of equity can be seen as a call option on the value of the assets, with maturity T, and strike price equal to the value of the debt, F. Hence, from the standard Black-Scholes formula,

$$S_t = V_t N(d_1) - F e^{-i\tau} N(d_2) \tag{5}$$

where i is the risk-free interest rate and

$$d_1 = \frac{\ln(V_t/F) + (i + \sigma^2/2)\tau}{\sigma\sqrt{\tau}}, \quad d_2 = d_1 - \sigma\sqrt{\tau}$$

At the end of each month, we use a window of daily data over the past year to compute the following values. First, we use daily stock returns to compute the volatility of equity, and use this as a starting value for the volatility of assets, σ. Second, we solve (5) each day, assuming that F equals the total debt of the bank and that all debt is due in one year from that day. This results in a daily time series for V_t. Third, we use this series to obtain the next estimate of σ. We then go back to step 2 and repeat this procedure until the estimates of σ converge; that is, until the distance between two consecutive estimates is less than 10^{-4}. The final time series of V_t is used to estimate μ.

We repeat this procedure at the end of each month for each bank. The final outcome is a monthly time series of Distances to Default for each bank. We then aggregate the individual DDs as in (2).

While this iterative approach is superior to the alternative approach of "solving two equations for two unknowns" (see Ericsson and Reneby (2005) or Dwyer and Qu (2007)), it often produces negative estimates for DD, which mainly result from negative estimates for the drift of the assets (μ). A negative DD might be problematic if we needed to proceed to estimate the actual probability of default for a given bank. However, since what we want is an indicator of the *evolution* of the state of the banking sector, negative drifts and the resulting negative DDs are actually helpful because they amplify the discriminatory power of our bank factor.[1]

[1] As an illustration, we apply the iterative approach to one of the most important case studies published by Moody's KMV: the default of Enron. On February 28, 2001, almost one year before Enron's default, our estimates are $\mu = 0.02$ and $DD = 3.02$, which implies a probability of default of $PD = 0.13\%$, reasonably close to the published

2.4 Data

We collect all banks trading on the NYSE, AMEX, or Nasdaq stock exchanges from the Compustat Bank Fundamentals Annual file. The Compustat Bank file includes all commercial banks and savings institutions with Standard Industrial Classification (SIC) codes between 6020 and 6036. Bank holding companies (SIC code 6712) are excluded from the computation of our factor because they may have nonbank subsidiaries. Investment banks, security brokers, dealers, exchanges, and similar financial companies (SIC codes between 6200 and 6299) are also excluded because lending is not their main activity.[2]

For each bank, we collect the total liabilities, which are defined as the sum of total deposits, total borrowings, capital notes and debentures, mortgage indebtedness, acceptances, and other liabilities. Then, we match these banks with the CRSP daily stock file to obtain daily time series for the banks' stock returns and market capitalizations. The daily risk-free rate is the one-year U.S. Treasury Constant Maturity series published by the Federal Reserve.

We follow the procedure described in section 2.3 to estimate the Distance to Default for each bank at the end of each month. Matching using daily data from CRSP leaves us with series that go back only to 1963. We further lose one year of data to compute the first DD. We are thus able to estimate distances to default for Dec/1964 through Dec/2012. The number of banks included starts from 4 in 1964, reaches a maximum of 596 banks in 1995, and then declines to 438 at the end of the sample in 2012. On average, there are 253 banks in each month.[3] To avoid the influence of extreme outliers, we truncate the DD of each individual bank to between -3 and +5, before computing the average DD.

Figure 1 shows the resulting monthly series of the average DD. While there is strong volatility, the series roughly declines from the beginning of the sample until 1980 and then roughly increases until the credit crisis of 2008.

Table 1 shows descriptive statistics of bank and market factors. The market factor is the value-weighted return on all NYSE, AMEX, and Nasdaq stocks minus the one-month Treasury bill rate, available at Kenneth French's website. For comparison with the model of Fama and French (1993), we also include their SMB and HML factors. The bank factor displays a near zero average value, but with a very disperse distribution (kurtosis of 20.8). The correlation between the bank factor and the market is 0.32, very similar to the correlation between the market and the SMB or HML factors. Interestingly, the correlation between BANK and SMB or HML is very low, not significantly different from zero. Finally, the autocorrelations of the bank factor are all very low,

EDF of 0.35%. On November 1, one month before default and after a deep fall in equity value, we obtain $\mu = -0.91$ and $DD = -2.07$. While this implies $PD = 98.08\%$, which is very far from the published EDF of 9.88%, the change in DD represents a strong signal of distress, which is precisely what we want our bank factor to capture.

[2]The sample composition may vary through time as banks enter or leave the Compustat database. This may happen for several reasons, including changes in main activity (i.e., in SIC code), changes in public/private status, mergers and acquisitions, and bankruptcy. Even though we do not specifically control for these idiosyncratic effects, the underlying assumption is that they do not prevent our sample from being a good proxy for the state of the overall bank population.

[3]We have a small number of banks at the beginning of the sample period because of lack of daily returns for many banks. The main results are robust to excluding the initial sample period.

and the Ljung-Box test does not reject the null hypothesis that the series is white noise. This justifies using the bank factor as defined in (2) instead of using innovations.

3 Interpretation of the bank factor

This section interprets the bank factor and motivates its usage as an asset pricing factor. We both provide new results and use the literature to argue that the state of the banking sector can be an exogenous source of risk for nonfinancial corporations. We also compare the Distance-to-Default to alternative measures of distress.

3.1 Direction of causality

The economic intuition for our bank factor is that when banks are in poorer condition, reflected in a low distance to default (DD), they restrict credit, leading to more defaults. In other words, there is a credit supply effect. This section provides evidence of causality from the banking sector to nonfinancial firms. First, we show that the banking sector average DD is correlated with banks' lending terms, but only weakly correlated with the demand for loans. Second, we show that DD Granger-causes the total number of bankruptcies in the U.S. economy. Finally, we use the literature to strengthen the argument that, at least in some periods, the bank state can be an exogenous source of risk, independent of other macroeconomic variables.

3.1.1 Relation of bank factor to the demand and supply of credit

We use the Federal Reserve's senior loan officer opinion survey on bank lending practices to measure the fraction of banks that tighten credit standards for commercial and industrial loans or that increase the spread charged on loans.[4] The survey is available only since 1990, so we limit the analysis to the 1990 to 2012 subsample. Since the survey data are quarterly, we compute a quarterly distance to default as the average DD of the three months in the quarter.

The top panel in figure 2 shows our DD measure (left axis) and the net percentage of banks tightening standards for commercial and industrial loans (right axis, inverted). A positive net percentage means that more banks have tightened credit standards, and a negative net percentage means that more banks have eased credit standards. There is a broad comovement between the series. For example, the recent crisis of 2008 shows a period of very low DD accompanied by a very high fraction (around 80%) of banks reporting tighter loan standards. More precisely, the correlation between DD and the fraction of banks tightening standards when dealing with large and medium firms is -0.43 (with a p-value < 0.01) and when dealing with small firms is -0.46 (p-value < 0.01).

The bottom panel in figure 2 compares DD (left axis) with the fraction of banks reporting an increase in spreads offered (right axis, inverted). Again, we see a broad comovement, and the crisis

[4] Data available at www.federalreserve.gov/boarddocs/SnloanSurvey

clearly stands out as a period when almost all banks increased loan spreads. More precisely, the correlation between DD and the fraction of banks increasing loan spreads to large and medium firms is -0.53 and to small firms is -0.56 (both with p-value < 0.01).

The analysis so far focuses on the *supply* side of the credit market, that is, on the effect that bank conditions have on credit supplied to nonfinancial firms. While in theory it is also possible that part of the drop in DD is due to a reduction in the *demand* for loans, we expect this demand effect to be very small. If a bank faces less of a demand for loans, the main effect is a reduction in both its assets (V) and debt (F) in relatively similar amounts, which has a small effect on the DD defined in (1). There is of course a limiting effect in the sense that a bank with very little business (very low demand for loans) will eventually go bankrupt, but again we expect this channel to be of minor importance, particularly for the aggregate average DD.

Nevertheless, we also use the survey data to measure the correlation between our aggregate DD and the net percentage of banks reporting stronger demand for commercial and industrial loans. The correlations are 0.15 for large and medium firms (p-value = 0.18), and 0.27 for small firms (p-value = 0.01). As expected, the correlation for large/medium firms is low and statistically insignificant. The correlation for small firms is also low, although statistically significant. Note, however, that small firms represent a small fraction of total loans. For example, according to the Federal Deposit Insurance Corporation, the value of small business loans made by all reporting lending institutions accounted for less than one quarter of the total business loans outstanding at the end of 2012.[5] Therefore, these results suggest that it is very unlikely that variations in the demand for loans cause changes in the banks' DD.

3.1.2 Relation of bank factor to bankruptcies

We now turn to the relation between average DD and the variable that in the end matters more to investors: bankruptcies. We collect quarterly data on the total number of bankruptcies from the American Bankruptcy Institute.[6] The data on bankruptcies are available only since 1980, so we limit the analysis to the 1980–2012 subsample. Since the data on bankruptcies are quarterly, we again compute a quarterly distance to default as the average DD of the three months in the quarter.

Figure 3 shows the two series. There is a clear relation between banks' DD and bankruptcies. For example, the sharp fall in DD around 1985, marking the beginning of the U.S. savings and loan crisis, is followed by a sharp increase in the number of bankruptcies (note that the right y axis is inverted). After that, there are several periods when DD increases are followed by declines in bankruptcies. The last period, as the DD fell in 2008 and 2009, clearly shows the financial crisis following the Lehman Brothers demise in late 2008, and the subsequent increase in bankruptcies in the so-called great recession.

To test the relation between DD and bankruptcies, we estimate a vector autoregression using

[5] Data available at www.fdic.gov.
[6] Data available at www.abiworld.org.

these variables. We also introduce the quarterly growth rate of real GDP, taken from the U.S. Bureau of Economic Analysis, to control for the fact that bankruptcies depend on the economic cycle. Table 2 shows the results for a VAR(1) with these three series.[7] The first equation for bankruptcies shows that all variables are statistically significant. A decline in DD leads to an increase in bankruptcies in the following period. The second equation for DD shows that bankruptcies do not determine DD in the next period. Hence, we conclude that DD Granger-causes bankruptcies, while the reverse is not true.

These results also provide a theoretical base for our bank factor. When there are many bankruptcies, stock returns are low. Hence, DD is a state variable that describes the investment opportunity set. The ICAPM then shows that expected stock returns should depend on the covariance with changes in DD.

3.1.3 Empirical literature on causes and consequences of bank distress

The results so far support the concept that the state of the banking sector can influence the state of nonfinancial firms. Nevertheless, the results do not establish an unequivocal causal relation. One way to establish causality is to identify, first, an episode of bank distress caused by factors clearly exogenous to the nonfinancial corporate sector and independent of other macroeconomic conditions. Subsequently, we would identify distress in nonfinancial firms caused directly by the initial problems in the banks. This is obviously a demanding task, beyond the scope of this paper, but there are already several pieces of evidence in the literature that point in this direction.

The cleanest experiment would occur when there is a shock that is clearly exogenous to an entire economy. One good example is Khwaja and Mian (2008), who show that the 1998 nuclear tests in Pakistan caused a liquidity shock to some banks, which in turn reduced the credit supplied to other firms, and the firms that were less able to get alternative sources of funding were more likely to be in financial distress a year after the nuclear tests. Unfortunately, there are not many such clean natural experiments.

A second alternative is to identify shocks that are at least exogenous to the domestic economy, in the sense that they originate in some foreign economy. Some examples are as follows. Peek and Rosengren (2000) use as a foreign shock the capital losses of Japanese banks due to the dramatic decline in Japanese equity and commercial real estate prices in the early 1990s. They show that this foreign shock led Japanese banks to reduce their lending in the United States. Given the substantial presence of Japanese banks in the U.S. commercial real estate loan markets, this credit reduction had a substantial impact on U.S. construction activity. Chava and Purnanandam (2011) use the 1998 Russian default to identify an exogenous shock to U.S. banks with exposure to Russian debt, and show that the affected U.S. banks reduced lending by more than unaffected banks, causing losses in their U.S. borrowers. Schnabl (2012) shows that the Russian default reduced international bank-to-bank lending to Peruvian banks and that these banks reduced lending to

[7] The lag order is determined with standard information criteria, but the results are robust to considering higher order lags.

