The Cost of Capital of the Financial Sector

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Abstract

Standard factor pricing models do not capture the common time series or cross sectional variation in average returns of financial stocks well. We propose a five factor asset pricing model that complements the standard Fama and French (1993) three factor model with a financial sector ROE factor (FROE) and the difference between the financial sector and the market return (RFIN). This five factor model helps to alleviate the pricing anomalies for financial sector stocks and also performs well for nonfinancial sector stocks when compared to the Fama and French (2014) five factor or the Hou, Xue, and Zhang (2014) four factor models. We find the aggregate expected return to financial sector equities to correlate negatively with aggregate financial sector ROE, which is puzzling, as ROE is commonly used as a measure of the cost of capital in the financial sector.

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Understanding the cost of capital for financial institutions is important for issues of financial stability, financial regulation, and economic growth. The question of whether increasing capital requirements will adversely affect the cost of capital for banks has featured prominently in the debate on optimal regulation for the financial sector. While there is general agreement that increased capital requirements will make these banks safer, there is considerable disagreement on how this will affect the cost of capital for banks, with practitioners sometimes arguing that the cost of capital will increase, while academics often argue that this is a fallacy. Without an empirical estimate of the cost of capital, it is difficult to begin to address this question. Banks' cost of capital will also translate directly into their lending decisions and hence affect the availability of credit which can have a potentially sizable macroeconomic impact.

Perhaps surprisingly, the market based cost of capital plays little role in the debate about capital adequacy, where the tendency is to rely on accounting based measures. Indeed, capital regulations typically do not refer to the market pricing of capital and are instead expressed in terms of the book value of equity.[1] Similarly, when financial firms discuss the impact of financial regulations, they usually refer to the impact of regulations on return on equity (ROE) in favor of market derived cost of capital measures.

Perhaps even more surprisingly, the lack of prominence among regulators and practitioners about market implied measures of the financial sector cost of equity capital is also present in the academic asset pricing literature. While papers on the pricing of equity are among the most cited in economics, many papers exclude financial firms and only very few papers specifically focus on the cost of equity capital of financial firms.[2] As such, we know little about financial firms' stock returns. In particular, we do not know the sources of risk

[1]See BCBS (2011) for Basel III regulating bank capital globally, EC (2011) for Solvency II regulating insurance capital in Europe, and SEC (2004) for the alternative net capital rule of US broker-dealers that are part of consolidated entities.

[2]The few exceptions include Barber and Lyon (1997), Schuermann and Stiroh (2006), Gandhi and Lustig (2015), and Baker and Wurgler (2014).

that drive returns in the financial sector, nor do we have an adequate model for estimating the cost of capital. This is surprising both because financial institutions play an important role in the economy, and also simply because they make up around 25% of the total market capitalization of stocks.This paper attempts to fill this gap by showing that existing models do *not* capture the variation in returns in the financial sector either over time or across institutions, and that a five factor model formed within the financial sector can account for this variation and thus give estimates for the cost of capital.

First, we document priced characteristics in the cross-section of financial intermediaries using both a standard panel regression and a portfolio sorting approach. We find that book leverage growth, return on equity (ROE), size, and book-to-market, among others, are all priced factors in panel regressions and we then form portfolio sorts based on these characteristics. In our panel regressions, we are able to compare the results of priced characteristics in financials to those of non-financials. We find that ROE strongly positively predicts returns at the intermediary level and that the effect is much stronger than for non-financials. A natural explanation for this result is that intermediaries take risk to meet ROE targets and thus high ROE is associated with high future market returns. Anecdotal evidence strongly suggests ROE targeting factors heavily into institutions objectives. In their 2014 annual letter to shareholders, JP Morgan calls ROE the "most important" benchmark to compare against competitors and the bank has specific annual ROE targets it seeks to meet. This suggests banks are specifically targeting ROE both on an absolute and relative (to other large banks) basis. The prevalence of this practice is widespread Chase (2014). Financial institutions are more able than non-financials to adjust risk exposure and capital structure in an immediate way to affect ROE.

Second, we show that standard models—including the CAPM and the Fama and French (2014) five factor model—do not explain the average returns to financial sector portfolios sorted on those characteristics.[3] The Fama and French (2014) five factor model includes the market factor, as well as factors related to size, book-to-market, profitability, and investment. These models, which are formed using both non-financial and financial stocks do not explain average returns in our financial sector portfolios meaning the alphas on portfolios formed within the financial sector are fairly large. Further, these models explain little of the common time-series variation in our portfolios, meaning time-series R^2's are low and residuals are highly correlated across portfolios.[4] Therefore, standard models appear insufficient to estimate the cost of capital for financial firms as they do not capture cross-sectional differences in expected returns or common time-series variation in returns.

