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ASSET PRICING WITH A BANK RISK FACTOR

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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 the banking sector. 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 2.67% higher than for a stock in the bottom quintile.

JEL classification: G12, G21.
Keywords: Asset pricing, factor model, distance to default, banking.

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1 Introduction

The financial crisis of 2008 highlights how the health of the financial sector influences the performance of other sectors of the economy. Many banks faced funding difficulties and tightened the credit supplied to other companies. Commercial and industrial firms faced less and more expensive credit, which contributed to a lower profitability and an increase in the number of bankruptcies.

This paper tests 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 includes a bank risk factor, in addition 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 in Merton's (1974) model and is similar to the one used by the consulting firm KMV (now part of Moody's Analytics).

The underlying assumption is that when banks' distance to default decreases (which means that the probability of default increases), banks find it harder and more expensive to obtain funds and therefore will also restrict and make more expensive the credit supplied to their customers. While there is not an obvious unique measure that captures the state of the credit market and how easy it is for other firms to obtain credit from banks, DD seems a good candidate to summarize the ability of banks to initiate the lending process.[1] To substantiate this assumption, we provide evidence that a decrease in the banking sector average DD is associated with tighter loan standards and higher spreads charged to other nonfinancial firms. Our factor model

[1] Some other variables might also seem good proxies. One candidate would be interbank rates. However, the ongoing crisis shows low interbank rates coupled with a decrease in commercial and industrial loans (this abnormal scenario is even stronger in the Euro zone, where Euribor rates at the lowest levels of the last 10 years, but credit markets remain very dry). The average credit rating of banks might also be a good candidate. However, ratings change at low frequencies and it is difficult to get long time series for all banks. Another interesting candidate would be the Fed's E2 series ("commercial and industrial loan rates spreads over intended federal funds rate"). However, this series in only available on a quarterly basis and since 1986. Our use of DD to measure bank risk is supported by the results in Munves, Smith, and Hamilton (2010) and Eichler, Karmann, Maltritz, and Sobanski (2011).

can be motivated by the ICAPM of Merton (1973). To preclude the "fishing licence" criticism of using the theoretical ICAPM to justify any ad hod empirical factor (Fama, 1991), we 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 U.S. market.

The bank risk factor is estimated from data on all NYSE and AMEX traded banks from 1963 to 2010. The model is tested on excess returns of portfolios of nonfinancial firms only, that is, our test assets do not include any banks. This separation prevents any mechanical relation between the bank factor and the test assets and allows for a cleaner interpretation of the results. In particular, we test the model on 10 portfolios sorted on the covariance with the bank factor (bank beta) and also on 25 portfolios double sorted on market and bank beta.

The results show that average excess returns increase with bank betas. For single-sorted portfolios, the difference between the top and bottom deciles is 7.68% per year. Using double-sorted portfolios, we find that bank risk exposure has a similar effect on average returns for portfolios without extreme market betas, which suggests that bank risk is an independent additional source of risk.

More formal cross-sectional and GMM-SDF asset pricing tests show that the two-factor model is not rejected and that both factors are priced and statistically significant. The cross-sectional estimate of the market risk premium is around 6.0% per year. Bank risk exposure commands a smaller, but still important premium: controlling for market beta, the expected excess return for a stock in the top quintile of bank risk exposure is on average 2.67% higher than for a stock in the bottom quintile.

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 payoff when the risk of the banking sector is decreasing (DD is increasing). These firms payoff in good times, in the sense that there are less 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. Furthermore, we 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 larger amounts of credit in need of renewal, and whose performance is thus more dependent on the state of the banking sector.

Our paper contributes to the literature on the effect that distress in the banking sector has in other sectors of the economy. Earlier examples include Peek and Rosengren (2000), Ashcraft (2005), Khwaja and Mian (2008), and Paravisini (2008). Perez-Quiros and Timmermann (2000) show that small stocks with little collateral are more sensitive to worsening credit market conditions. More recently, Chava and Purnanandam (2011) show that the 1998 Russian crisis led U.S. banks to reduce the supply of credit and increase loan interest rates, inducing losses in their borrowers. Carvalho, Ferreira, and Matos (2011) use bank distress events during the 2007–2008 period in a broad sample of 34 countries to show that firms with strong lending relationships suffer abnormal low returns when their relationship banks also suffer abnormal low returns. Further, they find the effect of bank distress to be concentrated in firms that most need to roll over their debt in the year of the shock, and also that firms with little leverage and high cash holdings at the time of the shock are not affected by relationship bank distress. 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. These papers provide evidence of mechanisms that correlate the performance of the banking sector with the performance of nonfinancial stocks. Our contribution is to show that this correlation carries a risk premium in equilibrium.

There is a long literature proposing new factors to augment the CAPM. One strand of the literature has focused on "stock market based" factors, that is, on factors built from returns on stock portfolios. Some examples include the small-minus-big (SMB) and high-minus-low (HML) factors of Fama and French (1993), the momentum factor of Carhart (1997), and the liquidity factors of Pástor and Stambaugh (2003) and Acharya and Pedersen (2005). Other papers have suggested "macro based" factors, that is, factors exogenous to the stock market with a deeper macroeconomic motivation. Some examples include the inflation, industrial production, term and credit spread factors of Chen, Roll, and Ross (1986), labor income of Jagannathan and Wang (1996), investment of (Cochrane, 1996), or the consumption-to-wealth ratio of Lettau and Ludvigson (2001), among others. While the first set of factors are typically able to increase substantially the explanatory power of the CAPM, the second set of macro factors provide a more satisfying description of the economic forces that ultimately should determine stock returns. In particular, the most referenced empirical alternative to the CAPM is the Fama-French 3-factor model, despite the continuing debate about the economic interpretation of the two additional factors. Both SMB and HML are based on firm characteristics and it is not clear which pervasive risk factors are they proxying for. While some papers argue that the size and value premiums are related to financial distress risk (e.g.,Vassalou and Xing (2004), Kapadia (2010)), others have found the opposite (e.g., Campbell, Hilscher, and Szilagyi (2008)).[2]

Our model is in the middle of these two strands of literature, that is, on an "exogeneity scale" the bank risk factor would lie somewhere in between "stock market based" factors and "macro based" factors. Our main contribution is to provide a clear and quantifiable mechanism through which distress in the financial sector influences expected returns of nonfinancial firms.

Lewellen, Nagel, and Shanken (2010) alert to potential problems with testing new factors on the 25 size and book-to-market portfolios of Fama and French (1992). Given the strong correlation structure of these portfolios (well captured by the 3 Fama-French factors), any new factor that is at least weakly correlated with the SMB or HML factors will seem to have a very

[2]Several other papers study the relation between stock returns and firms' default risk, such as, Dichev (1998), Griffin and Lemmon (2002), Avramov, Chordia, Jostova, and Philipov (2007), Garlappi, Shu, and Yan (2008), Avramov, Chordia, Jostova, and Philipov (2009), and Chava and Purnanandam (2010).

good explanatory power. Our results are not likely to be driven by this effect because our main test assets are not the 25 size and book-to-market portfolios. Instead, we test the model on market and bank beta sorted portfolios, more in line with the initial tests of the CAPM (e.g., Black, Jensen, and Scholes (1972), Fama and MacBeth (1973)). Furthermore, the firms used to estimate our factor (banks) are totally different from the set of assets that the model tries to explain: industrial and commercial companies. While this raises the statistical hurdles that our bank factor has to overcome, it guarantees a cleaner economic interpretation.

Our work is most similar to Vassalou and Xing (2004). However, while they build an aggregate probability of default using all firms in the market, our factor measures distress exclusively in the banking sector to focus on the relation between the financial and nonfinancial sectors of the economy.

2 Bank risk factor

2.1 Definition of the bank risk factor

We use the model of Merton (1974) 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,

$$dV_t/V_t = \mu dt + \sigma dW_t \tag{1}$$

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. The process (1) 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 less than the amount due ($V_T < F$), then it is rational for the shareholders to default on the debt. A natural risk measure for bank i, denoted Distance to Default, is thus defined as:

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

where $\tau = T - t$. The numerator captures how far from default do 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 and described for example in Dwyer and Qu (2007).[3]

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

$$\text{BANK}_t := \sum_{i=1}^{I}(DD_{i,t}w_{i,t} - DD_{i,t-1}w_{i,t-1}) \tag{3}$$

where $DD_{i,t}$ is the distance to default for bank i at time t, defined in (2), and $w_{i,t}$ is the weight of bank i in the total market capitalization of all banks at time t. Weighing by the market capitalization of each bank, which we assume to be a good proxy for the amount of outstanding business that each bank has, ensures that the average is more indicative of the state of the banks that matter to more nonfinancial firms.