Peruvian firms. Iyer, Peydró, Lopes, and Schoar (2014) find that Portuguese banks that relied more on interbank borrowing before the 2007–2009 crisis reduced credit more during the crisis, even though the European interbank liquidity crisis was unrelated to Portuguese banks.

A third alternative, perhaps less strong, is to consider shocks that are not independent of other macroeconomic conditions, but at least originate outside the corporate sector. The housing boom and bust that lead to the recent 2007–2009 crisis is a good illustration. For example, Chodorow-Reich (2014, p. 2) argues that "the origins of the 2008 crisis lay outside of the corporate loan sector," and thus considers the 2008 Lehman crisis as a source of exogenous variation in the availability of credit to borrowers. He then shows that U.S. firms that were more dependent on less healthy banks had less access to credit and reduced employment by more than clients of healthier banks.[8]

Another example would be a sovereign debt crisis, even though here it becomes harder to argue that such an event is exogenous to the nonfinancial corporate sector. Still, Gennaioli, Martin, and Rossi (2014) propose a model where sovereign defaults destroy the balance sheet of banks, thus disrupting domestic credit markets. Bedendo and Colla (2013) provide empirical evidence consistent with this credit squeeze, even for large nonfinancial firms that are rated and have access to public bond markets. Adelino and Ferreira (2016) show that exogenous shocks to bank ratings due to sovereign downgrades cause an increase in the cost of funding for the banks at the sovereign rating bound, and a consequent reduction in lending by those banks. Acharya, Eisert, Eufinger, and Hirsch (2015) show that the European sovereign debt crisis after 2009 caused a contraction in syndicated bank lending to European firms, due to both poorer bank health from exposure to impaired sovereign debt and risk-shifting behavior. The firms with significant business relationships with the affected banks showed lower investment, employment growth, and sales growth.[9]

Finally, other evidence shows that bank distress is associated with *subsequent* distress in nonfinancial firms, without fully explaining the initial reasons for bank distress. Bernanke (1983) studied the U.S. Great Depression and argued that the credit squeeze of 1930–1933, when some borrowers

[8] Related studies include Ivashina and Scharfstein (2010), who show that during the 2008 crisis banks that were more reliant on debt had to reduce their lending to a greater extent. Cornett, McNutt, Strahan, and Tehranian (2011) show that banks that relied more on wholesale funding reduced lending more than other banks with access to more stable sources of financing. Santos (2011) shows greater increases in loan spreads for firms that borrowed from banks that incurred larger losses. Almeida, Campello, Laranjeira, and Weisbenner (2011) show that firms with long-term debt maturing during a credit market contraction reduce their investment if long-term debt is their major source of funding. Carvalho, Ferreira, and Matos (2013) use a broad sample of 34 countries to show that firms with strong lending relationships suffer abnormally low returns when their relationship banks also suffer abnormally low returns. Laeven and Valencia (2013) stress the importance of supply-side credit market conditions by showing that bank recapitalization after the recent crisis had a positive effect on the growth of firms in other industries.

[9] These results further indicate that large firms are not immune to bank distress, as syndicated loans are typically granted to such firms. Anecdotal evidence also indicates that the state of the banking sector is relevant to large firms with access to public debt markets. For example, at the height of the credit crisis in October 2008, General Electric found it very difficult to roll over its commercial paper and eventually had to resort to a federal government support program, despite being at the time one of only six corporations worldwide with a triple-A credit rating. In our sample over the period from 1986 to 2012, firms with a Standard & Poor's credit rating have a median bank beta of 0.23, while nonrated firms have a bank beta of -0.98. While these values may sound surprising at first, one possible explanation is that the firms that decide to pay for a rating are probably the firms that are most in need of debt, be it public or bank debt. For example, Faulkender and Petersen (2006) show that firms with a bond rating have higher leverage ratios than those without. The results thus suggest that the bank factor also reflects, at least to some extent, the state of public debt markets.

"found credit to be expensive and difficult to obtain,... helped convert the severe but not unprecedented downturn of 1929–1930 into a protracted depression." Reinhart and Rogoff (2009) show that several banking crisis across the world were followed by large drops in equity markets, housing prices, output, and employment.[10]

In summary, all this literature supports regarding the state of the banking sector as an asset pricing factor, as it is sometimes driven by events originating outside the nonfinancial corporate sector and not reflected in other asset pricing factors or typical macroeconomic variables. Note that we obviously do not rule out the possibility that sometimes nonfinancials affect banks. Banks have claims on nonfinancial firms, so it is certainly true that in some periods banks respond to the state of nonfinancial firms. However, our primary point is that, at other times, it is the problems in banks themselves that lead to difficulties in nonfinancial firms. The next section formalizes this notion.

3.1.4 Theoretical models

Our empirical model can also be motivated by recent theoretical literature on how the balance sheet of financial intermediaries influences credit supply and asset prices.

The model of Gertler and Kiyotaki (2010) clearly illustrates how disruptions in financial intermediation can induce a crisis that affects real activity. Banks are constrained in their ability to obtain funds from depositors and from other banks due to an agency problem between borrowers and lenders. In turn, this agency problem introduces an endogenous balance sheet constraint on banks, in the sense that the bank's net worth must be at least as large as a weighted measure of assets (loans funded) net of interbank borrowing.

Disruptions in financial intermediation originate from exogenous random shocks to the value of assets held by banks. A negative shock to the quality of capital directly reduces the value of bank net worth, forcing banks to reduce asset holdings. A second round effect on bank net worth arises as the fire sale of assets reduces the market price of capital. Hence, the weakening of bank balance sheets disrupts credit flows, depressing real activity. Furthermore, the impact of the decline in asset values on bank net worth is proportional to the amount of bank leverage. With highly leveraged banks, the percentage drop in bank equity is steeper, leading to more significant disruptions of credit flows.

In Gertler and Kiyotaki (2010), crises are triggered by exogenous declines in the value of intermediary portfolios. Examples of such shocks include the decline in real estate values that precipitated the 2007–2009 crisis (as noted in their paper), and many of the events documented in the empirical literature reviewed in the previous section.

Other papers further explore the relation between the balance sheet of financial intermediaries and asset prices. The model of He and Krishnamurthy (2013) displays the non-linearity that

[10] Alternatively, Carlson, King, and Lewis (2011) show that when the financial sector is relatively healthy, employment and output are likely to grow faster in coming quarters, and argue that the condition of financial institutions is an "independent source of macroeconomic variability." Kishor and Koenig (2014) show that banks' willingness to lend is a good predictor of GDP growth.

characterizes many crises. When intermediary capital is low, negative shocks to intermediary capital have significant effects on risk premia. However, when capital is high, losses have little effect on risk premia. In Brunnermeier and Sannikov (2014, online appendix), the aggregate net worth of financial intermediaries is also related to the amount of financing available to entrepreneurs. The model displays strong nonlinear amplification effects. A large negative shock can move the system far away from the steady state and, once in a crisis regime, even small shocks are subject to amplification, leading to prolonged periods of disinvestment. Leverage determines the distance to crisis.

In summary, these models formalize how exogenous shocks to bank balance sheets may lead to a decrease in the supply of credit and lower asset prices. Our empirical model then tests whether firms with different sensitivities to this mechanism have different expected returns. Furthermore, the models above show that the net worth or leverage of financial intermediaries is the key state variable that determines how the system responds to shocks. Our empirical bank factor, based on the distance to default, captures this same notion.

3.2 Alternative measures of distress

Our bank factor is based on the Distance to Default (DD) defined in (1), but there can be alternative measures of distress. One simple modification would be to use Merton's (1974) model to estimate a probability of default (PD) for each bank. However, the Gaussian mapping from DD to PD loses discriminatory power, and gives PDs that are not reasonable. This is the reason Moody's-KMV uses a proprietary empirical mapping to get its expected default frequency (EDF). Alternatively, one could buy DD or EDF series estimated using the proprietary models of Moody's KMV. An advantage of our approach is that it is easy to replicate.

Other variables might also seem good proxies for the state of the banking sector. One candidate is the level of interbank rates or the difference from a government bond rate (like the TED spread). Yet the recent financial crisis showed low interbank rates coupled with a decline in commercial and industrial loans (this abnormal scenario was even stronger in the Euro zone, where Euribor rates were at historically low levels, but credit markets remained very dry). The average credit rating of banks might also be a good candidate, but ratings change infrequently, and it is difficult to get long time series for all banks. Likewise, the history of banks' credit default swaps is too short for asset pricing tests. Bonds issued by banks might be an alternative source of credit spreads, but bonds typically do not trade very often. Another candidate would be the Fed's E2 series ("commercial and industrial loan rates spreads over intended federal funds rate"), but this series in available only on a quarterly basis and since 1986.

Hence, while there is not an obvious unique measure that captures the state of the credit market and how easy it is for firms to obtain credit from banks, DD seems to be a good candidate. It captures the key state variable of the theoretical models reviewed in section 3.1.4, it has good empirical properties, and it is easy to estimate.

3.3 Other related literature

Our work is closely related to the following papers. In the Gorton and He (2008) model, strategic competition between banks leads to endogenous credit cycles.[11] They proxy for banks' beliefs about rivals' strategies through the dispersion of loan performance across banks. They build a factor mimicking portfolio by projecting this series on the returns of ten book-to-market portfolios and then test this factor on ten size portfolios. For data availability reasons, their tests run only from 1984 through 2006 with quarterly returns. They find that the smaller size portfolios load positively on their factor. Our work differs on the motivation and definition of the risk factor. Further, since our distance to default can be easily computed from publicly available data for longer periods and at higher frequencies, we are able to perform more extensive asset pricing tests for our bank factor.

From a slightly different perspective, some papers consider that financial intermediaries are themselves the marginal investors. Adrian, Etula, and Muir (2014) show that the aggregate leverage of security broker-dealers is a priced risk factor. Securities that have high covariance with leverage must offer high expected returns because they have low prices precisely in bad times, when intermediaries are forced to deleverage by selling at fire-sale prices. While their asset pricing effects result from the portfolio rebalancing of broker-dealers, our effects come from the transmission of financial distress from commercial banks to other sectors of the economy. He and Krishnamurthy (2013) calibrate a model where the equity capital of financial intermediaries determines the extreme behavior of credit spreads during crisis periods, particularly for securities where those intermediaries are crucial, such as mortgage-backed securities. In addition to the role of financial intermediaries, our work differs by focusing on the stock market.

Our work is also related to Allen, Bali, and Tang (2012), who show that the value-at-risk estimated from the cross-sectional distribution of financial stock returns forecasts future economic downturns. They also propose a conditional two-factor model and find that higher conditional covariance with their risk factor leads to higher future returns in a set of ten size portfolios. One important difference in our work is the definition of the bank factor. Since the factor of Allen, Bali, and Tang (2012) includes *all* financial companies (bank holding companies, investment banks, and any company with $6000 \leq \text{SIC} \leq 6999$), their results may be in part related to the portfolio rebalancing effect of broker-dealers (as in Adrian, Etula, and Muir (2014)). We focus only on commercial banks and savings institutions to isolate the bank lending effect. Additionally, we perform extensive asset pricing tests on a broader set of test assets.

Our methodology is similar to Vassalou and Xing (2004). While they build an aggregate probability of default using all firms in the market, our factor measures distress exclusively in the banking sector. Section 6.1 shows that the two factors convey substantially different information.

Other authors discuss whether financial distress in a given firm influences its expected return. Griffin and Lemmon (2002), Vassalou and Xing (2004), and Avramov, Chordia, Jostova, and

[11] See also Longstaff and Wang (2012), who propose a theoretical model in which endogenous variations in the size of the credit sector influence expected stock returns.