Third, we show that a five factor financial capital asset pricing model (FCAPM) which adds a financial sector specific ROE factor and the spread between financial and non-financial stocks to the three factors of Fama and French (1993), absorbs the common variation of financial sector equity returns and helps explain the cross-sectional variation in average returns for financial as well as non-financial stock returns. The two new factors, financial sector ROE and the excess return on financials over non-financials (SPREAD), have low correlation with non-financial factors. We show that our model produces economically low alphas in the cross-section of financial stocks compared to leading models. We show that, by adding standard non-financial pricing factors (Mkt, SMB, HML) our model does a good job describing both financials and non-financials and thus results in consistent pricing across both groups. Further, we perform principal components analysis on the residuals from time-series regressions. We find that when the standard benchmark pricing models are used, there is large common variation left unaccounted for – the first principal component of the residuals explains a large amount of the residual variance. In contrast, when the five factor

[3] In unreported results we find this is also true for the Fama and French (1993) three factor model which is a subset of the Fama and French (2014) five factor model and hence not shown in the paper.

[4] These findings are supported by Schuermann and Stiroh (2006) who find low R^2's for financial stocks with respect to the Fama and French (1993) three factor model and strongly correlated residuals indicating omitted systematic factors.

financial capital asset pricing model is used, the remaining residuals exhibit less common variation suggesting that our five factor model captures much of the common comovement between these portfolios. These facts demonstrate that our model can be used to price the cross-section of financial sector equities and thus provides an accurate market based estimate of the cost of equity capital for financial firms that can be used in practice.

Next, we turn to the time-series of the cost of capital for the financial sector. Here, we estimate conditional expected returns on the entire financial sector using the Kelly and Pruitt (2013) partial least squares method. We study how the expected returns in the financial sector vary over time, providing us with a conditional cost of capital for the financial sector. We relate the conditional cost of capital to aggregate ROE in the financial sector, a popular measure of the cost of capital used in practice. In contrast to the results at the institution level, aggregate ROE is *negatively* related to the expected return on the financial sector. We argue that this is consistent with the effect of risk appetite in the financial sector on the aggregate price of risk. Specifically, we assess the partial vs general equilibrium effect of these practices. In partial equilibrium, holding the price of risk fixed for a given time period, a bank taking on more risk to boost ROE will in fact increase its expected stock return. This can generate a positive relation between ROE and expected returns. However, this logic is very different in the aggregate level. If all banks boost ROE in a given period by taking more risk, or holding less capital making equity riskier, then this increase in risk appetite will tend to push the market price of risk downward. We find this to be true at the aggregate: aggregate financial sector ROE is strongly negatively related to the conditional expected return on the financial sector as a whole. This highlights the differential behavior of risk appetite at the bank vs aggregate level.

The results of the paper shed light on the role of regulation for the cost of capital. Our results on ROE and the ROE targeting practice of institutions suggests that increased risk taking increases expected future equity returns at the institution level. The intuition is straightforward and we provide results from a VAR that increases in ROE are associated with increases in leverage. Anecdotal evidence suggests that institutions adjust capital levels to achieve ROE targets and that they go to fairly great lengths to meet ROE objectives. As an example, in their annual report JP Morgan cites ROE as the "most important" benchmark in comparing them to competitors and indeed this is one of the first numbers they highlight. However, we strongly contrast this behavior at the institution level with the aggregate relationship between ROE and returns in the financial sector. Specifically, we find this relationship to be negative. Intuitively, an increase in risk appetite or a reach for yield of all institutions in order to raise ROE will have the general equilibrium effect of pushing the price of risk down and hence aggregate financial sector stock returns will be low going forward. Hence, the behavior of risk taking to improve performance at the institution level may result in excessive risk taking.

These findings also shed additional light on the pro-cyclicality of intermediary balance sheets (see Adrian and Shin (2010, 2014)). Aggregate ROE is generally procyclical, while expected returns tend to be countercyclical. Baron (2014) presents evidence that banks reduce equity in booms and increase it during market downturns, consistent with our results. A potential interpretation is simply that banks are reaching for yield in times when risk premiums are low in an effort to boost ROE. Market based cost of capital calculations, on the other hand, would suggest that capital is cheap in booms, and expensive in busts. To the extent that market prices are set rationally, this observation could rationalize a countercyclical macroprudential surcharge to increase capital in booms (when it is cheap), thus avoiding having to raise capital in busts when it is expensive. These findings certainly call for further study.

The remainder of the paper is organized as follows. Section 1 provides cross sectional evidence on financial sector equity returns. Section 2 presents the five factor financial capital asset pricing model composed of return-based factors from sorts on firm characteristics.

Section 3 presents the expected return estimation of the pricing factors. Section 4 discusses the weak link between market based cost of capital measures and ROE based measures. Section 5 concludes.