2.2 Asset Pricing Model

Our benchmark model includes two risk factors: the standard market excess return and the new bank factor. Expected returns in excess of the risk free rate, R_i^e, are given by

$$E(R_i^e) = \beta_{im}\lambda_m + \beta_{ib}\lambda_b \tag{4}$$

[3]We could also use Merton's model to proceed to a probability of default (PD) for each bank. However, the Gaussian mapping from DD to PD looses discriminatory power and gives PDs that are not reasonable. This is the reason why Moody's-KMV uses a proprietary empirical mapping to get their Empirical Default Frequencies (EDF).

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

$$R_{it}^{e} = a_i + \beta_{im}\mathrm{RMRF}_t + \beta_{ib}\mathrm{BANK}_t + \varepsilon_{it} \tag{5}$$

where RMRF_t is the market excess return and BANK_t is the bank factor defined in (3).

This model can be motivated by the Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1973). In section 2.5 we show that the average banks' Distance to Default helps to forecast aggregate bankruptcies in the overall economy. In other words, DD can be seen as a state variable that describes the investment opportunity set, and therefore the ICAPM 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 (4), to be positive. Intuitively, firms that have high covariance (high beta) with the bank factor are firms that payoff more(less) when the banks' distance to default increases(decreases). These are good(bad) times, in the sense that there are less(more) firms going bankrupt. Hence, firms with high bank beta payoff 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 procedure of the bank factor

To compute the distance to default in (2), we need to estimate the current value of the assets (V_t), and the drift (μ) and volatility (σ) parameters.

First, note that from Merton (1974) the market value of equity can be though of as 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,

$$S_t = V_t N(d_1) - F e^{-i\tau} N(d_2) \tag{6}$$

where i is the risk-free interest rate and

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

We then 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).[4] At the end of each month, we use a window of daily data over the past year to compute the following. 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 (6) at each day, assuming that F equals the total debt of the bank and that all debt is due in 1 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 (3).

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 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 increase the discriminatory power of our bank factor.[5]

[4] Alternatively, we could buy DD (or even EDF) series estimated with the proprietary models of Moody's KMV. However, the point of our paper is to find a transparent factor that is easily replicable and verifiable by the academic community.

[5] 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 a 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 EDF of 0.35%.

2.4 Data

From the Compustat Bank Fundamentals Annual file, we collect the total liabilities for each bank trading on the NYSE or AMEX stock exchanges, from 1963 until 2010. Then, we match these banks with the CRSP daily stock file to obtain daily time series for stock returns and market capitalizations. The daily risk-free rate is the 1-year US Treasury Constant Maturity series published by the Federal Reserve.

We follow the procedure described section 2.3 to estimate the Distance to Default for each bank at the end of each month. To avoid the influence of extreme outliers, we truncate the individual bank's DD between -3 and +5, before computing the average DD. Figure 1 shows the resulting monthly series of the average DD. Though with a strong volatility, the series roughly declines in the first sample period until 1980 and then roughly increases up to the credit crisis of 2008 (section 2.5 provides a more detailed interpretation).

The bottom panel in Figure 1 shows the number of banks in the sample. Even though the Compustat Bank file formally starts in 1950, the matching with daily data from CRSP leaves us with series that go back only to 1963. We further loose one year of data to compute the first DD. Hence, starting from a minimum of 4 banks in 1964, we reach a maximum of 134 in 1994, and then decrease to 77 at the end of the sample in 2010.

Table 1 shows descriptive statistics on the bank and market factors. The market factor is the value-weight return on all NYSE, AMEX, and NASDAQ stocks minus the one-month Treasury bill rate, available from 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 an average value of -0.0035, which is of the same order of magnitude as the other factors. However, the bank factor is much more volatile: its standard deviation is 10 times larger than the market's. Further, the bank factor displays negative skewness and strong kurtosis. The correlation be-

However, on November 1st, 1 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 very strong signal of distress, which is precisely what we want our bank factor to capture.

tween the bank factor and the market is 0.32, which is 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 0 (a 95% confidence interval for these correlations is between ± 0.0833). Finally, the autocorrelations of the bank factor are all very small and the Ljung-Box test does not reject that the series is white noise. This justifies using the bank factor as defined in (3) instead of using innovations.

2.5 Interpretation of the bank factor

The economic intuition for our bank factor is that when banks are in worse conditions, reflected in a low DD, they provide less or more expensive credit to other firms, leading to more defaults. This section provides evidence of this mechanism in two steps: first, we show that the banking sector average DD is correlated with the terms of the banks' lending; second, we show that DD causes the total number of bankruptcies in the U.S. economy. Given the quantity and quality of the data available, we do a more informal descriptive analysis of the relation with lending terms and then a more formal causality analysis with bankruptcies.

2.5.1 Relation to lending terms

We use Federal Reserve's "senior loan officer opinion survey on bank lending practices" to measure the fraction of banks that tightens credit standards for commercial and industrial loans or that increases the spread charged on their loans.[6] Credit standards are the internal guidelines or criteria that guide a bank's loan policy. The survey is only available since 1990, so we limit the analysis to the subsample from 1990 to 2010. Since the survey data is quarterly, we compute a quarterly DD 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

[6] The data is available online at www.federalreserve.gov/boarddocs/SnloanSurvey

loans (right axis, inverted). A positive net percentage means that a larger proportion of banks have tightened credit standards, whereas a negative net percentage means that a larger proportion of 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 is -0.43 for large and medium firms and -0.46 for small firms.

The bottom panel in figure 2 shows again DD (left axis), but now compared with the fraction of banks reporting an increase in the spread of the loans they offer to other firms (right axis, inverted). Again, we see a broad comovement, with the crisis clearly standing out as a period when almost all banks increased loan spreads. More precisely, the correlation between DD and the fraction of banks increasing spreads is -0.54 for large and medium firms and -0.58 for small firms.

The analysis above focus on the *supply* side of the credit market, that is, on the effect that bank conditions have on the credit supplied to nonfinancial firms. It is also possible that part of the decrease in DD is due to a decrease in the *demand* for loans. In theory, we expect this effect to be very small. If a bank faces a reduction in demand for loans, the main effect is a reduction of both its assets (V) and debt (F) in relatively similar amounts, which has a small effect on the DD defined in (2). Instead, DD decreases when the existing loans turn bad, which decreases the value of the assets assets (V) and the drift (μ), and increases volatility (σ). 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. Nevertheless, we use also 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 0.16 for large and medium firms, and 0.27 for small firms. As expected, these are very small correlations, suggesting that the association between DD and the demand for loans is weak.

To summarize, these results provide evidence that when banks' average

DD is low, that is, when they are in worse conditions, they provide less and more expensive credit to nonfinancial firms.

2.5.2 Relation 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.[7] The data on bankruptcies is only available since 1980, so we limit the analysis to the subsample from 1980 to 2010. Since the data on bankruptcies is quarterly, we again compute a quarterly DD 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 Loans crisis, is followed by a sharp increase in the number of bankruptcies (note that the right y axis in inverted). After that, there are several periods where DD increases are followed by decreases in bankruptcies. The last period, with the DD falling 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 context of the so-called great recession.

To formally test the relation between DD and bankruptcies, we estimate a vector autoregression with these variables. In addition to these two series, 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. The lag order is determined with standard information criteria, but the results are robust to considering higher order lags. We compute heteroscedasticity and autocorrelation consistent standard errors (HACSE) and present the resulting t-ratios. The first equation for Bankruptcies shows that all variables are statistically significant. In particular, we find that a decrease in DD leads to an increase in Bankruptcies

[7] The data is available online at www.abiworld.org.

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.

In summary, the banking sector average DD forecasts bankruptcies. Together with the previous section, these results provide direct evidence of the intuitive mechanism at work in our model linking the state of the banking sector to the returns on nonfinancial firms. Furthermore, these results provide a theoretical base for our bank factor. When bankruptcies are high, 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 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 the bank loadings are associated with leverage.