Philipov (2007) show that the positive abnormal returns to size, book-to-market, and momentum strategies are mostly due to firms with high credit risk. On the contrary, Dichev (1998), Campbell, Hilscher, and Szilagyi (2008), Garlappi, Shu, and Yan (2008), and Avramov, Chordia, Jostova, and Philipov (2009) find that a higher probability of default or a lower credit rating leads to lower future returns.[12] We do not analyze the probability of default of a given firm (a "characteristic"). Instead, we use the covariance with the state of the banking sector and show that higher bank betas are associated with higher expected returns. In this regard, our work is similar to Kapadia (2011). However, while he considers an aggregate factor built from economy-wide business failures, we show that the state of a specific sector of the economy (the banking sector) is a priced systematic risk factor for the rest of the economy.

4 Test portfolios

This section shows that there is dispersion in returns across firms with different sensitivity to the bank risk factor. We also show that bank loadings are associated with leverage.

4.1 Data and portfolio construction

We collect returns and market capitalizations on all U.S. firms trading on the NYSE, AMEX, or Nasdaq markets from the CRSP monthly file. To make sure that the sample does not include any firm hard-wired to the bank factor, we remove all commercial and investment banks, security brokers and dealers, exchanges, and similar financial companies (more precisely, we exclude all SIC codes between 6000 and 6299).[13] We match this data with the Compustat Fundamentals Annual file to obtain the book value of total liabilities and total assets. The risk-free rate is the one-month Treasury bill rate. The sample period is set to the period available for our bank factor, December/1964–December/2012.

Our test assets include portfolios single-sorted on the sensitivity to the bank factor (bank beta) and portfolios double-sorted on market and bank beta.

To form the simpler single-sorted portfolios, we start by estimating bank betas for each firm with a 60-month rolling window regression:

$$R^e_{it} = a_i + \beta_{ib}\text{BANK}_t + \varepsilon_{it} \tag{6}$$

At each month t, we use the cross-section of estimated betas to allocate each stock into a quintile portfolio. Then, using the market capitalization at t, we compute value-weighted portfolio excess returns for $t+1$. We repeat this procedure at the end of every month. This produces a time series of monthly excess returns for five test portfolios.

[12]Chava and Purnanandam (2010) show that the relation depends on how expected returns are estimated. Garlappi and Yan (2011) propose a model that helps to reconcile some of the previous literature.

[13]The results are robust to further excluding all SIC codes between 6000–6999.

Most of our asset pricing tests are applied to portfolios double-sorted on bank and market betas. The betas are estimated with the same rolling window procedure, but using the regression in (4). We do an independent sort into five bank beta by five market beta portfolios, obtaining 25 test portfolios. The final result is 25 series of monthly value-weighted excess returns.[14]

4.2 Portfolio returns

The first preliminary evidence for a priced risk factor should be dispersion in average returns of portfolios sorted on exposure to that risk factor. Table 3 shows average excess returns for the test portfolios. Panel A shows single-sorted portfolios. The results clearly show that average excess returns increase with bank beta. The portfolio with the lowest exposure to the bank factor (Bnk 1) earns an average excess return of 0.20% per month, while the portfolio with the highest bank beta (Bnk 5) earns 0.72%. The difference of 0.52 percentage points per month (6.24% per year) is strongly statistically significant. This pattern is not explained by the CAPM. While the lowest quintile portfolio has a negative alpha, the highest quintile has a positive alpha. The spread between these two portfolios has a statistically significant CAPM alpha of 0.45% per month (5.40% per year).

Panel B of table 3 shows average excess returns for 25 double-sorted portfolios. A given row represents the portfolios that fall into the same market-beta quintile and into five different bank-beta quintiles. Overall, we find that average returns increase with the bank-beta quintile for all levels of market beta (the extreme (5,5) portfolio is an exception). The bank risk effect seems to be more important for stocks with middle market betas. For example, the difference in average excess returns between the highest and lowest bank-beta quintiles ranges from 0.37 to 0.46 percentage points per month for portfolios in the second, third, and fourth market-beta deciles. These differences are statistically significant and represent an annual excess return difference between 4.38% and 5.55% per year, which is close to the difference found in single-sorted portfolios.

Again, the CAPM is not able to explain these return patterns. Eleven of the 25 CAPM alphas are statistically significantly different from zero, and they all increase with the bank-beta quintile for all levels of market beta (except for the extreme (5,5) portfolio). The alpha on the spread between the highest and lowest bank-beta quintiles ranges from 0.35% to 0.43% per month (4.20% to 5.16% per year) for portfolios in the second, third, and fourth market-beta deciles.

Hence, we conclude that there is a bank risk effect in average returns, even after controlling for the standard CAPM market risk. In other words, these results suggest that there may be a risk premium associated with the bank factor.

The last part of table 3 shows full-sample market and bank betas for each of the 25 portfolios. For each portfolio, the betas are estimated from a single time-series regression of monthly portfolio excess returns (constructed in section 4.1) on the two factors. These portfolio betas are different from the average individual beta estimated during the ranking period, and equal the estimates that will be obtained in the first step of the two-pass cross-sectional asset pricing test described in

[14]The results are robust to sequential sorts in either order.

section 5.1 below.

4.3 Interpretation of bank factor loadings

The economic intuition suggested by our model is that firms with higher sensitivity (beta) to the state of the banking sector must provide higher expected returns in equilibrium. The underlying assumption is that these firms are more dependent on the banking sector. When banks are healthy, these firms are able to obtain the financing that they need; when banks are having difficulty supplying credit, the firms also face difficulties in obtaining credit, leading to lower stock returns.

To provide evidence on this interpretation of the model, we compute debt ratios, defined as total liabilities over total assets, for the 25 portfolios sorted on market and bank betas.[15] In each month, we compute the debt ratio for a given portfolio as the average debt ratio across all firms that are allocated into that portfolio.

Table 4 reports the time-series average of monthly debt ratios for each portfolio. We find that leverage increases with the bank beta. Note that this positive relation is strongly statistically significant for all quintiles of market beta (all rows in the table). Figure 4 better illustrates this relation by plotting the debt ratios against the bank betas of table 3. Again, a positive relation between debt and bank beta is clearly visible. More precisely, the correlation between the two series is 0.58, and a straight line fitted by OLS has a strongly statistically significant positive slope (t-stat = 3.45).

These results support the hypothesis that firms that load more heavily on the bank factor are firms that are more levered and therefore more likely to depend on obtaining and renewing credit to maintain their activity.

5 Main asset pricing tests

This section shows formal asset pricing tests of the model in equation (3). As our bank factor is not a traded portfolio, we start with standard cross-sectional regression tests. Then, we allow for time-varying betas in Fama and MacBeth (1973) tests. Finally, we use GMM to test the equivalent SDF representation, which provides a clean control for the correlation between the two factors. All the tests in this section follow standard procedures (see, e.g., Cochrane (2005)). All econometric details are in the internet appendix to this paper.

5.1 Cross-sectional regressions

We perform a two-pass regression estimate of the model in (3). First, we use the time series of monthly excess returns for each test portfolio i to estimate full-sample betas. Second, we estimate

[15] The results are similar for portfolios sequentially sorted (in either order) and for portfolios sorted on univariate bank betas.

the risk premiums in (3) from a cross-sectional regression of average returns on betas:

$$\bar{R}^e_i = \beta_i' \lambda + \epsilon_i, \quad i = 1, \ldots, N \tag{7}$$

where $\bar{R}^e_i$ are the sample average excess returns on N test portfolios, β_i is the vector of factor betas, ϵ_i are the regression residuals or pricing errors, and λ is the vector of regression coefficients to be estimated.

We first estimate this regression with an intercept to obtain more robust estimates ($\lambda = [\lambda_0, \lambda_m, \lambda_b]'$); then, we impose the theoretical model and estimate the regression without a constant to get more efficient estimates ($\lambda = [\lambda_m, \lambda_b]'$). We show both OLS and GLS estimates. While the GLS procedure may produce estimates with lower asymptotic standard errors, that is conditional on the correct estimation of error covariance matrix. Otherwise, the GLS estimates may actually be worse than OLS. Also, the GLS extracts more statistical precision by focusing on combinations of the test portfolios that may be less economically interesting. In other words, the GLS has statistical advantages, while the OLS estimates are more robust and have a cleaner economic interpretation. In all cases, we include Shanken's (1992) correction for the fact that the β are not fixed regressors in the cross-sectional regression, but are instead estimated in the initial time-series regression.

Table 5 shows the estimation results using our 25 portfolios double-sorted on market and bank betas.[16] We start by estimating the single factor CAPM. It does not perform well. If we include a constant in the cross-sectional regression (7), the market risk premium (λ_m) is not statistically different from zero. Only if we ignore the evidence that the intercept is statistically significant and impose the restriction that $\lambda_0 = 0$ do we obtain a statistically significant λ_m. However, when we force the CAPM theory on the data, the pricing errors become too large, that is, the χ^2 test rejects the CAPM.

Our main focus is on estimates of the two-factor bank model. We start by estimating the cross-sectional regression with a constant. We find that the market risk premium is again not statistically significant, while the bank risk premium is statistically significant with a value of 0.26% (OLS) or 0.20% (GLS) per month. The intercept is not statistically significant, so we proceed to estimate the cross-sectional regression without a constant.

We find that both the market and the bank factor are priced, i.e., they both carry a positive risk premium. All values are statistically significant and almost identical across the OLS and GLS methods. Specifically, taking the GLS as reference values, the market risk premium is 0.52% per month, which represents 6.24% per year. The bank risk premium is 0.24% per month, or 2.88% per year. The t-ratio on the bank risk premium is 3.45, which is higher than the cutoff of 3.0 suggested by Harvey, Liu, and Zhu (2013) as necessary to show that the significance of a new factor is not the result of data mining and multiple testing.

The size of the risk premium λ_b depends on the arbitrary scaling factor used in (2), but that

[16] The results are similar using five or ten portfolios single-sorted on univariate bank betas.

scaling does not affect the t-statistic on the λ_b estimate, nor the contribution of bank risk to expected returns, $\beta_{ib}\lambda_b$. For example, consider an asset x with a bank beta of $\beta_{xb} = -0.74$ and an asset y with $\beta_{yb} = 0.24$ (these values are the average bank betas for the five portfolios in, respectively, the first and the last column of the last panel of table 3). The difference in expected excess returns due to exposure to the bank factor is $(\beta_{yb} - \beta_{xb})\lambda_b = 0.24\%$, or 2.83% per year. This value does not depend on the scaling of the bank factor.

The χ^2 tests show that the two-factor model is not rejected; that is, the pricing errors of the model are not statistically significantly different from zero. Furthermore, the χ^2 tests for the two-factor model show a substantial improvement over the single-factor CAPM. To provide an intuitive idea of the goodness-of-fit of these models, figure 5 plots realized average returns versus predicted mean returns. A perfect model would show all points along the 45-degree diagonal line. When we include an intercept, the CAPM risk premium is essentially zero, and the model is not able to generate any dispersion in predicted returns, thus producing the vertical relation in the top left panel. Excluding the intercept allows the CAPM to generate some dispersion, but the χ^2 test, with a p-value of 0.07, indicates that the pricing errors are still too great. The two-factor bank model, however, shows all portfolios close to the diagonal, and the χ^2 tests do not reject the null that these distances to the diagonal are in fact jointly zero. The performance of the two-factor bank model is essentially unchanged by the inclusion or exclusion of an intercept. Hence, these results suggest that the two-factor bank model is a substantial improvement over the CAPM.

5.2 Fama-MacBeth tests

To allow for time-varying betas, we perform Fama and MacBeth (1973) cross-sectional regression tests. We run rolling 60-month time-series regressions to obtain a monthly series of time-varying factor betas for each test asset, and then compute the usual Fama-MacBeth statistics (all details are in the internet appendix).

Table 6 shows the results. We present the same set of tests as in the full-sample constant-beta case. Starting with the CAPM, if we allow the cross-sectional regressions to have an intercept, we find that the risk premium for the single-factor CAPM is not statistically significant. Without the intercept, we obtain a statistically significant market risk premium of 0.58% per month.