I. Empirical Approach and Cross-Sectional Evidence

Our approach closely follows the techniques used in Fama and French (1992, 1993, 1996) using both panel regressions and portfolio sorts. Data come from CRSP and the merged CRSP-Compustat databases. Monthly returns from CRSP are merged with quarterly accounting data from Compustat. In our implementation, we closely follow Hou, Xue, and Zhang (2014) in assessing when accounting data are available in a given quarter and we form portfolios for the next corresponding quarter using the latest possible information. Using the entire CRSP universe of common stocks with a share code of 10 or 11, quarterly characteristics are winsorized at the 1% and 99% levels within each cross section. This is particularly important for ROE and leverage where extreme low values of book equity can overly influence the results. The monthly risk free rate we use is pulled from Ken French's website, ultimately from Ibbotson Associates. The sample period begins in January 1980 and ends in December 2013.

Identifying financial stocks: We classify financial stocks as those with 4 digit SIC codes in the range 6000 to 6799. This includes commercial and investment banks, brokers and dealers, real estate, and insurance companies, and thus represents a broad definition of the financial sector. Both CRSP and Compustat provide SIC codes. Kahle and Walking (1996) have found Compustat SIC codes to be more reliable, so using the procedure of Goyal (2014), we give pre-eminence to Compustat SIC codes. If the Compustat historical SIC code is not available, we backfill using the first available value. If the Compustat historical SIC code is not available, we use the Compustat header SIC code, and if that is not available, we use the CRSP SIC code.

Portfolio formation: All portfolios are rebalanced quarterly, based on quarterly characteristics even for variables such as size and momentum that can be measured at higher frequency (but here are taken to be the last non-missing monthly value within each quarter). This differs from the approach of Fama and French (1992, 1993, 1996) who sort annually, but results in similar portfolio returns and is more consistent with our panel regressions. All portfolio returns are value-weighted. We define book equity as total assets minus total liabilities and market equity as stock price times shares outstanding. Book leverage is defined as total assets divided by equity. We form these variables at the end of each quarter. Market beta is estimated over the past year using daily stock return data for each firm at each point in time.

While we use similar methodology to many previous studies, our main point of departure is to focus only on financial institutions, which are typically omitted from asset pricing studies. Notable exceptions include Barber and Lyon (1997), Schuermann and Stiroh (2006) and Gandhi and Lustig (2015). However, those papers do not present or analyze an asset pricing model for the financial sector, the main aim of this paper.

Why do we choose these characteristics to look at? Size and book-to-market are chosen for their well known relation to expected returns in non-financials, so we naturally include them in our study. Similarly, ROE is used among non-financials by Chen, Novy-Marx, and Zhang (2010), Novy-Marx (2013), and Hou, Xue, and Zhang (2014). However, despite the fact that these characteristics are priced among non-financials as well, we find that factors formed on these characteristics within the financial sector have little in common with non-financials. Instead, the characteristics seem to be good ways to summarize cross-sectional variation in average returns, while picking up different underlying sources of systematic risk.

Regarding leverage growth, our motivation comes from recent studies that find a strong negative association with book leverage growth in the financial sector and expected returns (see Adrian, Moench, and Shin (2010, 2014), as well as theoretical work by Geanakoplos

(2009), among others). In particular, increases in book leverage growth signify aggressive balance sheet expansion and tend to coincide with compressed risk premia and low expected returns. These studies focus on aggregate leverage and aggregate returns (i.e., the total market return) whereas here we study this behavior at the institution level. Our findings for leverage growth do not extend to non-financials which partly highlights the difference in balance sheet management of financial firms. In fact, the price of risk for leverage growth is positive (though statistically insignificant) for non-financial firms. Also, we use leverage growth rather than levels for several reasons. The first is that there is large, stable variation in the level of leverage across different types of intermediaries (i.e., insurance, depository institutions, etc.) that we do not want to pick up in our sorts. Second, the level of leverage will be conflated with the amount of risk exposure a bank has and thus will tend to be positively associated with expected returns. Instead, our goal is to pick up financial intermediaries which are actively increasing leverage and expanding balance sheets to better capture their risk appetite.

Understanding the empirical link between ROE and the cost of capital in the financial sector has not received a lot of attention. ROE is commonly assumed to be related to the cost of capital among practitioners and much of the current debate on capital ratios focuses on how changes in regulation will affect ROE and the cost of capital. For example, in a recent **Bloomberg article**, Admati and Hellwig summarize the focus on ROE as follows: "The focus on ROE is deeply embedded in the culture of banking. A typical statement in a leading textbook, written by a prominent academic and former central banker, is that bank capital has both benefits and costs. Bank capital is costly because, the higher it is, the lower will be the ROE for a given return on assets," referring to Mishkin (2012). Many academics argue that such a usage of ROE is flawed, as the pricing of market equity adjusts. As a result, expected returns derived from market values, not accounting values such as ROE are the relevant units for capital allocation.