3.1 Data and portfolio construction

We collect from the CRSP monthly file returns and market capitalizations on all U.S. firms trading on the NYSE, AMEX, and NASDAQ markets. To make sure that the sample does not include any firm hard-wired to our bank factor, we remove all financial firms (SIC codes between 6000 and 6999). Hence, our test assets only include nonfinancial firms. 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, Dec/1964–Dec/2010.

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

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

$$R^e_{it} = a_i + \beta_{ib}\text{BANK}_t + \varepsilon_{it} \tag{7}$$

At each month t, we use the cross section of estimated betas to allocate each stock into a quintile or decile 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 either 5 or 10 test portfolios.

We also consider double sorted portfolios on bank and market betas. The betas are estimated with the same rolling window procedure, but using the regression in (5). We do an independent sort into 5 bank beta by 5 market beta portfolios, obtaining 25 test portfolios.

3.2 Portfolios returns

Table 3 shows average excess returns for the test portfolios described in the previous section. Panel A shows single-sorted portfolios. The results clearly show that average excess returns increase with bank beta. For example, the lowest quintile portfolio earns an average excess return of 0.14% per month, while the highest quintile earns 0.71%. The difference of 0.57% per month (6.84% per year) is strongly statistically significant. If we instead sort stocks into 10 deciles, we get a stronger effect. The difference between the excess return on the highest and lowest deciles is on average 0.64% per month (7.68% 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. Average returns increase with the bank-beta quintile for all levels of market beta, except for the top decile of market beta (and even here there is an increase if we exclude the two extreme portfolios). Interestingly, the bank risk effect is more visible in stocks with "middle" market betas. For example, the difference in average excess returns between the highest and lowest bank-beta deciles is around 0.60% per month for portfolios in either the second or fourth market-beta deciles. These differences are statistically significant and represent a annual excess return difference around 7.2% per year, which is very similar to the differences found in single-sorted portfolios.

Hence, we conclude that there is a bank risk effect in average returns, even after controlling for market risk. In other words, these results suggest that there may be a risk premium associated with the bank factor, which we formally test in section 4.

3.3 Interpretation of the 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 those firms are more dependent on the banking sector: when banks are healthy, those firms are able to obtain the financing that they need; when banks are having difficulties in supplying credit, those 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.[8] At 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 then reports the time-series average of the 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.

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

[8]The results are similar for portfolios sorted on univariate bank betas.

Nonetheless, we stress that our model poses that what is priced is the covariance (beta) with the bank risk factor, not a characteristic like leverage. In addition to the theoretical (ICAPM) arguments for using betas rather than characteristics, our specification relies on the stock market being efficient. More precisely, we assume that the bank beta of a given firm may be a better measure of the financial risk of that firm than simple accounting variables. If the market is efficient, investors will impound in the return of the stock not only the total amount of debt, but also how likely it is that the firm will be able to service and renew its debt, given the state of the banking sector. This in turn may depend on many factors, such as, whether the firm has a privileged relation with some bank, the quality of the assets in place, the quality of new projects, the uncertainty and trends in the sector, and so on. This assumption parallels Moody's-KMV use of stock market information to estimate the probability of default for a given firm.

4 Asset Pricing Tests

This section provides formal asset pricing tests of the model in (4). We start with cross-sectional regression tests. Since our bank factor is correlated with the market factor, we then also use GMM to estimate the equivalent SDF specification and test whether the new bank factor survives in a multivariate specification, i.e., to test whether it adds explanatory power to the traditional market factor. Note that our bank factor is not a traded portfolio, so we do not do time-series tests. The tests in this section follow Cochrane (2005).

4.1 Cross-sectional regressions

4.1.1 Procedure

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

$$R^e_{it} = a_i + \beta_i' f_t + \varepsilon_{it}, \quad t = 1, \ldots, T \tag{8}$$

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 (4) from a cross-sectional regression of average returns on betas:

$$\bar{R}^e_i = \beta_i' \lambda + \alpha_i, \quad i = 1, \ldots, N \tag{9}$$

where $\bar{R}^e_i$ are the sample average excess returns on the N test portfolios (either $N = 10$ or $N = 25$), α_i are the regression residuals or pricing errors, and λ is the vector of K regression coefficients to be estimated. For the 2-factor model, $\lambda = [\lambda_m, \lambda_b]'$.

We estimate (9) first by OLS and then also by GLS. While the GLS procedure may give estimates with lower asymptotic standard errors, that is conditional on the error covariance matrix being correctly estimated. 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 OLS estimates are more robust and have a cleaner economic interpretation. Hence, we focus the discussion on the OLS estimates and use the GLS only to confirm the statistical significance of results.

OLS cross-sectional regression. The OLS cross-sectional point estimates of risk premiums are the usual

$$\hat{\lambda} = (\beta' \beta)^{-1} \beta' \bar{R}^e \tag{10}$$

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 $\hat{\alpha} = \bar{R}^e - \beta \hat{\lambda}$. From Cochrane (2005, p.237), the covariance matrix of the OLS estimates that accounts for errors in (8) correlated across assets (though i.i.d. over time and independent of the factors) is

$$\mathrm{Cov}(\hat{\lambda}) = \frac{1}{T}\left[(\beta'\beta)^{-1}\beta'\Sigma\beta(\beta'\beta)^{-1} + \Sigma_f\right] \tag{11}$$

and the covariance of the residuals is

$$\mathrm{Cov}(\hat{\alpha}) = \frac{1}{T}\left[I - \beta(\beta'\beta)^{-1}\beta'\right]\Sigma\left[I - \beta(\beta'\beta)^{-1}\beta'\right]' \tag{12}$$

where $\Sigma := \mathrm{Cov}(\varepsilon_t)$ and $\Sigma_f := \mathrm{Cov}(f_t)$. The test for the null that all N pricing errors are zero is given by

$$\hat{\alpha}'\,\mathrm{Cov}(\hat{\alpha})^{-1}\hat{\alpha} \sim \chi^2_{(N-K)} \tag{13}$$

GLS cross-sectional regression. The alternative GLS cross-sectional regression corrects for residuals correlated with each other in (9). The point estimates are

$$\hat{\lambda} = (\beta'\Sigma^{-1}\beta)^{-1}\beta'\Sigma^{-1}\bar{R}^e \tag{14}$$

and the residuals are $\hat{\alpha} = \bar{R}^e - \beta\hat{\lambda}$. Since the β are not fixed regressors in the cross-sectional regression (9), but are instead estimated in the time-series regression (8), we further add Shanken's (1992) correction to the standard GLS formulas. From Cochrane (2005, p.240),

$$\mathrm{Cov}(\hat{\lambda}) = \frac{1}{T}\left[(\beta'\Sigma^{-1}\beta)^{-1}(1 + \lambda'\Sigma_f^{-1}\lambda) + \Sigma_f\right] \tag{15}$$

and

$$\mathrm{Cov}(\hat{\alpha}) = \frac{1}{T}\left[\Sigma - \beta(\beta'\Sigma^{-1}\beta)^{-1}\beta'\right](1 + \lambda'\Sigma_f^{-1}\lambda) \tag{16}$$

To test whether all pricing errors are zero, we use (13) with (16).

4.1.2 Results

Table 5 shows the results for our two sets of test portfolios: in panel A, the 10 portfolios sorted on bank beta; in panel B, the 25 portfolios double sorted on market and bank betas.

We start by estimating the single factor CAPM. The market factor is priced, i.e., carries a positive risk premium in both sets of test assets. For example, the OLS estimate on the 10 bank-beta sorted portfolios is $\lambda_m = 0.40\%$ per month, which represents and annual market risk premium of 4.8%.

Our main focus in on the estimates of the 2-factor bank model. The results show that both factors command a statistically significant positive risk premium. The premium for the market factor is similar to the single factor specification, increasing slightly to around 0.50% per month, or 6.0% per year. The premium for exposure to the bank factor is on a very different scale: the OLS estimate on the 25 portfolios is $\lambda_b = 22.29\%$ per month, which represents and annual bank risk premium of 267%.