For the two-factor bank model, we start by including an intercept. Again, we find that the market premium is not significant, while the bank risk premium of 0.12% per month is statistically significant. But since the intercept is not statistically significant, we proceed to the restricted version to get more efficient estimates. The results show that both the market and the bank factor are priced, with positive and statistically significant risk premiums. Specifically, the market risk premium is 0.64% per month and the bank factor risk premium is 0.14% per month.

Overall, these results show that our main result that the bank factor is priced still holds when betas are allowed to vary according to the Fama-MacBeth procedure.

5.3 GMM estimation of a linear stochastic discount factor

As the bank factor is correlated with the market factor, we use the generalized method of moments (GMM) to estimate the equivalent stochastic discount factor (SDF) representation, and test whether the new bank factor survives in a multivariate specification. That is, we test whether the bank factor adds explanatory power to the traditional market factor. The GMM approach is also useful because it yields estimates that are asymptotically robust to serial correlation and conditional heteroskedasticity in the joint distribution of returns and factors.

The beta pricing model in (3) is equivalent to the linear SDF model:

$$0 = \mathrm{E}(mR^e), \quad \text{with } m = 1 - b'[f - E(f)] \tag{8}$$

For the two-factor model, $b = [b_m, b_b]'$. A significant coefficient in the b vector indicates that the corresponding factor helps to price the assets, given the other factors, and should thus be included in the model (see, e.g., Cochrane, 2005). We report both first-stage estimates and iterated last-stage estimates (all details are in the internet appendix).

Table 7 shows the estimation results using the 25 portfolios double-sorted on market and bank betas. We start by estimating the single-factor CAPM. The market factor is statistically significant, but the CAPM is rejected at the 5% level.

Then, we estimate the two-factor bank model. First and most important, the results show that the coefficient on the bank factor is positive and strongly statistically significant with both first stage and iterated estimates. Second, the coefficient on the market factor is not statistically different from zero, which results from the correlation between the market and bank factors. In untabulated results (available upon request), we verify that the significance of the bank coefficient and insignificance of the market coefficient persists with other test assets, such as 25 size and book-to-market portfolios or even 10 market-beta portfolios. In this regard, our results are consistent with Adrian, Etula, and Muir (2014), who find that a single factor is enough to explain the cross-section of size, book-to-market and momentum portfolios. We do not pursue a single-factor specification because we have no theoretical argument to justify using our bank factor as the only factor. Finally, we find that the χ^2 test does not reject the null that the pricing errors from the two-factor model are jointly zero.

These results show that, despite its correlation with the market, the bank factor helps to price the assets and improves the fit of the model.

6 Additional asset pricing tests

6.1 Additional factors

One might ask whether our bank factor is truly different from other factors that have been proposed in the literature. We consider three sets of factors below, running two tests for each model. First, we estimate risk premiums (λ) through GLS cross-sectional regressions. This allows us to see whether the size of the bank risk premium is affected by inclusion of other factors. Second, we estimate the b coefficients in the equivalent SDF specification through an iterated GMM. This procedure helps to distinguish between competing factors that are potentially correlated. The test assets are the 25 portfolios sorted on market and bank betas. All results are in table 8.

6.1.1 Stock market factors

We start by considering the most successful standard factors that can be directly computed from the stock market: the Small-Minus-Big (SMB) and High-Minus-Low (HML) of Fama and French (1993); the Up-Minus-Down (UMD) momentum of Carhart (1997); and the non-traded liquidity factor of Pástor and Stambaugh (2003).

The results in table 8 for the models denoted (1a) and (2a) show that while the market factor is priced, neither the SMB, HML, UMD, nor liquidity are priced in our sample, as their risk premiums are all statistically insignificant. Furthermore, these factors appear in the SDF with the wrong sign or with a statistically insignificant coefficient. The only exception is the HML factor; while its λ is not significant, its b coefficient in the SDF is significantly positive.

When we add our bank factor — models (1b) and (2b) in the table — we find that the bank risk premium is statistically significant and with a magnitude of 0.28% or 0.27% per month, which is almost the same value obtained with our benchmark two-factor model (0.24%, table 5). Furthermore, we find that the coefficient of the bank factor in the SDF is always positive and statistically significant. Interestingly, the SDF coefficient of the HML factor becomes insignificant when the model also includes the bank factor. This suggests that the information embedded in the HML factor may in part be related to the state of the banking sector.

6.1.2 Distance to default of nonfinancial firms

Our bank factor is similar to the factor proposed by Vassalou and Xing (2004), but with the difference that they build a factor using *all firms*, while our factor includes *only banks* to focus on the effect of the banking sector on other sectors of the economy. It is thus important to verify that our factor is truly different, i.e., that the information in financial and nonfinancial firms is not the same.

Hence, we compute the Distance to Default (DD) for all nonfinancial firms. More precisely, we include all firms trading on the NYSE and AMEX, except those with an SIC code between 6000 and 6299. The estimation procedure is the same as described in section 2.3. The number of firms for which we are able to estimate the DD increases from 589 in December/1964 to $1,894$ in December/2012, with an average across all months of $1,603$ firms. Figure 6 shows the value-weighted average DD for both sets of banks and nonfinancial firms. The DD for nonfinancials is higher than the DD for banks, which reflects the typical high leverage of financial institutions. The correlation between the two series is 0.45, which suggests that the DD of banks captures some information that is not reflected in the DD of nonfinancial firms.[17]

[17] While our bank factor includes all banks in the NYSE, AMEX, and Nasdaq markets, the group of nonfinancial

To proceed to formal asset pricing tests, we define the nonfinancial factor, denoted "dDD nonfin", as the change in the Distance to Default of nonfinancial firms. While our "dDD nonfin" factor is not strictly identical to the change in the aggregate probability of default used in Vassalou and Xing (2004), they both capture the same information, namely time variation in the likelihood of default of the average firm.

The results for model (3a) in table 8 show that the factor "dDD nonfin" does not carry a significant risk premium and does not help to price our test assets. On the contrary, when we include both distress factors (model 3b), the change in the Distance to Default of the banking sector (our BANK factor) remains priced and statistically significant in the SDF, while "dDD nonfin" remains insignificant.

In summary, these results show that our bank factor is substantially different from the factor in Vassalou and Xing (2004). While distress in the banking sector is important to price our test assets, distress in nonfinancial firms is not.

6.1.3 Aggregate uncertainty and bond market factors

Since our bank factor depends on the drift and volatility of the banks' assets, we also consider factors that may capture similar information. In particular, we include: the change in VIX (dVIX) to capture the overall market uncertainty (Ang, Hodrick, Xing, and Zhang, 2006); a credit spread, defined as the yield on BBB bonds minus the yield on AAA bonds, and a term spread, defined as the yield on ten-year government bonds minus the one-year yield, to capture bond market conditions (Chen, Roll, and Ross, 1986).

The results for model (4a) in table 8 show that both dVIX and the two bond spreads have insignificant risk premiums and are generally insignificant in the SDF. On the contrary, our bank factor remains significantly priced, even in the presence of these additional factors (model 4b).

Overall, these results show that both the risk premium and the relevance of the bank factor are robust to inclusion of other typical asset pricing factors.

6.2 Alternative test assets

The results in section 5 show that the market and bank factors are priced in the cross-section of 25 portfolios formed on market and bank betas. This section tests whether the factors are also priced in alternative test assets. In particular, we want to verify that the magnitude of the bank risk premium is reasonably robust to different test assets.

Following Adrian, Etula, and Muir (2014), we start by estimating the two-factor model using the 25 size and book-to-market portfolios of Fama and French (1992) and 10 momentum-sorted portfolios.[18] Panel A in table 9 shows the results. Both the market and the bank risk premiums

firms includes only NYSE and AMEX firms (we do this for computational reasons, as even this smaller set already requires more than one week of processing time in a quad-core computer to estimate all the DD). If we compute the average DD using only banks that trade on the NYSE and AMEX, the correlation with nonfinancials' DD drops to 0.39.

[18]The data are from Kenneth French's website.

are clearly statistically significant, and of similar magnitude across the OLS and GLS methods. More precisely, in the GLS procedure the market premium is 0.48% per month (which compares with our reference value of 0.52% in table 5), and the bank premium is 0.15% per month (which compares with our reference value of 0.24%).

Given that the 25 size and book-to-market portfolios alone are widely used in the literature, panel B in table 9 shows the risk premiums for this subset of test assets. The results are very similar to panel A, i.e., the GLS risk premium for the market drops by only 1 basis point (bp), and the premium for the bank factor drops by only 3 bp. Both the market and the bank risk premiums remain statistically significant at the 5% level or better in the OLS method and at the 10% level or better in the GLS method.

Finally, in a more extreme case, we consider portfolios of stocks sorted only on market betas. This sorting generates a dispersion in returns that favors the market factor over the bank factor, thus making it harder to find a significant bank risk premium. Panel C shows the results. The OLS estimates for both market and bank risk premiums are statistically significant and remarkably similar to our reference values, i.e., both premiums are within 3 bp of the OLS values obtained in table 5. The GLS procedure, focusing on statistical precision in this sample of market beta portfolios, still generates a bank risk premium of 0.14% per month, statistically significant at the 10% level.

Overall, these results show that the risk premium on the bank factor is robust to different test assets, in particular to the 25 size and book-to-market portfolios commonly used in the literature.

6.3 Robustness to the 2008 financial crisis

The financial crisis centered around the year 2008 is an extreme event featuring abnormal banking sector performance. It is thus important to verify that the importance of the bank risk premium does not hinge on this particular period.

Hence, we re-estimate the model eliminating the 2007–2012 period. Panel A in table 10 shows the results for the 25 portfolios double-sorted on market and bank betas, during the 1969–2006 period. The estimates for this subsample are very similar to the full sample results. In particular, the market risk premium is statistically significant, and just 2 basis points below the full sample value. The OLS estimate of the bank risk premium is 0.25% per month (just 1 bp different from the full-sample value) and the GLS estimate is 0.18% per month (6 bp below the full sample value). Both values are strongly statistically significant (the p-values corresponding to the t-statistics in the table are less than 0.01). Furthermore, the χ^2 test, with a p-value of between 0.76 and 0.59, does not reject the null that the pricing errors are jointly zero

To further support the idea that our results do not depend on any specific sample period, panel B in table 10 estimates the model using only the first 30 years in the sample, and panel C uses only the last 30 years. We find that both the market and the bank factor are significantly priced in all the subsamples, with premiums that do not differ much from the full-sample results.

Hence, we conclude that our results are not driven solely by the 2008 financial crisis. Nonetheless, we expect this recent financial crisis to make investors more aware of the bank risk effect and perhaps to lead to a stronger pricing effect in the future.

6.4 Time-series tests with a factor mimicking portfolio

Nontraded factors can be directly tested with the cross-sectional procedures that we have used. However, one can also replace the nontraded factor with a portfolio of assets with maximum correlation with the original factor, and then perform standard time-series tests on this factor mimicking portfolio. For example, Balduzzi and Robotti (2008) show that time-series tests with the factor mimicking portfolio can sometimes be more informative than cross-sectional tests with the nontraded factor, suggesting that both sets of test be analyzed.[19] Hence, we build a bank factor mimicking portfolio and then provide time-series regressions for different test assets.

6.4.1 Bank factor mimicking portfolio

We build a bank factor mimicking portfolio by projecting the original nontraded bank factor on the excess returns of the 25 portfolios double-sorted on market and bank beta (R^e),

$$\text{BANK}_t = c_0 + c' R_t^e + \varepsilon_t, \quad t = 1, \ldots, T \tag{9}$$

The return on the factor mimicking portfolio, R_{BANK}, is given by

$$R_{\text{BANK},t} := \hat{c}' R_t^e \tag{10}$$

where $\hat{c}$ is the vector of coefficients estimated with the previous regression, rescaled to sum to one.[20]

The correlation between the return on the factor mimicking portfolio thus obtained and the original nontraded BANK factor is 0.43. The mimicking portfolio has an average excess return of 0.80% per month and a standard deviation of 4.28% per month. Furthermore, the CAPM alpha of the mimicking portfolio is 0.47% per month, with a t-statistic of 3.86. Note that the positive correlation means that the factor mimicking portfolio tends to have higher returns when DD increases, i.e., when banks are doing better. Hence, the positive abnormal return is consistent with the notion that firms that pay off more (less) when banks are doing better (worse) must compensate investors for this additional risk through higher expected returns relative to the simple CAPM.