Our analysis sheds light on this debate by showing how the cost of equity capital varies over time and across firms as functions of variables such as leverage, ROE, and book-to-market ratio. While such an analysis will not be able to discriminate among theories, it will highlight suggestive empirical facts.

Figure 1 plots the time-series of our five characteristics where we take the value-weighted average of the characteristics across all financial institutions at each point in time. We can see that size is pro-cyclical while book-to-market is counter-cyclical. Book leverage growth are pro-cyclical, with persistent drops in book leverage during the financial crisis. ROE also collapses during the crisis, becoming strongly negative.

[Figure 1 about here]

We start with our asset pricing explorations by running panel regressions of monthly returns on characteristics from the previous quarter. This specification provides us with financial sector firm characteristics that forecast equity returns.

$$r_{i,t+k} = a + b \times \Delta lev_{i,t} + c \times ROE_{i,t} + d \times ln(size_{i,t}) + e \times ln(BM_{i,t}) + f \times \beta_{i,t} + \varepsilon_{i,t+k}.$$

Table 1 gives the results of these regressions. The first seven columns run different specifications of the above regressions that include or exclude certain variables and control for time and firm fixed effects. The eighth column runs the above regression using earnings growth rather than stock returns to see whether the variables contain news about cash flows as well. Finally, the last column runs the above regression using stock returns of non-financials. This allows us to directly compare the results of our characteristics in financials and non-financials to see if the pricing behavior is different for these different sectors.

We find that ROE forecasts returns positively. This is consistent with work for non-financials as implied by column (9),[5] but is somewhat contrary to the popular banking

[5]It is also consistent with the results from Novy-Marx (2013) that profitability is positively related to expected returns.

wisdom that high ROE implies a low cost of capital. Also, notably, we find that the coefficient on ROE for financials is more than four times higher than that of non-financials suggesting that the relationship between ROE and future returns is particularly strong in the financial sector. One interpretation is that institutions can increase ROE but only by increasing risk and hence increasing the cost of capital.

We find a *negative* price of risk for book leverage growth, meaning an increase in book leverage is associated with lower future returns. This is consistent with time-series evidence in Adrian, Moench, and Shin (2010, 2014) where increases in leverage negatively predict returns and is related to Adrian, Etula, and Muir (2014) who find leverage growth is priced in the cross-section of returns. Those papers find pro-cyclical book leverage for the financial sector and thus find that risk premia tend to be low in booms when leverage growth is high. We find similar results for individual institutions and, notably, this characteristic is uniquely priced for financial intermediaries. In column (9) we find the price of risk for leverage growth for non-financials to be *positive*, rather than negative, though this is not statistically significant. This highlights that leverage management by financial institutions is significantly different than for non-financial firms and that leverage growth are uniquely priced among the financial stocks.

We interpret these findings in line with balance sheet expansion of intermediaries coinciding with low expected returns. This is consistent with the idea that a loosening of funding conditions is associated with higher leverage and higher prices, and hence lower expected returns. We provide evidence for this theory below by showing that book leverage growth is strongly associated with balance sheet expansion as it correlates positively with asset growth. A second, related, possible explanation is the “reaching for yield” hypothesis. It is possible that individual institutions take on more leverage exactly when risk premia, or expected returns, are low. The increase in leverage is an attempt to boost equity returns which are otherwise dampened by low risk premiums. It is likely that, because increases in leverage beyond a target ratio is costly, a firm would not fully offset the decline in expected returns through an increase in leverage. Hence, we would expect to see a low expected return be associated with an increase in leverage. Both of these explanations rely on the idea that increases in leverage for financial intermediaries reflect increases in risk appetite for these institutions and our results again highlight the unique role for leverage in the financial sector.

We find financial intermediaries that are smaller and have higher book-to-market ratios earn higher returns, consistent with previous work by Barber and Lyon (1997) for financials and with Fama and French (1992). Interestingly, the coefficients here are slightly weaker for financials compared to non-financials though overall the magnitudes are quite similar. We do not find market beta to significantly forecast returns as much as in non-financials.

[Table 1 about here]

Our finding that ROE forecasts expected returns positively, while leverage growth forecast returns negatively presents a challenge to the arguments of both Mishkin (2012) and Admati and Hellwig. The "bankers" argument put forward by Mishkin (2012) would say that increasing ROE lowers the cost of capital for a given firm. That would suggest that ROE forecast returns negatively, but we find the opposite. The sign on ROE goes in the right direction from the point of view of Admati-Hellwig. Based on the logic of Modigliani and Miller (1958), increasing ROE has to be accompanied with more equity risk, suggesting the positive sign on ROE that we find. However, the finding that higher leverage forecasts *lower* returns conflicts with that logic, as Modigliani and Miller (1958) would suggest that higher leverage would have to be associated with a higher cost of capital. The finding that leverage growth forecasts earnings growth positively might resolve this puzzling finding, as positive economic news might drive both results. However, the sign is the same when including time effects or firm effects, showing that the result holds both in the cross section and the time series.