To interpret this number, note that bank betas are very small numbers when compared to typical market betas — see panel B in table 3. For example, for the five portfolios in the middle quintile of market beta, bank betas range from -0.009 to 0.003. Hence, the additional expected excess return due to exposure to the bank factor, the $\beta_{ib}\lambda_b$ term in (4), ranges from -0.20% per month for the lowest bank-beta portfolio to 0.07% per month for the highest bank-beta portfolio. This represents a difference in annual expected excess returns of 3.21% per year. For a more broad example, consider the average bank beta of the five portfolios in the bottom bank-beta quintile, -0.011, versus the average bank beta for the five portfolios in the top quintile, -0.001. This difference in bank beta represents an additional expected excess return of 2.67% per year.[9]

Since the bank factor has a 0.32 correlation with the market factor (see table 1), we also test the effect of part of the bank factor that is truly different from the market factor. More precisely, we test a two-factor model that includes the original market factor, but where the bank factor is replaced by an orthogonal bank factor, estimated as the residuals of the time series

[9] An equivalent alternative to this interpretation of the bank risk premium would be to rescale the original bank factor, multiplying it by a constant like 0.01. This would make β_{ib} become larger numbers, closer to the scale of market betas, and would also decrease λ_b. Of course, the final effect in expected excess returns would not change. Since the rescalling would be arbitrary, we opt for reporting the values resulting from the raw bank factor.

regression

$$\text{BANK}_t = a_0 + a_1\text{RMRF}_t + \varepsilon_t \tag{17}$$

Note that this method favors the traditional 1-factor CAPM model, since the market factor is not changed and it is only the second bank factor that is replaced by the potentially less informative residuals. In other words, if the bank factor was spurious, the orthogonal bank factor would not be priced. Table 5 shows the risk premium estimates for the orthogonal factor, denoted $\lambda_b^{\perp}$. We find that all values are positive, statistically significant, and very similar to the values obtained with the original bank factor (the only exception is the GLS estimate on the 25 portfolios, which has a t-statistic of 1.51). Hence, we conclude that the bank factor is not spurious.[10]

The χ^2 tests show that the 2-factor model is not rejected, that is, the pricing errors of the model are not statistically significantly different from zero. Furthermore, the tests for the OLS estimates show an substantial improvement relative to the CAPM when testing on the 10 bank portfolios: the p-value increases from 0.34 to 0.61. With the 25 market and bank portfolios there is still an improvement in the p-value (though naturally less strong) from 0.07 to 0.09.

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. For the 10 portfolios sorted on univariate bank betas, we see a substantial improvement: while the CAPM gives a basically flat relation, the two-factor bank model shows all portfolios close to the diagonal. For the 25 portfolios double sorted on market and bank betas, our two factor model still shows an improvement in fit relative to the CAPM, though the improvement looks less striking.

[10]In fact, this also shows a close but different result. Namely, it shows that adding the bank factor to the market factor results in a model that prices the assets better (Cochrane, 2005, sec. 13.4). Nevertheless, we provide more precise tests in section 4.2.

4.2 GMM estimation of a linear stochastic discount factor

4.2.1 Procedure

The beta pricing model in (4) is equivalent to the linear stochastic discount factor model

$$m = 1 - b'f, \quad 0 = \mathrm{E}(mR^e) \tag{18}$$

For the 2-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. When factors are correlated, the appropriate test to decide whether to include factor k is $b_k = 0$, rather than $\lambda_k = 0$ (Cochrane, 2005, sec.13.4).

Define the (N by 1) sample mean of the pricing errors as

$$g(b) = \frac{1}{T}\sum_{t=1}^{T} u_t(b), \quad \text{with } u_t(b) = m_t(b)R_t^e \tag{19}$$

The GMM estimate of b is

$$\hat{b} = \arg\min_b g(b)'Wg(b) \tag{20}$$

We start by computing first-stage estimates, setting W equal to the identity matrix. We focus the interpretation on these first-stage estimates because they are more transparent (each portfolio gets the same weight, 1). Then, we compute second-stage estimates, where we use the statistically optimal weighting matrix $W = S^{-1}$, 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 statistically efficient iterated estimates are used to check the first-stage results. The formulas for $\hat{b}$, $\mathrm{Cov}(\hat{b})$, $\mathrm{Cov}(g)$, and for the χ^2 test are all from Cochrane (2005, sec.13.2).

4.2.2 Results

Table 6 shows the results for our two sets of test portfolios: in panel A, the 10 portfolios sorted on bank beta; in panel B, 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 model is rejected at the 10% level with the 25 portfolios.

Our main focus in on the estimates of the 2-factor bank model. The model is not rejected with the 10 test portfolios, nor with first-stage estimates on the 25 portfolios. Most results show that the bank factor coefficient is statistically significant (the only exception is the iterated estimate with 25 portfolios). However, the significance of the bank coefficient is associated with a coefficient on the market factor that becomes either negative or statistically insignificant. While this might seem a good statistical result in support of our model, it is not economically reasonable. It is likely that the coefficients are unstable due to the correlation between the market and bank factors.

Hence, we replace the original bank factor with the orthogonal bank factor defined in (17). Now, the 2-factor model becomes economically and statistically meaningful: the coefficients on both factors are positive and statistically significant. Again, the only exception is the iterated estimate, where the t-statistic for bank factor coefficient is 1.35. Nevertheless, recall that the our construction of the orthogonal bank factor biases the tests against finding a significant bank effect: the market factor is preserved, while the bank factor gets the residuals. Further, note that the market factor is itself an average of the same stocks that it is trying to price; on the contrary, the bank factor results from firms totally different from the test assets. Hence, it is encouraging that first stage estimates find that both factors are significant and it is not surprising that the iterated procedure ends up focusing more on the market factor than on the bank factor.

4.3 Robustness

4.3.1 The financial crisis of 2008

The financial crisis that started in 2008 is an extreme event where the banking sector performed in an abnormal way. To make sure that our results do not depend on this particular sample period, we delete the last three years, Jan/2008–Dec/2010, from the sample.

Table 7 shows the results for the 25 portfolios double sorted on market and bank betas, during the 1969–2007 period. We find that the new results from the subsample without the financial crisis are even stronger than the full sample results. The OLS estimate of the bank risk premium λ_b (panel A) increases to 0.27 (from 0.22 in the full sample), and the t-statistic also increases to 3.14. The GLS estimates and the orthogonal bank factor also show a consistent increase in the magnitude of the premium and in the statistical significance. The GMM SDF tests (panel B) show a similar picture. Even though the estimates are still influenced by the collinearity between the two factors, the results with the orthogonal bank factor show that the two factors are even more strongly statistically significant.

The increase in the magnitude of the risk premium is expected. The financial crisis of 2008 is a period where the banks' DD decreased very sharply, which lead firms with high bank betas to experience very low returns. This crisis period thus pushes down the sample average return for firms with high betas. Our cross-sectional estimate of the relation between betas and average returns is therefore steeper when the 2008 financial crisis is excluded from the sample.

Hence, we conclude that our results are not driven by the 2008 financial crisis. Nonetheless, we expect the current financial crisis to make investors more aware of the bank risk effect and perhaps to price it even more strongly in the future.

4.3.2 Fama-French factors and portfolios

Testing new factors on the 25 size and book-to-market portfolios and comparing it with the SMB and HML factors of Fama and French (1993) has become the standard in the empirical literature. While we do not expect our bank factor to statistically outperform factors built from portfolios of the same nonfinancial firms that the model tries to explain, it is still important to show that our economic intuition is robust.

Table 8 shows the results of testing several factors on the 25 size and book/market portfolios.

The first four rows in each panel show our 2-factor model. We find that the bank factor is priced and the magnitude of the risk premium is similar to the one found in section 4.1. The risk premium for the orthogonal bank factor and the GMM tests show that this factor helps to price the 25 Fama-French portfolios. These results suggest that part of the difference in average returns across size and book-to-market portfolios is due to different sensitivities to the state of the banking sector. 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) and thus our results are not likely to be influenced by the issues raised in Lewellen, Nagel, and Shanken (2010). However, these results have to be read with some caution because the 2-factor bank model is rejected with the χ^2 test, that is, the pricing errors are too large.

The last four rows in each panel show the standard Fama-French 3-factor model and a 4-factor model that includes the 3 Fama-French factors plus our bank factor. First, note that the Fama and French 3-factor model is also rejected by the χ^2 test in this sample, even though all 3 factors are priced and statistically significant in the SDF. Second, when we add the (orthogonal) bank factor to the other 3 factors, we find that OLS estimate of the bank risk premium (λ) is statistically significant. Further, the first-stage GMM estimate of the bank factor coefficient in the SDF (b) is also statistically significant at the 10% level. These results suggest that exposure to the bank factor is an important economic channel to explain the expected returns of the 25 size and book/market portfolios. When we use the techniques that focus on statistical efficiency (GLS and iterated GMM), the bank factor becomes insignificant, but this is not surprising. For example, the iterated GMM looks for a linear combination of the factors (SDF) that is orthogonal to excess returns on the test assets. It is certainly easier to find one with factors (SMB, HML) that are built with the same stocks and in the same way as the test portfolios, than with a factor (BANK) that uses information from a different set of nonfinancial firms and is not even a return.