[19] Earlier applications include Breeden (1979) and Breeden, Gibbons, and Litzenberger (1989), among others. Huberman, Kandel, and Stambaugh (1987) characterize the mimicking portfolios that can be used in place of nontraded factors.

[20] Rescaling c is not strictly necessary, but it guarantees that the level of the mimicking factor and its CAPM alpha do not depend on the particular scaling factor of 0.01 used in (2).

6.4.2 Time series regressions for market and bank beta portfolios

If the two-factor bank model is correct, the time series regression

$$R_{it}^{e} = \alpha_i + \beta_{im}\mathrm{RMRF}_t + \beta_{ir}R_{\mathrm{BANK},t} + \varepsilon_{it}, \quad t = 1, \ldots, T \tag{11}$$

should have a zero intercept (α_i), for each test asset i. Gibbons, Ross, and Shanken (1989) provide a test statistic (GRS) for the null that the intercepts are zero across all test assets.

Table 11 shows the alphas for the 25 portfolios double-sorted on bank and market betas. The two-factor bank model is a substantial improvement over the single-factor CAPM. While there are 11 significant CAPM alphas (shown in table 3), there is only one alpha relative to the bank model that is still statistically significant. In fact, the GRS test shows a p-value of 0.77, thus not rejecting the null that all alphas are jointly zero. Even the five alphas on the spreads between high bank beta and low bank beta portfolios now all become statistically insignificant.

These time-series tests show that the bank factor adds explanatory power to the simple market factor, thus confirming the previous cross-sectional and GMM/SDF tests.

6.4.3 Time series regressions for size and book-to-market portfolios

Given that the 25 portfolios of Fama and French (1992) are widely used in the literature, we also perform time-series regressions for the 25 size and book-to-market portfolios. Panel A in table 12 shows alphas for the single factor CAPM. As expected, the CAPM performs poorly on the 25 size and book-to-market portfolios. The results show that 15 of the 25 alphas are statistically significantly different from zero. The GRS test clearly rejects that the alphas are jointly zero.

Panel B shows alphas for the two-factor bank model, using the factor mimicking portfolio defined in (10). The number of statistically significant alphas drops from 15 to 10. These results suggest that the abnormal returns for some size and book-to-market portfolios are due to exposure to the state of the banking sector. In other words, the bank factor is a useful addition to the single market factor.

Yet the GRS test still rejects the two-factor model. To check the relevance of this rejection of the two-factor model, we compare it to the three-factor model of Fama and French (1993) (FF3). Panel C in table 12 shows that even with the FF3 model there are still eight statistically significant alphas. The GRS test also rejects the FF3 model. Consistent with the number of significant alphas, we see more of an improvement in the GRS statistic from the CAPM to the bank model and less of an improvement from the bank to the FF3 model. The FF3 model thus seems to provide just a modest additional ability to explain the returns on the 25 size and book-to-market portfolios. Given that it would be unreasonable to expect the two-factor model to outperform the FF3 on the size and book-to-market portfolios that this model was built to explain, these results are actually supportive of the two-factor bank model.

Finally, recall from table 1 that the correlation between the BANK factor and SMB or HML is very weak (in fact, not statistically different from zero), so our results are not likely to be influenced by the issues raised in Lewellen, Nagel, and Shanken (2010). Furthermore, note that the significant alphas in the FF3 and bank models overlap for only three portfolios, which suggests that the SMB and HML factors may not be capturing the same risk source as our bank factor.

These results suggest that the bank factor improves the explanatory power of the market factor and that the two-factor bank model does almost as well as the Fama-French three-factor model in pricing the 25 size and book-to-market portfolios.

7 Conclusion

Our results show that the risk of the banking sector is a priced factor in the cross-section of nonfinancial firms. A two-factor linear pricing model shows that exposure to the bank factor has almost half the impact on expected returns as exposure to the traditional market factor.

The intuition is simple. When banks are doing well, they are able to obtain funding and to lend freely; when banks face funding difficulties, they tighten the credit supply, which leads to higher default rates as some firms are not able to roll over current debt. In short, BANKruptcy starts with "bank". Industrial and commercial firms whose performance covaries more with the health of the banking sector must therefore offer higher expected returns.

From a policy perspective, it should be clear that changes in the health of the banking sector have real economic effects, despite all the regulation that tries to ensure bank stability. Investors are aware of this connection and price nonfinancial firms accordingly. Furthermore, our results come solely from the effect of commercial bank lending (we exclude all investment banks and broker-dealers), indicating that the banking sector influences security prices even when banks are not marginal investors in those securities.

The financial crisis of 2008 may have made investors more aware of how bank risk influences the performance of nonfinancial firms. In this case, the bank risk factor we propose is likely to become even more important in the future.

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Table 1: Descriptive statistics

This table shows descriptive statistics on four factors. The bank factor, BANK, is computed as in (2). RMRF is the excess return on the market, SMB is the Small Minus Big factor, and HML is the High Minus Low factor, all obtained from Kenneth French's website. The bottom panel shows the autocorrelation function for the new BANK factor and also the Ljung-Box test for the null that the series is white noise, against the alternative that it is an AR(p) or MA(p), where p is the lag order. The sample is monthly from Dec/1964 to Dec/2012 (577 observations).

	RMRF	BANK	SMB	HML
Moments				
Mean	0.0044	0.0000	0.0027	0.0037
Stdev	0.0457	0.0046	0.0317	0.0293
Skewness	-0.5004	-2.0789	0.5202	0.0073
Kurtosis	4.7651	20.8144	8.2906	5.3830
Percentiles				
Min	-0.2324	-0.0402	-0.1639	-0.1260
25%	-0.0227	-0.0015	-0.0152	-0.0123
Median	0.0074	0.0000	0.0008	0.0036
75%	0.0349	0.0018	0.0214	0.0176
Max	0.1610	0.0191	0.2200	0.1384
Cross-Correlations				
RMRF		0.3185	0.3113	-0.3080
(p-value)		(0.00)	(0.00)	(0.00)
BANK			-0.0289	0.0444
(p-value)			(0.49)	(0.29)

Auto-correlations for BANK factor

		Ljung-Box	
Lag	Autocorr.	statistic	p-value
1	0.0151	0.1319	0.7165
2	0.0006	0.1321	0.9361
3	-0.0407	1.0972	0.7777
6	-0.0402	2.6657	0.8495

Table 2: Granger causality between Bankruptcies and Banks' DD

This table shows the estimation of a VAR(1) with three variables. "Bankruptcy" is the total number of bankruptcies, "DD" is the value-weighted average Distance to Default of all banks, "GDP_QoQ" is the growth rate of GDP. "_1" after a variable name denotes 1 lag. We compute heteroscedasticity and autocorrelation consistent standard errors (HACSE) and present the resulting t-ratios. All data is quarterly and the sample period is 1980/Q1–2012/Q3.

	Coefficient	t-HACSE	t-prob
Equation for Bankruptcy			
Bankruptcy_1	0.877	17.00	0.000
DD_1	-262.1	-2.65	0.009
GDP_QoQ_1	-300.8	-2.65	0.009
Constant	2237.3	3.00	0.003
Equation for DD			
Bankruptcy_1	0.000	-0.10	0.918
DD_1	0.923	22.30	0.000
GDP_QoQ_1	-0.012	-0.15	0.879
Constant	0.180	0.76	0.450
Equation for GDP_QoQ			
Bankruptcy_1	0.000	2.98	0.003
DD_1	0.114	2.06	0.042
GDP_QoQ_1	0.381	3.49	0.001
Constant	-0.433	-1.32	0.190

Table 3: Portfolio returns

This table shows average portfolio excess returns and CAPM alphas, both in percent per month, and full sample betas. Single sorts are based on univariate betas (equation 6) and double sorts on bivariate betas (equation 4). The last two columns present the difference between the two extreme portfolios in each row and a t-test for the null that this spread is zero. For alphas, statistical significance at the 10%, 5%, or 1% level is denoted by *, **, or ***, respectively. The sample is monthly from Dec/1969 to Dec/2012 (517 observations).

Panel A: Single-sorted portfolios on bank beta

Quintiles	Bnk 1	Bnk 2	Bnk 3	Bnk 4	Bnk 5	Hi-Lo	t-stat
Exc. Returns	0.20	0.37	0.49	0.58	0.72	0.52	2.71
CAPM alphas	-0.28^{**}	-0.08	0.07	0.12^{**}	0.18^{**}	0.45	2.39
Bank Beta	2.86	3.22	3.44	4.12	4.62		

Panel B: Double-sorted portfolios on market and bank betas

Excess Returns							
Quintiles	Bnk 1	Bnk 2	Bnk 3	Bnk 4	Bnk 5	Hi-Lo	t-stat
Mkt 1	0.32	0.46	0.52	0.50	0.57	0.25	0.90
Mkt 2	0.25	0.50	0.62	0.67	0.71	0.46	2.02
Mkt 3	0.23	0.28	0.65	0.60	0.59	0.37	1.87
Mkt 4	0.26	0.36	0.55	0.59	0.66	0.41	2.10
Mkt 5	0.33	0.40	0.54	0.83	0.37	0.04	0.17
CAPM alphas							
Quintiles	Bnk 1	Bnk 2	Bnk 3	Bnk 4	Bnk 5	Hi-Lo	t-stat
Mkt 1	-0.08	0.19	0.23^{**}	0.24^{**}	0.27^{**}	0.35	1.24
Mkt 2	-0.12	0.13	0.25^{**}	0.29^{***}	0.31^{***}	0.43	1.87
Mkt 3	-0.25	-0.19^{*}	0.19^{**}	0.12	0.10	0.35	1.77
Mkt 4	-0.32^{**}	-0.20	0.00	0.01	0.05	0.37	1.92
Mkt 5	-0.38^{**}	-0.33^{*}	-0.19	0.09	-0.38	0.00	0.01
Market Betas							
Quintiles	Bnk 1	Bnk 2	Bnk 3	Bnk 4	Bnk 5		
Mkt 1	0.85	0.59	0.61	0.53	0.61		
Mkt 2	0.82	0.80	0.78	0.79	0.86		
Mkt 3	1.04	1.02	0.99	1.01	1.05		
Mkt 4	1.27	1.24	1.21	1.26	1.31		
Mkt 5	1.59	1.64	1.60	1.60	1.65		
Bank Betas							
Quintiles	Bnk 1	Bnk 2	Bnk 3	Bnk 4	Bnk 5		
Mkt 1	0.11	0.25	0.53	0.91	1.19		
Mkt 2	-0.55	0.06	0.31	0.65	0.78		
Mkt 3	-0.44	-0.08	0.35	0.57	0.51		
Mkt 4	-0.91	-1.30	-0.15	-0.18	-0.04		
Mkt 5	-1.92	-1.91	-1.45	-0.51	-1.22		

Table 4: Debt ratios for 25 portfolios

This table shows average debt ratios (Total Liabilities over Total Assets) for the 25 portfolios sorted on bivariate betas (equation 4). The last two columns present the difference between the two extreme portfolios in each row and a paired t-test for the null that the two means are equal. The sample is monthly from Dec/1969 to Dec/2012 (517 observations).

Quintiles	Bnk 1	Bnk 2	Bnk 3	Bnk 4	Bnk 5	Hi-Lo	t-stat
Mkt 1	0.44	0.51	0.54	0.56	0.57	0.13	22.04
Mkt 2	0.46	0.50	0.52	0.55	0.58	0.12	22.69
Mkt 3	0.48	0.51	0.54	0.56	0.59	0.11	26.27
Mkt 4	0.48	0.52	0.55	0.56	0.57	0.09	21.10
Mkt 5	0.46	0.47	0.51	0.54	0.56	0.10	21.54

Table 5: Cross-sectional regression tests

This table shows estimates of the market (λ_m) and bank (λ_b) risk premiums, and an intercept (λ_0), in percent per month. The test assets are 25 portfolios sorted on market and bank betas. The last two columns present the test for the null that the pricing errors are jointly zero. The sample is from Dec/1969 to Dec/2012.