The finding that higher leverage growth forecast lower returns in the cross section is in the spirit of Hong and Sraer (2014) and Frazzini and Pedersen (2014), who argue that speculative investors drive down expected returns of stocks with high embedded leverage. It is also noteworthy that higher betas do not predict returns significantly, a finding which is related to Baker and Wurgler (2014), who argue that market beta is actually negatively related to future returns.[6]

To better understand the firm characteristics, we compute cross-sectional correlations between leverage growth, ROE, and various other balance sheet measures. Figure 2 plots these cross-sectional correlations over time. Table 2 provides unconditional estimates of these correlations. The cross-sectional correlations in the table do not materially if we adjust for firm and time fixed effects.

[Figure 2 about here]

[Table 2 about here]

We find leverage growth to be *positively* correlated with asset growth and negatively correlated with book equity growth. These findings emphasize the pro-cyclical behavior of book leverage on two dimensions. The first is the balance sheet expansion dimension, whereby increases in leverage are driven by the ability or desire for financial institutions to expand their balance sheet as in Adrian and Shin (2010). We see at least part of the leverage growth driven by this balance sheet expansion, which shows up as a positive correlation with asset growth. However, equally important is the negative correlation between leverage growth and book equity growth.

At the bank level, leverage management is achieved through both changes in book equity as well as changes in debt. In unreported results, we find that both movements in leverage

[6] Baker and Wurgler (2014) also focus on the positive relationship between leverage levels and market beta. Our findings are different in that we use book leverage growth and control for market betas in our regression, so our findings on leverage are substantially different than theirs.

appear important for capturing differences in expected returns. In other words, sorts on book equity growth and asset growth also capture cross sectional differences in average returns, with asset growth having a negative sign and equity growth having a positive sign. However, leverage growth subsume both of these measures, suggesting that each only matters in so far as they contribute to leverage growth.

The positive relationship between equity growth and future returns highlights how our result is different from simple investment theories for non-financials where declines in the cost of capital can lead firms to issue and invest. In such theories, one would expect both increases in book equity and increases in assets to be negatively associated with the cost of capital. Importantly, for financial firms, asset growth and book equity growth only work through their affect on leverage, therefore using leverage growth provides a more powerful characteristic for expected returns that drives out either of these other variables.

To shed further light on the balance sheet management of financial institutions, we next report results from a vector autoregression (VAR) with equity, book-to-market, ROE, and leverage as endogenous variables. To compute the impulse response functions of the VAR, we use a recursive identification where equity is the most exogenous, and leverage the most endogenous variable. The VAR is estimated employing the panel VAR approach of Holtz-Eakin, Newey, and Rosen (1988) that is relying on all of the individual firm data. We employ annual log changes for each of the variables, except for ROE, for which we use annual changes. This data transformation ensures that all of the endogenous variables are stationary. Furthermore, we choose two lags using standard lag order selection criteria. The regression output is reported in Table 3, while the impulse response functions are provided in Figure 3.

[Figure 3 about here]

[Table 3 about here]

The VAR provides very intuitive results. A positive shock to book equity leads to an increase in the book-to-market ratio, a decline in leverage, and a decline in ROE. A positive shock to the book-to-market ratio is followed by a decline in book equity, an increase in leverage, and a decline in ROE. A positive shock to leverage is followed by an increase in book equity, an increase in book-to-market, and an increase in ROE. Finally, a shock to ROE is followed by an increase in book equity, an increase in book-to-market, and a decline in leverage.

Book equity thus tends to be a countercyclical variable, as financial firms tend to pay out (via dividends and repurchases) in booms, and issue equity during bad times. Hence a positive book equity shock forecasts lower ROE, lower leverage, and a higher book-to-market ratio. Leverage, on the other hand, is procyclical. Higher leverage forecasts higher ROE. Somewhat mechanically, higher ROE predicts higher market equity going forward and hence also higher book-to-market, and lower leverage (as leverage has equity in the denominator).

We offer the interpretation that leverage growth are potentially driven by an attempt to manage ROE and to increase returns back towards a target level (i.e., reach for yield). Consistent with this interpretation, banks would attempt to increase leverage the most when expected returns are particularly low. By increasing leverage enough, banks would be able to achieve the same expected return on equity as before. However, if there are costs or constraints to increasing leverage, it is likely that the bank will not immediately take on enough leverage to fully offset the changes in expected return. Therefore, lower expected return on equity will naturally be associated with increases in leverage. Similarly, these will tend to coincide with low ROE as book equity is compressed and as ROE is a signal for low expected returns.