5 Conclusion

The results in this paper 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 the impact on expected returns of exposure to the bank factor is almost half of the impact of 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 to other companies; when banks face funding difficulties, they tighten the credit supplied to other firms, which leads to higher default rates as some firms are not able to rollover existing debt. Industrial and commercial firms that covary more with the health of the banking sector must therefore offer higher expected returns. In short, BANKruptcy starts with “bank”.

The financial crisis of 2008 may have made investors more aware of the effect of bank risk on the performance of nonfinancial firms. In this case, the bank risk factor proposed in this paper is likely to become even more important in the future.

References

Acharya, V. V., and L. H. Pedersen, 2005, “Asset Pricing with Liquidity Risk,” *Journal of Financial Economics*, 77, 375–410.

Almeida, H., M. Campello, B. A. Laranjeira, and S. J. Weisbenner, 2011, "Corporate Debt Maturity and the Real Effects of the 2007 Credit Crisis," *SSRN eLibrary*.

Ashcraft, A., 2005, "Are banks really special? New evidence from the FDIC-induced failure of healthy banks," *The American Economic Review*, 95(5), 1712–1730.

Avramov, D., T. Chordia, G. Jostova, and A. Philipov, 2007, "Momentum and credit rating," *The Journal of Finance*, 62(5), 2503–2520.

———, 2009, "Credit ratings and the cross-section of stock returns," *Journal of Financial Markets*, 12(3), 469–499.

Black, F., M. C. Jensen, and M. Scholes, 1972, "The Capital Asset Pricing Model: some empirical tests," in *Studies in the Theory of Capital Markets*, ed. by M. C. Jensen. Praeger Publishers.

Campbell, J., J. Hilscher, and J. Szilagyi, 2008, "In Search of Distress Risk," *Journal of Finance*, 63, 2899–2939.

Carhart, M., 1997, "On Persistence in Mutual Fund Performance," *Journal of Finance*, 52(1), 57–82.

Carvalho, D. R., M. A. Ferreira, and P. P. Matos, 2011, "Lending Relationships and the Effect of Bank Distress: Evidence from the 2007-2008 Financial Crisis," *SSRN eLibrary*.

Chava, S., and A. Purnanandam, 2010, "Is default risk negatively related to stock returns?," *Review of Financial Studies*, 23(6), 2523–2559.

———, 2011, "The effect of banking crisis on bank-dependent borrowers," *Journal of Financial Economics*, 99(1), 116 – 135.

Chen, N.-F., R. Roll, and S. A. Ross, 1986, "Economic Forces and the Stock Market," *Journal of Business*, 59, 383–403.

Cochrane, J., 1996, "A cross-sectional test of an investment-based asset pricing model," *Journal of Political Economy*, 104(3), 572.

Cochrane, J. H., 2005, *Asset Pricing*. Princeton University Press.

Dichev, I., 1998, "Is the risk of bankruptcy a systematic risk?," *the Journal of Finance*, 53(3), 1131–1147.

Dwyer, D., and S. Qu, 2007, "EDF 8.0 Model Enhancements," Moody's KMV.

Eichler, S., A. Karmann, D. Maltritz, and K. Sobanski, 2011, "What Do Equity Markets Tell Us About the Drivers of Bank Default Risk? Evidence from Emerging Markets," *SSRN eLibrary*.

Ericsson, J., and J. Reneby, 2005, "Estimating structural bond pricing models," *The Journal of Business*, 78, 707–735.

Fama, E. F., 1991, "Efficient Markets II," *Journal of Finance*, 46, 1575–1618.

Fama, E. F., and K. R. French, 1992, "The Cross-Section of Expected Stock Returns," *Journal of Finance*, 47, 427–465.

——— , 1993, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, 33, 3–56.

Fama, E. F., and J. D. MacBeth, 1973, "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy*, 81(3), 607–636.

Garlappi, L., T. Shu, and H. Yan, 2008, "Default risk, shareholder advantage, and stock returns," *Review of Financial Studies*, 21(6), 2743.

Griffin, J., and M. Lemmon, 2002, "Book-to-market equity, distress risk, and stock returns," *The Journal of Finance*, 57(5), 2317–2336.

Jagannathan, R., and Z. Wang, 1996, "The Conditional CAPM and the Cross-Section of Expected Returns," *Journal of Finance*, 51(1), 3–53.

Kapadia, N., 2010, "Tracking down distress risk," *Journal of Financial Economics*, Forthcoming.

Khwaja, A., and A. Mian, 2008, "Tracing the impact of bank liquidity shocks: Evidence from an emerging market," *The American Economic Review*, pp. 1413–1442.

Lettau, M., and S. Ludvigson, 2001, "Resurrecting the (C)CCAPM: A Cross-Sectional Test When Risk Premia Are Time-Varying," *Journal of Political Economy*, 109(6).

Lewellen, J., S. Nagel, and J. Shanken, 2010, "A skeptical appraisal of asset pricing tests," *Journal of Financial Economics*, 96(2), 175–194.

Merton, R. C., 1973, "An Intertemporal Capital Asset Pricing Model," *Econometrica*, 41, 867–887.

——— , 1974, "On the Pricing of Corporate Debt: the Risk Structure of Interest Rates," *Journal of Finance*, 28, 449–470.

Munves, D. W., A. Smith, and D. T. Hamilton, 2010, "Banks and their EDF measures now and through the credit crisis: too high, too low, or just about right?," *Moody's Capital Market Reseach*, Report Number 129462.

Paravisini, D., 2008, "Local bank financial constraints and firm access to external finance," *The Journal of Finance*, 63(5), 2161–2193.

Pástor, Ľ., and R. F. Stambaugh, 2003, "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy*, 111(3), 642–685.

Peek, J., and E. Rosengren, 2000, "Collateral damage: effects of the Japanese bank crisis on real activity in the United States," *American Economic Review*, pp. 30–45.

Perez-Quiros, G., and A. Timmermann, 2000, "Firm size and cyclical variations in stock returns," *The Journal of Finance*, 55(3), 1229–1262.

Shanken, J., 1992, "On the Estimation of Beta Pricing Models," *Review of Financial Studies*, 5, 1–34.

Vassalou, M., and Y. Xing, 2004, "Default risk in equity returns," *Journal of Finance*, 59(2), 831–868.

Table 1: Descriptive statistics

This table shows descriptive statistics on four factors. The bank factor, BANK, is computed as in (3). 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/2010 (553 observations).

	RMRF	BANK	SMB	HML
Moments				
Mean	0.0043	-0.0035	0.0029	0.0039
Stdev	0.0459	0.4675	0.0322	0.0298
Skewness	-0.5430	-1.8302	0.5072	-0.0109
Kurtosis	4.8709	20.5766	8.3372	5.3395
Percentiles				
Min	-0.2314	-4.0242	-0.1667	-0.1278
25%	-0.0226	-0.1595	-0.0153	-0.0130
Median	0.0077	-0.0017	0.0011	0.0038
75%	0.0355	0.1725	0.0220	0.0179
Max	0.1605	2.1185	0.2219	0.1384
Cross-Correlations				
RMRF	1	0.3158	0.3091	-0.3081
BANK	0.3158	1	-0.0391	0.0582
SMB	0.3091	-0.0391	1	-0.2359
HML	-0.3081	0.0582	-0.2359	1

Auto-correlations for BANK

		Ljung-Box	
Lag	Autocorr.	statistic	p-value
1	0.0025	0.0035	0.9525
2	0.0012	0.0043	0.9978
3	-0.0261	0.3836	0.9436
6	-0.0378	1.9259	0.9264

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. All data is quarterly and the sample period is 1980/Q1–2010/Q4.