				χ^2 test	
	λ_0	λ_m	λ_b	statistic	p-value
OLS					
Coefficient	0.51	-0.01		28.18	0.21
t-value	2.35	-0.04			
GLS					
Coefficient	0.48	0.04		28.18	0.21
t-value	2.61	0.14			
OLS					
Coefficient		0.42		34.69	0.07
t-value		2.00			
GLS					
Coefficient		0.51		34.57	0.08
t-value		2.44			
OLS					
Coefficient	0.02	0.49	0.26	14.46	0.88
t-value	0.06	1.39	2.40		
GLS					
Coefficient	0.2	0.32	0.2	16.25	0.80
t-value	0.88	1.03	2.53		
OLS					
Coefficient		0.51	0.26	14.97	0.90
t-value		2.38	2.83		
GLS					
Coefficient		0.52	0.24	15.83	0.86
t-value		2.49	3.45		

Table 6: Fama-MacBeth tests

This table shows Fama-MacBeth estimates of the market (λ_m) and bank (λ_b) risk premiums, and an intercept (λ_0), in percent per month. The test assets are 25 portfolios sorted on market and bank betas. Time-varying betas are estimated with rolling 60-month regressions. The last two columns present the test for the null that the pricing errors are jointly zero. The sample is from Dec/1969 to Dec/2012, with 457 cross-sectional estimates.

				χ^2 test	
	λ_0	λ_m	λ_b	statistic	p-value
Coefficient	0.35	0.30		31.34	0.11
t-value	1.58	0.96			
Coefficient		0.58		38.79	0.03
t-value		2.65			
Coefficient	0.24	0.45	0.12	29.50	0.13
t-value	1.06	1.45	2.75		
Coefficient		0.64	0.14	36.67	0.04
t-value		3.00	3.05		

Table 7: GMM-SDF tests

This table shows GMM estimates of the b coefficients in the stochastic discount factor representation (8). The test assets are 25 portfolios sorted on market and bank betas. The last two columns present the test for the null that the pricing errors are jointly zero. The sample is from Dec/1969 to Dec/2012.

			χ^2 test	
	b_m	b_b	statistic	p-value
First stage				
Coefficient	1.95		40.22	0.02
t-value	1.76			
Iterated				
Coefficient	3.67		39.52	0.02
t-value	3.53			
First stage				
Coefficient	-2.69	165.50	23.41	0.44
t-value	-1.11	2.54		
Iterated				
Coefficient	-1.80	154.29	23.81	0.41
t-value	-1.05	3.83		

Table 8: Additional factors

The left panel shows risk premiums (monthly values, in percentage) from different factor models estimated through GLS cross-sectional regressions. The right panel shows the coefficients in the corresponding SDF estimated through iterated GMM. Values in parenthesis are t-ratios. The last two rows present the test for the null that the pricing errors are jointly zero. The test assets for all models are 25 portfolios sorted on market and bank betas. The sample is monthly from Dec/1969 to Dec/2012 (517 observations).

	Risk premiums (λ, in %)								SDF coefficients (b)							
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
RMRF	0.51	0.56	0.48	0.54	0.51	0.57	0.59	0.73	5.67	−0.82	8.01	2.08	4.02	0.19	7.06	5.69
	(2.41)	(2.63)	(2.23)	(2.44)	(2.42)	(2.64)	(2.13)	(2.53)	(4.66)	(−0.32)	(3.58)	(0.59)	(1.34)	(0.06)	(1.17)	(0.99)
BANK		0.28		0.27		0.29		0.27		142.91		123.44		160.96		143.59
		(2.90)		(2.69)		(2.88)		(2.59)		(2.57)		(2.30)		(2.36)		(2.47)
SMB	−0.20	−0.33	−0.25	−0.36	−0.18	−0.36	−0.15	−0.40	−6.16	−6.47	−3.77	−4.47	−6.08	−6.05	−1.13	−12.78
	(−0.96)	(−1.38)	(−1.11)	(−1.45)	(−0.83)	(−1.45)	(−0.52)	(−1.20)	(−2.41)	(−2.36)	(−1.55)	(−1.78)	(−2.38)	(−2.18)	(−0.33)	(−3.41)
HML	0.21	−0.15	0.30	−0.06	0.14	−0.12	0.28	−0.02	5.62	−3.17	7.80	0.00	4.65	−3.05	8.22	−1.86
	(0.88)	(−0.50)	(1.12)	(−0.18)	(0.54)	(−0.39)	(0.95)	(−0.05)	(1.92)	(−0.77)	(2.54)	(0.00)	(1.42)	(−0.74)	(2.17)	(−0.45)
UMD			−0.11	−0.11							−0.95	0.43				
			(−0.20)	(−0.17)							(−0.41)	(0.18)				
Liquidity			−1.99	−1.33							−7.34	−5.08				
			(−1.22)	(−0.72)							(−1.60)	(−1.03)				
dDD nonfin					7.50	7.91							0.25	−0.27		
					(1.37)	(1.21)							(0.59)	(−0.52)		
dVIX							−0.53	−0.27							−3.32	5.04
							(−0.87)	(−0.39)							(−0.42)	(0.64)
Credit Spread							0.01	0.01							−201.79	55.82
							(0.15)	(0.10)							(−2.86)	(1.42)
Term Spread							−0.09	−0.02							−5.99	−10.28
							(−0.41)	(−0.07)							(−0.28)	(−0.44)
χ^2	29.01	13.06	22.67	12.32	28.19	12.35	29.62	16.50	30.15	18.56	23.12	17.34	29.30	18.23	19.53	19.74
p-value	0.14	0.91	0.31	0.87	0.13	0.90	0.06	0.56	0.11	0.61	0.28	0.57	0.11	0.57	0.42	0.35

Table 9: Risk premiums for alternative test portfolios

This table shows estimates of the market (λ_m) and bank (λ_b) risk premiums, in percent per month, for different test portfolios as indicated in the heading of each panel. The last two columns present the test for the null that the pricing errors are jointly zero. The sample is from Dec/1969 to Dec/2012.

			χ^2 test	
	λ_m	λ_b	statistic	p-value
A: 25 Size and B/M plus 10 Momentum port.				
OLS				
Coefficient	0.56	0.18	120.81	0.00
t-value	2.61	2.07		
GLS				
Coefficient	0.48	0.15	125.95	0.00
t-value	2.35	2.41		
B: 25 Size and B/M portfolios				
OLS				
Coefficient	0.64	0.21	87.82	0.00
t-value	2.91	2.33		
GLS				
Coefficient	0.47	0.12	102.23	0.00
t-value	2.30	1.84		
C: 10 market beta portfolios				
OLS				
Coefficient	0.49	0.23	5.39	0.71
t-value	2.34	2.09		
GLS				
Coefficient	0.49	0.14	6.44	0.60
t-value	2.35	1.71		

Table 10: Subsamples

This table shows estimates of the market (λ_m) and bank (λ_b) risk premiums, in percent per month, for different sample periods as indicated in the heading of each panel. The test assets for all periods are 25 portfolios sorted on market and bank betas. The last two columns present the test for the null that the pricing errors are jointly zero.

			χ^2 test	
	λ_m	λ_b	statistic	p-value
A: Without crisis period (1969/12–2006/12)				
OLS				
Coefficient	0.49	0.25	18.03	0.76
t-value	2.17	2.82		
GLS				
Coefficient	0.50	0.18	20.81	0.59
t-value	2.27	3.18		
B: First 30 years (1969/12–1999/11)				
OLS				
Coefficient	0.54	0.28	22.92	0.47
t-value	2.18	2.69		
GLS				
Coefficient	0.61	0.14	31.29	0.12
t-value	2.46	2.05		
C: Last 30 years (1983/01–2012/12)				
OLS				
Coefficient	0.66	0.20	19.45	0.67
t-value	2.68	2.53		
GLS				
Coefficient	0.70	0.19	19.63	0.66
t-value	2.86	3.31		

Table 11: Time-series regressions for market and bank beta portfolios

This table shows alphas (in % per month) and betas for the time-series regression (11). The test assets are excess returns on the 25 portfolios double sorted on market and bank betas. The last two columns present the difference between the two extreme portfolios in each row and a t-test for the null that this spread is zero. Statistical significance at the 10%, 5%, or 1% level is denoted by *, **, or ***, respectively. GRS is the Gibbons, Ross, and Shanken (1989) F-statistic for the null that all the alphas are jointly zero. The sample is monthly from Dec/1969 to Dec/2012 (517 observations).

Alphas

Quintiles	Bnk 1	Bnk 2	Bnk 3	Bnk 4	Bnk 5	Hi-Lo
Mkt 1	−0.14	0.10	0.08	0.01	−0.03	0.11
Mkt 2	−0.04	0.08	0.15	0.11	0.09	0.12
Mkt 3	−0.20	−0.22**	0.06	−0.06	−0.07	0.13
Mkt 4	−0.17	0.04	−0.03	0.00	0.00	0.17
Mkt 5	−0.02	0.03	0.07	0.14	−0.18	−0.16
GRS	0.7795					
p-value	0.7698					

Betas with market factor

Quintiles	Bnk 1	Bnk 2	Bnk 3	Bnk 4	Bnk 5
Mkt 1	0.75***	0.47***	0.40***	0.21***	0.20***
Mkt 2	0.94***	0.73***	0.63***	0.53***	0.55***
Mkt 3	1.10***	0.98***	0.81***	0.76***	0.82***
Mkt 4	1.46***	1.56***	1.17***	1.22***	1.23***
Mkt 5	2.08***	2.12***	1.94***	1.65***	1.92***

Betas with bank factor mimicking portfolio

Quintiles	Bnk 1	Bnk 2	Bnk 3	Bnk 4	Bnk 5
Mkt 1	0.14	0.18***	0.32***	0.49***	0.64***
Mkt 2	−0.19***	0.11**	0.22***	0.39***	0.46***
Mkt 3	−0.11**	0.06*	0.27***	0.37***	0.35***
Mkt 4	−0.32***	−0.51***	0.05	0.04	0.11**
Mkt 5	−0.78***	−0.76***	−0.54***	−0.09	−0.43***

Table 12: Time-series regressions for size and book-to-market portfolios

This table shows time-series alphas (in % per month) for three models. The test assets are excess returns on the 25 Fama and French portfolios sorted on size and book to market (B/M). For the two-factor bank model, the nontraded bank factor is replaced by the factor mimicking portfolio defined in (10). Statistical significance at the 10%, 5%, or 1% level is denoted by *, **, or ***, respectively. GRS is the Gibbons, Ross, and Shanken (1989) F-statistic for the null that all the alphas are jointly zero. The sample is monthly from Dec/1969 to Dec/2012 (517 observations).

A: Alphas w.r.t. CAPM

Quintiles	Size 1	Size 2	Size 3	Size 4	Size 5
B/M 1	−0.65***	−0.30*	−0.20	−0.02	−0.06
B/M 2	0.12	0.11	0.19*	0.04	0.12*
B/M 3	0.24	0.34***	0.27**	0.21**	0.06
B/M 4	0.45***	0.41***	0.35***	0.33***	0.16
B/M 5	0.54***	0.41***	0.55***	0.32**	0.20
GRS	4.3283				
p-value	0.0000				

B: Alphas w.r.t. 2-factor bank model

Quintiles	Size 1	Size 2	Size 3	Size 4	Size 5
B/M 1	−0.38*	−0.11	−0.02	0.11	−0.02
B/M 2	0.27	0.15	0.15	−0.03	0.02
B/M 3	0.29*	0.28**	0.16	0.09	−0.06
B/M 4	0.45***	0.30**	0.19*	0.17*	−0.04
B/M 5	0.53***	0.31**	0.39***	0.13	0.08
GRS	3.7431				
p-value	0.0000				

C: Alphas w.r.t. Fama-French 3-factor model

Quintiles	Size 1	Size 2	Size 3	Size 4	Size 5
B/M 1	−0.59***	−0.18**	−0.04	0.15**	0.14***
B/M 2	0.01	−0.02	0.05	−0.09	0.08
B/M 3	0.02	0.07	0.00	−0.04	−0.07
B/M 4	0.15**	0.07	0.01	0.03	−0.12*
B/M 5	0.11*	−0.07	0.12	−0.10	−0.17*
GRS	3.5462				
p-value	0.0000				

Figure 1: Distance to Default

The figure shows the estimated value-weighted average Distance to Default of all commercial banks trading on the NYSE, AMEX, or Nasdaq markets. The sample is from Dec/1964 to Dec/2012.