Indeed, we find changes in ROE to have a contemporaneously negative correlation with leverage growth, but find that leverage is positively correlated with *future* changes in ROE. We offer the following interpretation. A drop in ROE results in a decline in expected returns for the bank, which prompts the bank to increase leverage. The increase in leverage is targeted at increasing future ROE, thus we see the increase in leverage resulting in a positive change to future ROE. Overall, these results support that leverage is being used to counteract compression in expected returns.

A second interpretation would be that, all else equal, investors simply prefer companies with higher leverage as investors receive more risk exposure without having to take on leverage themselves (Frazzini and Pedersen (2014)). However, this interpretation could only explain why, *controlling* for all other factors, such as market beta, increases in leverage are negatively associated with returns, but they would be less consistent with the unconditional evidence that simple sorts on leverage growth are associated with negative future returns even when not controlling for market betas or other factors. Overall, the evidence does not appear to be easily understood by theories that emphasize an investor preference for leverage.

II. The Financial Capital Asset Pricing Model

A. Return Pricing Factors

We next explore the pricing behavior of various factor models. We form quintile portfolios on change in ROE. We derive a high minus low factor formed using portfolio sorts into quintiles (i.e., portfolio 5 minus portfolio 1). All portfolio sorts and factors formed are value-weighted to avoid over weighting small, illiquid stocks. The high minus low portfolio for ROE is called “FROE”. We also form an excess financial sector market factor which is the value-weighted return on all financials in excess of the market return formed using non-financials, called SPREAD. Our benchmark pricing model consists of five factors: FROE, SPREAD, MktRF, SMB, HML. However, we also form additional portfolios on leverage growth called “FLEV”, on size called “FSMB”, and on book-to-market called “FHML”. We study these to see if they add any additional information compared to our five factor pricing model.

Table 4 summarizes the average returns, standard deviations, Sharpe ratios, and correlation of our factors with the standard Fama and French (1993), Fama and French (2014) and Hou, Xue, and Zhang (2014) factors. The FROE factor has a large mean and sharpe ratio, while the spread factor's mean and sharpe ratio are close to zero. The correlation of FROE and SPREAD with the benchmark factors is very low. The only notable correlations are between the financial and real sector ROEs (FROE and rROE), and between SPREAD and HML. However, even those correlations are below 50 percent.

We plot the returns to each of the factors formed in Figure 4 along with shaded areas for recessions. While it is hard to see systematic variation in these factors during typical recessions, we see increased volatility of the factors during the recent financial crisis, consistent with the idea that these portfolios pick up factors that primarily affect the financial sector.

[Table 4 about here]

[Figure 4 about here]

B. Cross Sectional Pricing Performance

We demonstrate that our five-factor model, the Financial Capital Asset Pricing Model (FCAPM), captures the cross-sectional variation in returns of portfolios sorted on various characteristics in the financial sector and hence can be used as a pricing model for the financial sector. We test our model against the CAPM and the Fama and French (2014) five factor model. We use the Fama and French (2014) five factor model as benchmark, as recent evidence by Hou, Xue, and Zhang (2014) shows that a model with the market factor, a size factor, a profitability factor, and an investment factor explains the cross section of expected returns across many portfolios sorts. In comparison to the model by Hou, Xue, and Zhang (2014), the Fama and French (2014) adds a book-to-market factor as fifth factor. We prefer this five factor model as benchmark as it comprises the Fama and French (1993) three factor by adding profitability and investment. Furthermore, the Fama and French (2014) five factor model has the same number of factors as our five factor financial model, where the profitability factor corresponds to our ROE factor and the investment factor corresponds to our financial spread factor. Our benchmark models are therefore:

$$\begin{aligned}
R_{i,t} &= \alpha_i + \beta_i' R_t^{fac} + \varepsilon_{i,t} & \\
R^{fac} &= [MKT, SMB, HML, RMW, CMA] & \text{Fama and French (2014)} \\
R^{fac} &= [MKT, SMB, ROE, INV] & \text{Hou, Xue, and Zhang (2014)} \\
R^{fac} &= [MKT, SMB, HML, FROE, SPREAD] & \text{FCAPM}
\end{aligned}$$

As portfolios, we first consider five portfolios sorted on each of the following characteristics: book leverage growth, ROE, size, book-to-market, market beta, earnings, volatility, and momentum. These are motivated by studies in the literature documenting anomalies with respect to the CAPM for each and from our earlier panel regressions showing links between characteristics and future returns for financials and non financials. Market beta and volatility are meant to capture the "low risk anomaly" that expected returns are roughly flat or even decreasing in beta and volatility sorted portfolios (Frazzini and Pedersen (2014), Baker and Wurgler (2014), Ang, Hodrick, Xing, and Zhang (2006)). These are true for financials as well as non-financials.

We study these portfolios in financials as well as non-financials across different models. To compare models, we look at the average absolute α from the time series regression of each portfolio on the factors. By studying the absolute value of these αs across these cross-sections, we are asking which model features the lowest pricing error for each cross-section. Figure 5 and Table 5 contain these results. We show results taking the average α across every cross section in the financials and non-financials separately as well as together in Panel A and then show the results of each individual cross section in more detail in Panels B and C.