	Coefficient	t-HACSE	t-prob
Equation for Bankruptcy			
Bankruptcy_1	0.880	16.70	0.000
DD_1	-232.0	-2.28	0.025
GDP_QoQ_1	-312.1	-2.71	0.008
Constant	2159.5	2.81	0.006
Equation for DD			
Bankruptcy_1	0.000	0.18	0.858
DD_1	0.929	21.60	0.000
GDP_QoQ_1	-0.028	-0.35	0.728
Constant	0.101	0.40	0.691
Equation for GDP_QoQ			
Bankruptcy_1	0.000	2.35	0.020
DD_1	0.086	1.52	0.132
GDP_QoQ_1	0.401	3.24	0.002
Constant	-0.262	-0.72	0.472

Table 3: Portfolio returns

This table shows average portfolio excess returns (monthly values, in percentage) and full sample betas. Single sorts are based on univariate betas (equation 7) and double sorts on bivariate betas (equation 5). 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 Jan/1969 to Dec/2010 (504 observations).

Panel A: Single-sorted portfolios on bank beta

Quintile	20	40	60	80	100	Hi-Lo	t-stat
Return	0.14	0.31	0.47	0.55	0.71	0.57	2.8
Bank Beta	0.027	0.033	0.034	0.041	0.044		

Decile	10	20	30	40	50	(contd...)	
Return	0.04	0.18	0.34	0.29	0.44		
Bank Beta	0.030	0.027	0.036	0.032	0.032		
(... contd)	60	70	80	90	100	Hi-Lo	t-stat
Return	0.48	0.55	0.56	0.70	0.68	0.64	2.68
Bank Beta	0.036	0.041	0.041	0.043	0.044		

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

Returns (in %)

Quintiles	Bnk_20	Bnk_40	Bnk_60	Bnk_80	Bnk_100	Hi-Lo	t-stat
Mkt_20	0.36	0.35	0.44	0.54	0.51	0.15	0.42
Mkt_40	0.06	0.55	0.50	0.64	0.67	0.62	2.48
Mkt_60	0.20	0.13	0.53	0.61	0.54	0.33	1.56
Mkt_80	0.12	0.38	0.52	0.58	0.73	0.61	2.89
Mkt_100	0.41	0.31	0.56	0.66	0.29	-0.12	-0.48

Market Betas

Quintiles	Bnk_20	Bnk_40	Bnk_60	Bnk_80	Bnk_100
Mkt_20	0.95	0.66	0.69	0.59	0.64
Mkt_40	0.98	0.86	0.81	0.83	0.93
Mkt_60	1.11	1.08	1.04	1.08	1.14
Mkt_80	1.29	1.36	1.31	1.33	1.35
Mkt_100	1.64	1.62	1.72	1.65	1.69

Bank Betas

Quintiles	Bnk_20	Bnk_40	Bnk_60	Bnk_80	Bnk_100
Mkt_20	-0.007	-0.002	0.002	0.009	0.011
Mkt_40	-0.012	-0.002	0.003	0.005	0.001
Mkt_60	-0.009	-0.002	0.000	0.002	0.003
Mkt_80	-0.008	-0.016	-0.008	-0.005	-0.008
Mkt_100	-0.020	-0.018	-0.024	-0.012	-0.013

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 5). 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 Jan/1969 to Dec/2010 (504 observations).

Quintiles	Bnk_20	Bnk_40	Bnk_60	Bnk_80	Bnk_100	Hi-Lo	t-stat
Mkt_20	0.43	0.50	0.52	0.54	0.55	0.13	22.67
Mkt_40	0.45	0.49	0.51	0.52	0.53	0.09	20.11
Mkt_60	0.47	0.50	0.53	0.54	0.54	0.07	17.35
Mkt_80	0.46	0.48	0.52	0.53	0.51	0.05	12.17
Mkt_100	0.46	0.45	0.48	0.49	0.51	0.05	11.50

Table 5: Cross-sectional regression tests

This table shows estimates of the risk premiums λ in (4). $\lambda_b^\perp$ denotes the risk premium on the part of the bank factor that is orthogonal to the market factor. The GLS t-values also include Shanken's (1992) correction. The last two columns present the test for the null that the pricing errors are jointly zero. The sample is from Jan/1969 to Dec/2010.

	λ_m	λ_b	$\lambda_b^\perp$	χ^2	p-value
Panel A: 10 bank portfolios					
OLS					
Coefficient	0.0040			10.1060	0.3420
t-value	1.8600				
GLS					
Coefficient	0.0046			10.0095	0.3497
t-value	2.1871				
OLS					
Coefficient	0.0056	0.2884		6.3699	0.6059
t-value	2.6317	2.7951			
GLS					
Coefficient	0.0051	0.1661		5.4855	0.7046
t-value	2.3876	1.9604			
OLS					
Coefficient	0.0056		0.2703	6.3699	0.6059
t-value	2.6317		2.6542		
GLS					
Coefficient	0.0051		0.1497	5.4855	0.7046
t-value	2.3876		1.7906		
Panel B: 25 market and bank portfolios					
OLS					
Coefficient	0.0037			35.0168	0.0682
t-value	1.7051				
GLS					
Coefficient	0.0045			34.6939	0.0731
t-value	2.1370				
OLS					
Coefficient	0.0049	0.2229		32.5499	0.0892
t-value	2.3159	2.6055			
GLS					
Coefficient	0.0047	0.1135		30.2831	0.1414
t-value	2.2068	1.7208			
OLS					
Coefficient	0.0049		0.2070	32.5499	0.0892
t-value	2.3159		2.4389		
GLS					
Coefficient	0.0047		0.0984	30.2831	0.1414
t-value	2.2068		1.5072		

Table 6: GMM-SDF tests

This table shows GMM estimates of the b coefficients in the stochastic discount factor representation (18). $b_b^{\perp}$ denotes the coefficient on the part of the bank factor that is orthogonal to the market factor. The last two columns present the test for the null that the pricing errors are jointly zero. The sample is from Jan/1969 to Dec/2010.

	b_m	b_b	$b_b^{\perp}$	χ^2	p-value
Panel A: 10 bank portfolios					
First stage					
Coefficient	1.7921			11.3541	0.2522
t-value	1.6675				
Iterated					
Coefficient	2.5648			10.9873	0.2766
t-value	2.4535				
First stage					
Coefficient	-2.8957	1.7981		7.0596	0.5302
t-value	-1.0223	2.0370			
Iterated					
Coefficient	-1.1050	1.0948		7.6565	0.4677
t-value	-0.5311	1.8670			
First stage					
Coefficient	2.8030		1.7542	7.2077	0.5144
t-value	2.4875		2.1048		
Iterated					
Coefficient	2.3647		1.1189	7.6445	0.4689
t-value	2.3508		1.9755		
Panel B: 25 market and bank portfolios					
First stage					
Coefficient	1.6687			36.0858	0.0538
t-value	1.5299				
Iterated					
Coefficient	3.3306			35.3824	0.0629
t-value	3.2183				
First stage					
Coefficient	-1.9025	1.3636		31.7964	0.1045
t-value	-0.7947	2.0288			
Iterated					
Coefficient	2.1760	0.3823		35.5993	0.0453
t-value	1.3434	0.9766			
First stage					
Coefficient	2.4412		1.3633	32.2831	0.0944
t-value	2.2335		2.1106		
Iterated					
Coefficient	3.3932		0.5189	35.5795	0.0455
t-value	3.3184		1.3467		

Table 7: Subsample excluding the 2008 financial crisis

This table shows estimates of the risk premiums (panel A) and SDF coefficients (panel B) for the two factor model. Parameters with $\perp$ correspond to the orthogonal bank factor. The GLS t-values also include Shanken's (1992) correction. The last two columns present the test for the null that the pricing errors are jointly zero. The test assets are the 25 portfolios double sorted on market and bank betas. The sample is from Jan/1969 to Dec/2007, thus excluding the financial crisis that started in 2008.