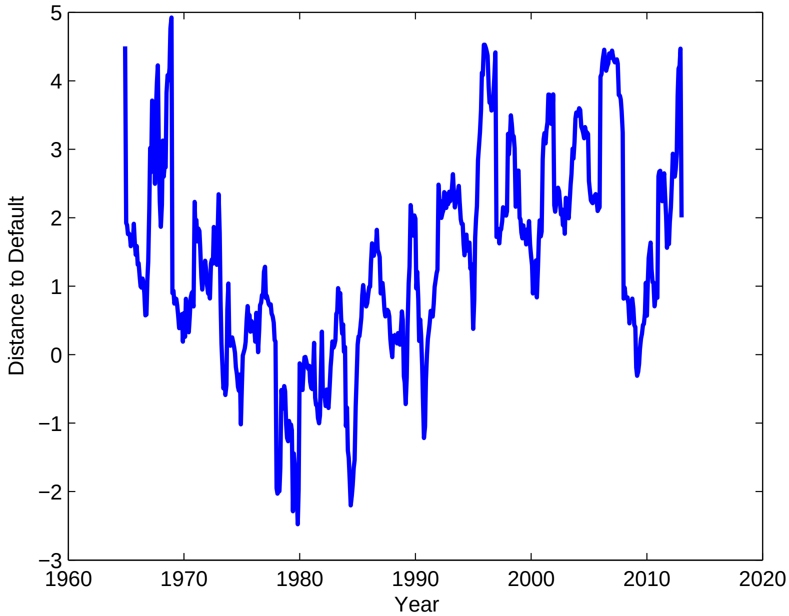


Figure 2: Bank lending terms and Distance to Default

This figure shows the evolution of the average Distance to Default of all banks (solid line, left axis) and two measures of bank lending terms (right axis, inverted) obtained from the "senior loan officer opinion survey on bank lending practices" published by the Federal Reserve Board. The top panel shows the net percentage of banks tightening standards for commercial and industrial loans. The bottom panel shows the net percentage of banks increasing spreads on loans. In both panels, the dashed line represents large and medium firms and the dotted line represents small firms. The sample period is 1990/Q2–2012/Q4.

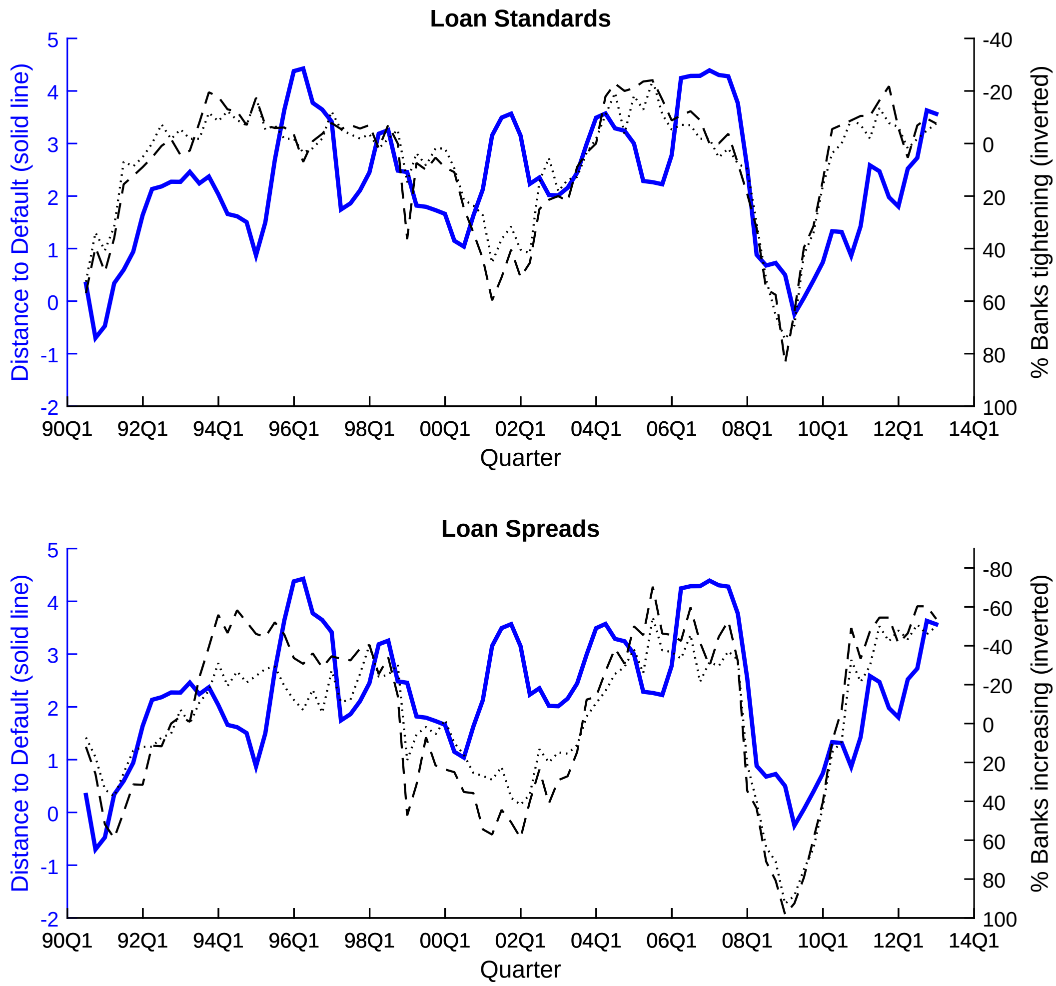


Figure 3: Bankruptcies and Banks' Distance to Default

This figure shows the evolution of the total number of bankruptcies (dotted line, right axis, inverted) and the average Distance to Default of all banks (solid line, left axis). The sample period is 1980/Q1–2012/Q3.

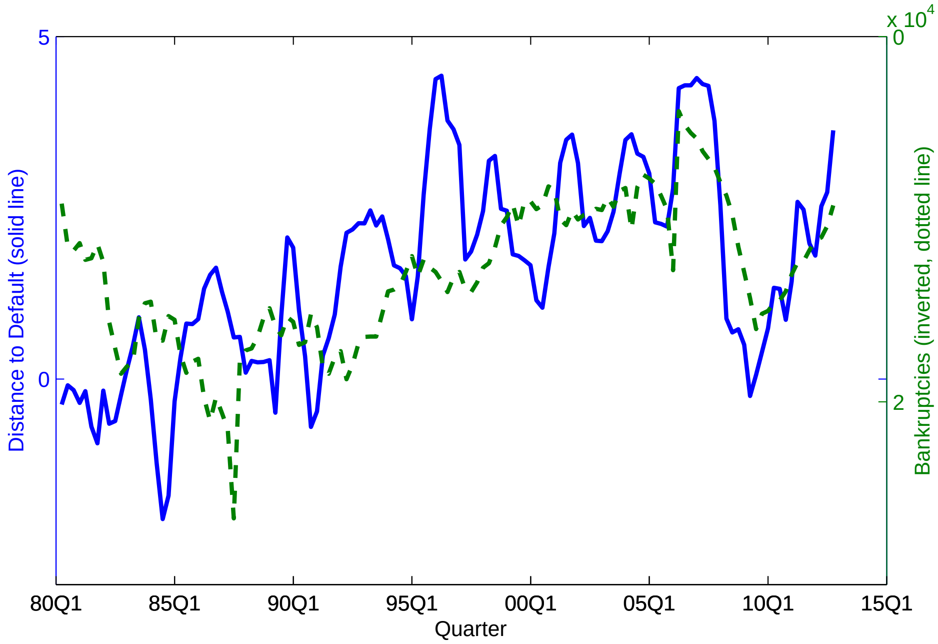


Figure 4: Debt ratios and bank betas for 25 portfolios

This figure plots average debt ratios (total liabilities over total assets) against bank betas for 25 portfolios sorted on market and bank betas (equation 4). The dotted line is an OLS best fit. The sample is from Dec/1969 to Dec/2012.

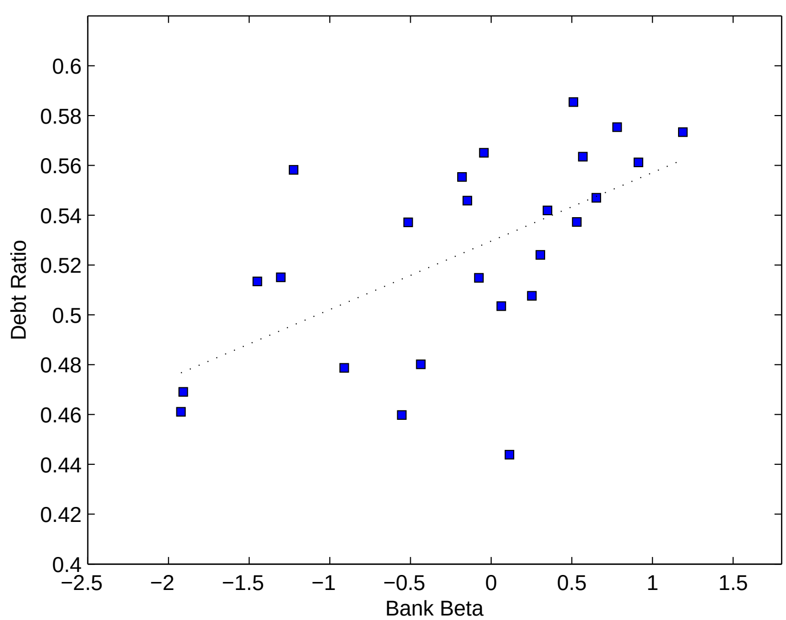


Figure 5: Realized versus predicted returns

This figure plots realized average monthly excess returns against mean excess returns predicted by the models on the 25 portfolios sorted on market and bank beta. In the left column, returns are predicted with the single factor CAPM; in the right column, returns are predicted with the two-factor bank model. Both models are estimated with OLS. The sample is from Dec/1969 to Dec/2012.