The annualized average absolute α within financial stocks is 1.67% for our FCAPM model, 3.26% for Fama and French, and 2.80% for the Hou Xue and Zhang model. Thus the FCAPM outperforms these models substantially when considering financial stocks and hence serves a better estimate for the cost of capital for financial firms. Moreover, the model is fairly successful on an absolute basis and not just a relative one: the absolute α of 1.7% per year is economically fairly small. In contrast, the pricing error for non-financials for our FCAPM is larger than either FF or HXZ, although the difference is less than 0.5%. Thus the FCAPM provides a fairly similar, though slightly inferior, description of expected returns for non-financials.

Moving to the lower panels, we can study exactly where the models differ in terms of portfolio pricing errors. Here, we find it easiest to see these patterns in Figure 5 and we restrict the comparison only to the FF5 model. Within financials, the biggest differences in pricing errors come from portfolios sorted on ROE and Momentum, followed by book-to-market and earnings. It is worth comparing this to non-financials. Here our model is very comparable to FF5 on almost every dimension, but does substantially worse on portfolios sorted by idiosyncratic volatility. We do not have specific intuition for this result. Comparing Panel A and B gives the following insights. First, the behavior of ROE is clearly different in financials vs non-financials. The FF5 model is able to perfectly price ROE in the non-financials but leaves large pricing errors in the financials. A similar fact holds for book-to-market.

These results suggest that, while similar characteristics are priced among financials and non-financials, the behavior of the portfolios sorted on these characteristics is quite different. The underlying economic forces driving discount rates may well be very different among financials even if the way to capture that discount rate variation in terms of characteristics is similar. As an example, Berk (1995) points out that a higher discount rate mechanically reduces book-to-market, so that "size" related anomalies should not be surprising. This suggests that the same characteristics will generally be priced in different groups of stocks though they may pick up very different forms of discount rate variation.

[Table 5 about here]

[Figure 5 about here]

We conclude that our model does well on the majority of the eight cross-sections we form within the financial sector. We offer an improvement in portfolios sorted on leverage growth and especially in ROE relative to existing models leaving alphas that are economically small and show no systematic pattern. For the size and book-to-market portfolios our model performs about as well as the benchmark models.

These pricing results have two alternative interpretations, following earlier literature. Fama and French (1992, 1993, 1996) argue that the high minus low factors formed on characteristics proxy for risk factors. Their interpretation is thus that stock returns are fairly priced relative to a pricing kernel, i.e. that no arbitrage opportunities exist. Daniel and Titman (1997), on the other hand, argue that high minus low factors such as HML and SMB do not represent pricing factors of an arbitrage free pricing kernel, but instead result from various market frictions such as behavioral biases or institutional constraints to arbitrage.

Our preferred interpretation of these pricing results is that there is a true pricing kernel, which prices all assets, and that the pricing factors of the FCAPM represent a projection of the true pricing kernel onto the span of financial sector equity returns (see Cochrane (2005) for a geometric representation of these projections). Factors that price the cross section of financial sector equities (Mkt, SMB, HML, FROE, FSPREAD) and the factors that price the cross section of non financial sector equities (RM, HML, SMB, RMW, CMA) are thus representations of the same pricing kernel, projected onto the span of different assets.

C. Principal Component Analysis

Having shown that our five-factor FCAPM explains the *cross-section* of average returns, we next show that the FCAPM also absorbs much of the *time-series* variation in these portfolios. This matters for three reasons. First, the R^2 values from the regressions of our portfolios on our factor model are very high, whereas this is not the case for the other models. This is not a necessary feature of a good pricing model (which only requires low alphas), but it is useful in showing that we are likely absorbing the bulk of the systematic drivers of returns in these portfolios, leaving little variation left. Second, the residual variation left unaccounted for by our model appears largely uncorrelated across portfolios, meaning we have captured the majority of the systematic movements in returns. In reference to the arbitrage pricing theory of Ross (1976), it is unlikely that there are additional relevant pricing factors for these portfolios because there is little systematic variation left in the returns. Third, Kleibergen and Zhan (2013) show that a high R^2 improves inference for prices of risk and alphas and provide examples of the literature where asset pricing models with low explanatory power in the time series have spuriously high second stage t-statistics.

To demonstrate this, we study the principal components of the residuals from each model (in the above equation, the principal components of $\varepsilon_{i,t}$). These results are given in Figure 6. To show this more concretely, we form four cross-sections in financial and non-financial stock returns. Our financial sector cross-sections are 25 portfolios sorted on size and book-to-market (5x5 sorts), and 25 portfolios sorted on leverage and ROE. For each individual cross-section, we also form a "5 PC" model which takes the first five principal components for that cross-section and is hence designed to capture as much of the time-series variation as possible.