Panel A: Cross-sectional regression tests					
	λ_m	λ_b	$\lambda_b^{\perp}$	χ^2	p-value
OLS					
Coefficient	0.0049	0.2708		30.4564	0.1367
t-value	2.2959	3.1434			
GLS					
Coefficient	0.0047	0.1512		26.8804	0.2611
t-value	2.2204	2.2264			
OLS					
Coefficient	0.0049		0.2551	30.4564	0.1367
t-value	2.2959		2.9786		
GLS					
Coefficient	0.0047		0.1361	26.8804	0.2611
t-value	2.2204		2.0200		

Panel B: GMM tests					
	b_m	b_b	$b_b^{\perp}$	χ^2	p-value
First stage					
Coefficient	-2.8967	1.6815		27.2275	0.2464
t-value	-1.0549	2.3093			
Iterated					
Coefficient	1.1048	0.6030		33.8872	0.0668
t-value	0.6294	1.5083			
First stage					
Coefficient	2.4509		1.6653	27.7297	0.2262
t-value	1.9834		2.3982		
Iterated					
Coefficient	3.0167		0.7236	33.3961	0.0744
t-value	2.8065		1.8411		

Table 8: Testing on 25 Size and Book-to-Market portfolios

This table shows risk premiums (panel A) and SDF coefficients (panel B) estimated with the 25 Fama and French's portfolios sorted on Size and Book-to-Market. Parameters with $\perp$ correspond to the orthogonal bank factor; smb and hml denote the corresponding Fama and French (1993) factors. The GLS t-values also include Shanken's (1992) correction. The last two columns present the test for the null that the pricing errors are jointly zero. The sample is from Dec/1964 to Dec/2010.

Panel A: Cross-sectional regression tests								
		λ_m	λ_b	$\lambda_b^\perp$	λ_{smb}	λ_{hml}	χ^2	p-value
OLS	Coefficient	0.0065	0.1737				105.5	0.00
	t-value	3.1443	2.1119					
GLS	Coefficient	0.0043	0.1782				92.0	0.00
	t-value	2.1695	2.4934					
OLS	Coefficient	0.0065		0.1528			105.5	0.00
	t-value	3.1443		1.8535				
GLS	Coefficient	0.0043		0.1645			92.0	0.00
	t-value	2.1695		2.3025				
OLS	Coefficient	0.0042			0.0025	0.0046	91.0	0.00
	t-value	2.1022			1.8178	3.5199		
GLS	Coefficient	0.0045			0.0028	0.0040	86.9	0.00
	t-value	2.2672			2.0545	3.1260		
OLS	Coefficient	0.0035		0.3341	0.0030	0.0046	88.6	0.00
	t-value	1.7654		2.4181	2.1927	3.5499		
GLS	Coefficient	0.0043		0.1634	0.0029	0.0040	75.4	0.00
	t-value	2.1604		1.5046	2.0832	3.1346		
Panel B: GMM tests								
		b_m	b_b	$b_b^\perp$	b_{smb}	b_{hml}	χ^2	p-value
First stage	Coefficient	0.7175	0.7346				94.4	0.00
	t-value	0.3410	1.5389					
Iterated	Coefficient	0.7529	0.5278				98.0	0.00
	t-value	0.4567	1.4946					
First stage	Coefficient	3.0478		0.7698			93.9	0.00
	t-value	2.6430		1.6389				
Iterated	Coefficient	2.1250		0.7460			93.9	0.00
	t-value	2.2261		2.1401				
First stage	Coefficient	2.6785			2.7081	6.9674	81.8	0.00
	t-value	2.4038			1.8967	3.9877		
Iterated	Coefficient	4.6685			3.3588	8.4615	79.2	0.00
	t-value	4.3473			2.5991	5.3539		
First stage	Coefficient	0.9374		1.5494	6.2052	3.3407	60.6	0.00
	t-value	0.7380		1.9114	2.9186	1.2462		
Iterated	Coefficient	3.8141		0.3102	3.9256	7.5482	77.9	0.00
	t-value	3.1773		0.6271	2.5326	3.8738		

Figure 1: Distance to Default

The top panel shows the estimated average Distance to Default of all banks. The bottom panel shows the number of banks used to construct the average Distance to Default.

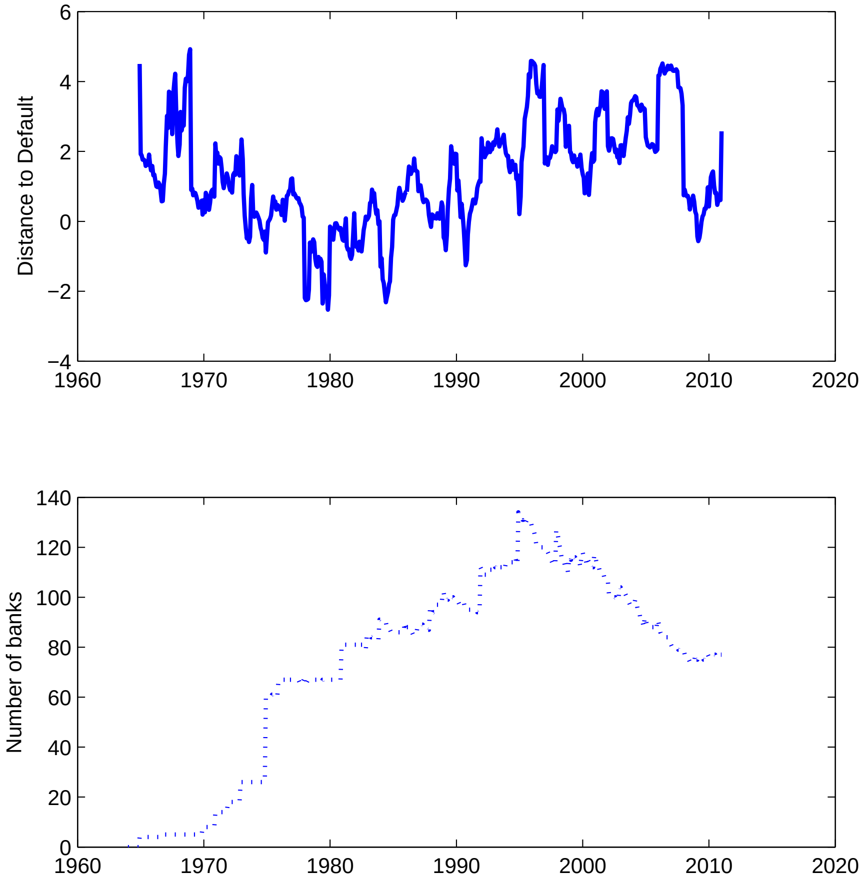


Figure 2: Bank lending terms and Distance to Default

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 from 1990/Q2–2010/Q4.

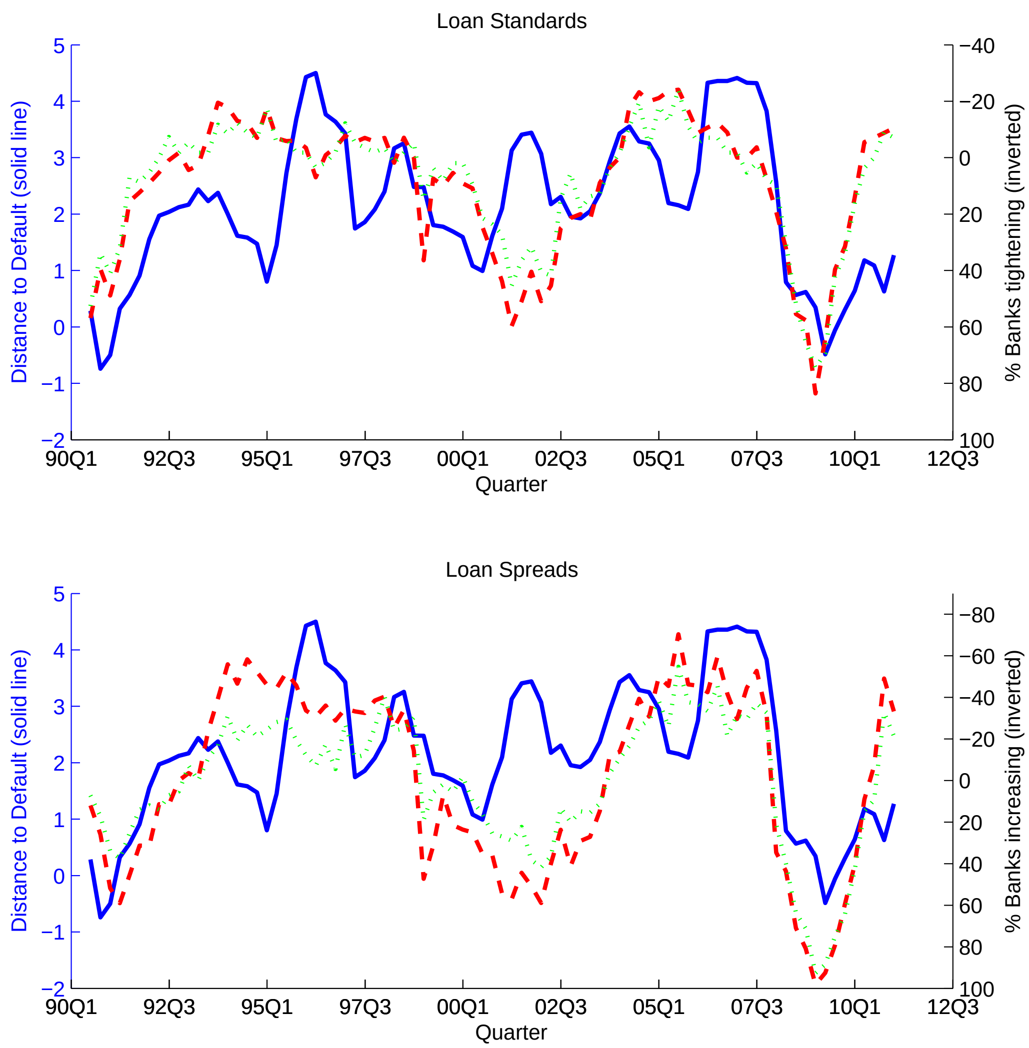


Figure 3: Bankruptcies and Banks' Distance to Default

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/Q1–2010/Q4.