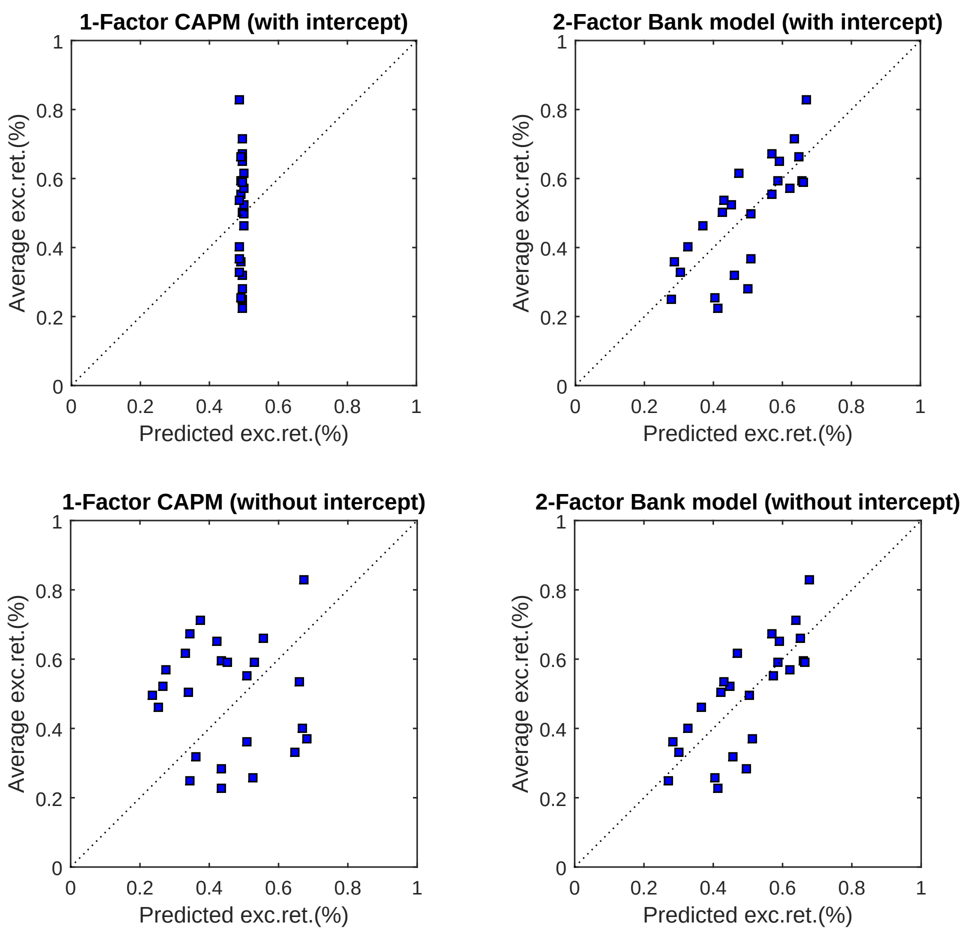
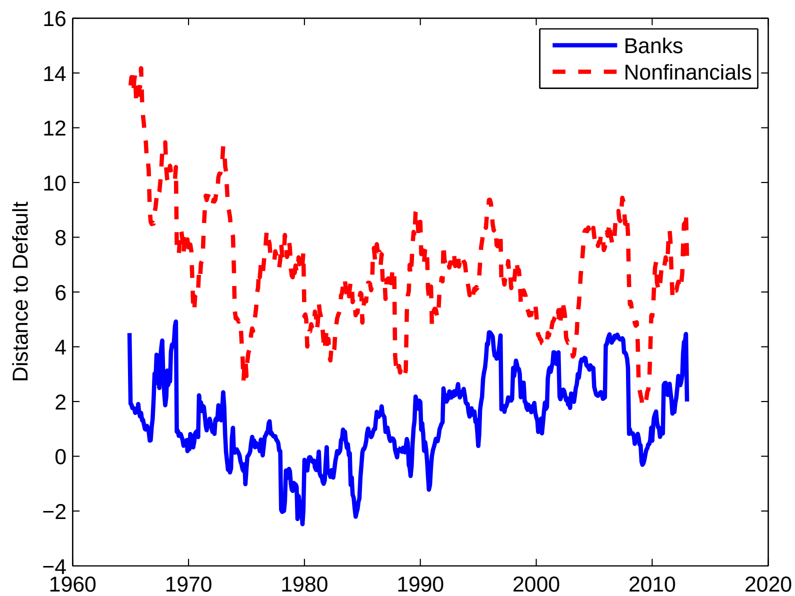


Figure 6: Banks' versus Nonfinancial firms' Distance to Default

This figure compares the value-weighted average Distance to Default (DD) of all banks included in our sample with the value-weighted average DD of all nonfinancial firms trading in the NYSE and AMEX markets. The sample is from Dec/1964 to Dec/2012.



Internet appendix for "Asset pricing with a bank risk factor"

A Econometric details of main asset pricing tests

A.1 Cross-sectional regressions

We perform a two-pass regression estimate of the model in (3). First, we use the time series of monthly excess returns for each test portfolio i defined in section 4 to compute full-sample betas from the time-series regression:

$$R^e_{it} = a_i + \beta'_i f_t + \varepsilon_{it}, \quad t = 1, \ldots, T \tag{A.1}$$

where f_t denotes the vector of K factors and β_i the corresponding vector of betas. For the 2-factor model, $f_t = [\text{RMRF}_t, \text{BANK}_t]'$ and $\beta_i = [\beta_{im}, \beta_{ib}]'$.

Second, we estimate the risk premiums in (3) from a cross-sectional regression of average returns on betas:

$$\bar{R}^e_i = \beta'_i \lambda + \alpha_i, \quad i = 1, \ldots, N \tag{A.2}$$

where $\bar{R}^e_i$ are the sample average excess returns on N test portfolios, α_i are the regression residuals or pricing errors, and λ is the vector of regression coefficients to be estimated. We first estimate this regression with an intercept to get more robust estimates ($\lambda = [\lambda_0, \lambda_m, \lambda_b]'$); then, we impose the theoretical model and estimate the regression without a constant to get more efficient estimates ($\lambda = [\lambda_m, \lambda_b]'$). We estimate (A.2) by both OLS and GLS.

OLS cross-sectional regression. The OLS cross-sectional point estimates of risk premiums are the usual $\hat{\lambda} = (\beta'\beta)^{-1}\beta'\bar{R}^e$ where β is the (N by K) matrix of betas, and $\bar{R}^e$ is the (N by 1) vector of average excess returns. The (N by 1) residuals are $\hat{\alpha} = \bar{R}^e - \beta\hat{\lambda}$. The covariance matrix of the OLS estimates that accounts for errors in (A.1) correlated across assets is

$$\text{Cov}(\hat{\lambda}) = \frac{1}{T}\left[(\beta'\beta)^{-1}\beta'\Sigma_\varepsilon\beta(\beta'\beta)^{-1}(1 + \lambda'\Sigma_f^{-1}\lambda) + \Sigma_f\right] \tag{A.3}$$

and the covariance of the residuals is

$$\text{Cov}(\hat{\alpha}) = \frac{1}{T}\left[I - \beta(\beta'\beta)^{-1}\beta'\right]\Sigma_\varepsilon\left[I - \beta(\beta'\beta)^{-1}\beta'\right]'(1 + \lambda'\Sigma_f^{-1}\lambda) \tag{A.4}$$

where $\Sigma_\varepsilon := \text{Cov}(\varepsilon_t)$ and $\Sigma_f := \text{Cov}(f_t)$. The term $(1 + \lambda'\Sigma_f^{-1}\lambda)$ in both formulas is Shanken's (1992) correction for the fact that the β are not fixed regressors in the cross-sectional regression (A.2), but are instead estimated in the time-series regression (A.1). The test for the null that all N pricing errors are zero is given by

$$\hat{\alpha}'\,\text{Cov}(\hat{\alpha})^{-1}\hat{\alpha} \sim \chi^2_{(N-K)} \tag{A.5}$$

GLS cross-sectional regression. The alternative GLS cross-sectional regression corrects for residuals correlated with each other in (A.2). The point estimates are

$$\hat{\lambda} = (\beta'\Sigma_\varepsilon^{-1}\beta)^{-1}\beta'\Sigma_\varepsilon^{-1}\bar{R}^e \tag{A.6}$$

and the residuals are $\hat{\alpha} = \bar{R}^e - \beta\hat{\lambda}$. The covariance of the risk premium estimates is

$$\text{Cov}(\hat{\lambda}) = \frac{1}{T}\left[(\beta'\Sigma_\varepsilon^{-1}\beta)^{-1}(1 + \lambda'\Sigma_f^{-1}\lambda) + \Sigma_f\right] \tag{A.7}$$

and the covariance of the pricing errors is

$$\text{Cov}(\hat{\alpha}) = \frac{1}{T}\left[\Sigma_\varepsilon - \beta(\beta'\Sigma_\varepsilon^{-1}\beta)^{-1}\beta'\right](1 + \lambda'\Sigma_f^{-1}\lambda) \tag{A.8}$$

Again, both include Shanken's (1992) correction. To test whether all pricing errors are zero, we use (A.5) with (A.8).

A.2 Fama-MacBeth tests

For each test asset, we run rolling 60-month time-series regressions to obtain a monthly series of time-varying factor betas. Then, we run T cross-sectional regressions to estimate the risk premiums and pricing errors.

Denoting by λ_t the vector of risk premiums estimated with the cross section at time t, the Fama-MacBeth point estimate is sample average, $\hat{\lambda} = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_t$, and the covariance matrix is

$$\text{Cov}(\hat{\lambda}) = \frac{1}{T^2}\sum_{t=1}^{T}\left(\hat{\lambda}_t - \hat{\lambda}\right)\left(\hat{\lambda}_t - \hat{\lambda}\right)' \tag{A.9}$$

Similarly for the pricing errors, $\hat{\alpha} = \frac{1}{T}\sum_{t=1}^{T}\hat{\alpha}_t$, with covariance matrix

$$\text{Cov}(\hat{\alpha}) = \frac{1}{T^2}\sum_{t=1}^{T}\left(\hat{\alpha}_t - \hat{\alpha}\right)\left(\hat{\alpha}_t - \hat{\alpha}\right)' \tag{A.10}$$

We replace these matrices in (A.5) to test whether all pricing errors are jointly zero.

A.3 GMM estimation of a linear stochastic discount factor

The beta pricing model in (3) is equivalent to the linear SDF model

$$0 = \text{E}(mR^e), \quad \text{with } m = 1 - b'[f - E(f)] \tag{A.11}$$

For the 2-factor model, $b = [b_m, b_b]'$. The GMM estimate of b is

$$\hat{b} = \arg\min_b g(b)'Wg(b) \tag{A.12}$$

where $g(b) := \frac{1}{T}\sum_{t=1}^{T} m_t(b)R_t^e$ is the (N by 1) sample mean of the pricing errors. We start by computing first-stage estimates, setting W equal to the identity matrix. Then, we compute second-stage estimates with the statistically optimal weighting matrix W, i.e., the inverse of the spectral density matrix (estimated with a Newey-West kernel with 3 lags). We then proceed to an iterated n-stage GMM and report the last estimate. The formulas for $\hat{b}$, $\text{Cov}(\hat{b})$, $\text{Cov}(g)$, and for the χ^2 test are all from Cochrane (2005, sec.13.2).

B Additional investment perspective

To provide an additional perspective on the importance of bank risk, we analyze how the mean-variance frontier is improved by in the inclusion of the bank factor mimicking portfolio. While a mean-variance efficient portfolio is not necessarily the optimal choice when expected returns depend on multiple factors, the mean-variance analysis is still of practical interest for many investors. Furthermore, if a return is mean-variance efficient, then there is a beta model with that return as reference variable (Cochrane, 2005, ch. 6). Hence, a candidate factor should contribute to increase the maximal attainable Sharpe ratio.

Table B.1 shows the ex post full sample Sharpe Ratio (SR) for the bank factor mimicking portfolio (R_{BANK}). The monthly excess return on R_{BANK} has a mean of 0.80% and a standard deviation of 4.28%, which implies a SR of 0.19 on a monthly basis (multiplying by $\sqrt{12}$, this represents an annual SR of 0.66). The SR on the bank factor mimicking portfolio (0.19) is higher than the SR on the market factor (0.10), and on the SMB (0.08) and HML (0.14) factors.

Considering now optimal combinations of different factors, we find that the tangency portfolio formed by the market and bank factors has a SR of 0.20. This value is almost as high as the maximum SR of 0.22 obtained by combining the market and the empirically motivated SMB and HML factors. Finally, we note that adding R_{BANK} to the other 3 factors (RMRF, SMB, HML) increases the SR to 0.24. Hence, these results suggest that the bank factor helps us to get closer to the true stochastic discount factor.

Table B.1: Tangency portfolios

This table shows the weights and returns of several ex post tangency portfolios resulting from different combinations of the market excess return (RMRF), the excess return on the bank factor mimicking portfolio (R_{BANK}) as defined in (10), and the returns on the SMB and HML factors. $E[R^e]$ and $\sigma[R^e]$ denote, respectively, the mean and standard deviation of excess returns, both in % per month. The Sharpe ratio equals $E[R^e]/\sigma[R^e]$ and is also presented on a monthly basis. The sample is monthly from Dec/1969 to Dec/2012 (517 observations).

Weights				Returns		
RMRF	R_{BANK}	SMB	HML	$E[R^e]$	$\sigma[R^e]$	Sharpe
1.00				0.47	4.50	0.10
	1.00			0.80	4.28	0.19
		1.00		0.25	3.12	0.08
			1.00	0.40	2.89	0.14
-0.55	1.55			0.98	4.96	0.20
0.24		0.21	0.54	0.38	1.75	0.22
-0.08	0.41	0.28	0.39	0.51	2.10	0.24