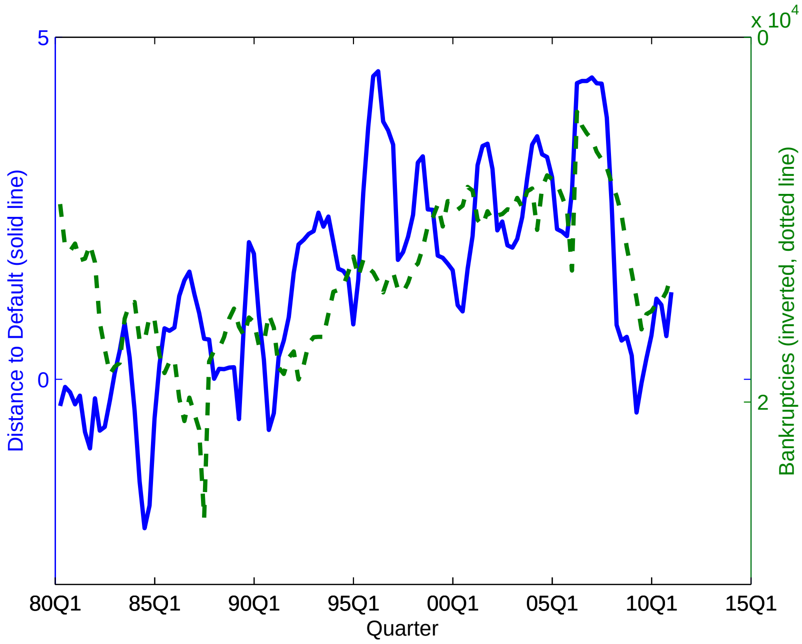


Figure 4: Debt ratios and bank betas for 25 portfolios

This figure plots average debt ratios (total liabilities over total assets) against bank betas for 25 portfolios sorted on market and bank betas (equation 5). The sample is from Jan/1969 to Dec/2010.

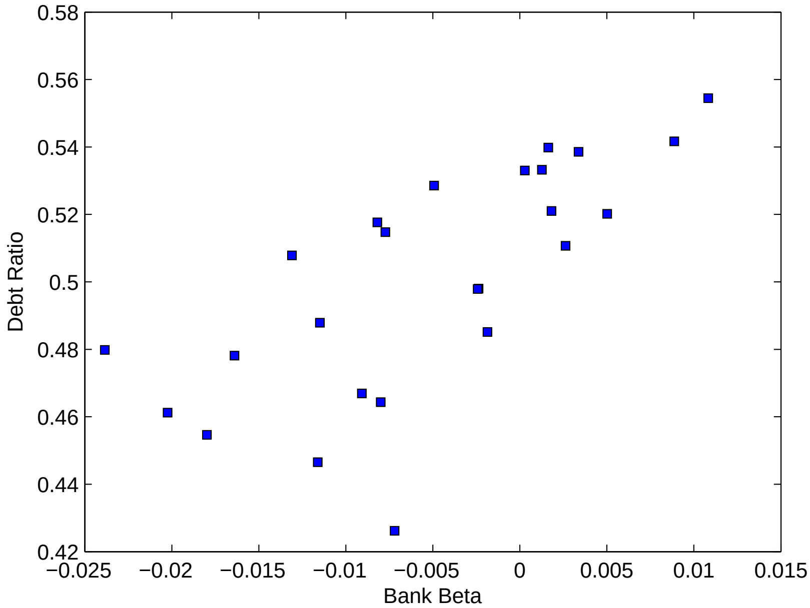
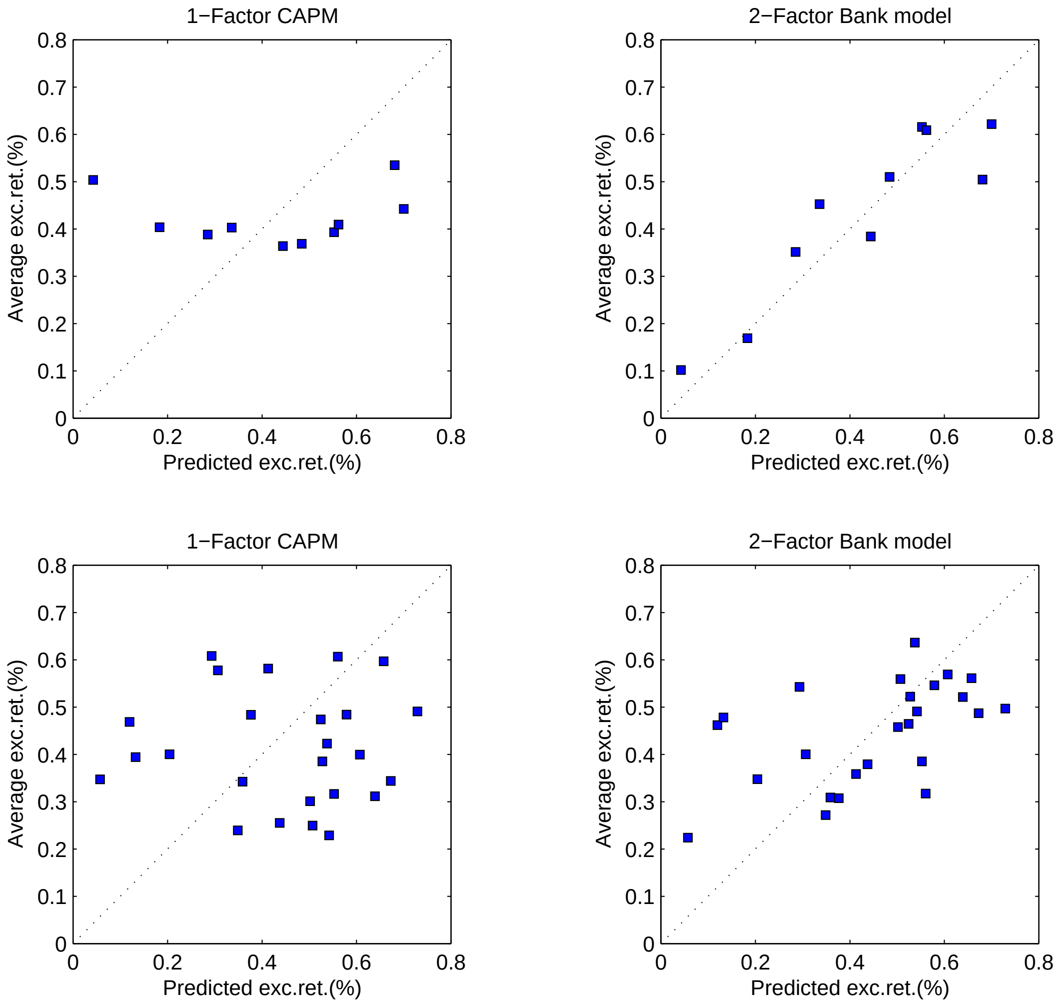


Figure 5: Realized versus predicted returns

This figure plots realized average excess monthly returns (y axis) against mean excess returns predicted by the models (x axis). The two plots on the top row show 10 portfolios sorted on univariate bank betas, while the two plots on the bottom row show 25 portfolios double sorted on market and bank betas. The sample is from Jan/1969 to Dec/2010.



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