We find that for the financial sector portfolios, our five factor model essentially accounts for as much of the time-series variation as the "5 PC" model. In contrast, using the Fama-French factors, the first PC of the residuals still explains a fairly large fraction of the remaining variation. In contrast, when looking at non-financials, the Fama-French model *does* absorb most of the time-series variation, a fairly well known result. This highlights how different the cross-sectional performance is across financials and non-financials as our FCAPM explains very little variation for non-financials. For financial sector returns, our five factor model accurately accounts for cross-sectional and time-series variation in returns as it picks up the main drivers of systematic risk across these institutions. Our five factors essentially span the entire cross-section of financial returns sorted on these characteristics.

[Table 7 about here]

[Figure 6 about here]

III. Expected Returns

A. Forecasting Results

We next extend our original panel regression estimates of the price of risk reported in Table 1 to various time horizons. We plot the prices of risk by horizon for each characteristic in Figure **??** going from 1 month to 60 months (5 years). We obtain these from the following regression,

$$r_{i,t\to t+k} = a + b \times x_{i,t} + \varepsilon_{i,t+k} \qquad k = 1, ..., 60$$

where $x_{i,t}$ are different variables known at time t. Standard error bands are computed using Newey-West adjustment for autocorrelation and heteroskedasticity.

We find the coefficients on size and book-to-market to generally become stronger as we increase the time horizon (see Table **??** and Figure 7). This is not surprising as these are highly persistent variables and hence predictability typically increases as we increase horizon. In contrast, the coefficients on ROE and leverage growth decay much more quickly over time.

In general, the plots show that our predictability result is robust to using alternative horizons up to around one year and hence don't depend heavily on our choice of holding periods or frequency of rebablancing.

The sign on book leverage switches from negative to positive as we increase the forecasting horizon to around 5 years. This finding is consistent with theories of the leverage cycle that generate the "volatility paradox" (see Adrian and Boyarchenko (2012)). In booms, intermediary constraints are loose, leading to endogenously high leverage, low volatility, and compressed risk premia. However, the high leverage generates vulnerability at longer time horizons, leading to lower frequency mean reversions in leverage, volatility, and risk premia. The switch in the sign of the leverage forecasting relationship is precisely compatible with such a leverage cycle that leads to a volatility paradox.

[Table **??** about here]

[Figure 7 about here]

B. Time-Series of Expected Returns for the Financial Sector

We have shown that our five factor FCAPM model does a good job summarizing the time-series and cross-sectional variation in returns within the financial sector. The model thus provides an estimate for the unconditional expected return on these portfolios. We next attempt to estimate conditional expected returns (or risk premiums) on the financial sector. The goal in doing so is to then provide a conditional estimate of the expected return. This could be useful in understanding how a financial institution's cost of capital changes over time, a topic of recent debate.

We use the methodology from Kelly and Pruitt (2013) to forecast the value weighted return on the financial sector over the risk free rate. We use this forecast as an estimate of the conditional risk premium on the financial sector at any point in time. Our goal is to learn how the expected return changes over time.

In implementing the partial least squares (PLS) filter of Kelly and Pruitt (2013), we allow the expected return to depend on the following five characteristics of all financial stocks: leverage growth, ROE, size normalized by the size of the financial system, book-to-market, and dividend yield. We use leverage growth and ROE as we had earlier documented that these were significant forecasting variables using the panel regressions (see Table 1). We add size and book-to-market, as those are standard forecasting factors. We normalize size by the total size of the financial system to obtain a stationary forecaster. Finally, we add the dividend yield as a forecasting factor, as that is the baseline variable that Kelly and Pruitt (2013) use. PLS is designed to extract the linear combination of this large amount of right hand side variables as the single factor that best forecasts the respective variable. We implement Kelly-Pruitt as an expanding window out-of-sample estimator by creating forecasting factors in book leverage growth, ROE, B/M, size, and dividend yield. We then regress each of the FCAPM factors on the respective forecasting factors, e.g. we regress the 5-1 ROE factor, the 5-1 leverage factor, etc. on the forecasting leverage factor, the forecasting ROE factor, etc.

Table 8 shows the summary statistics of the forecasting factors, scaled appropriately. We plot the conditional expected return from out of sample estimates in Figure 8. We find that expected returns on the financial sector are counter cyclical, decreasing in booms and increasing in busts.

[Table 8 about here]

[Figure 8 about here]

IV. Expected Returns and Return on Equity

Figure 9 compares our estimated expected returns from the five factor model with the accounting based ROE. The first thing to note is that those two alternative measures of the cost of capital of banks behave very differently. While ROE is strongly procyclical, the equity return behaves more countercyclically. In fact, the cross correlogram shows that the market based expected equity returns forecast future ROE, reflecting the fact that asset prices are forward looking measures, while ROE is a realized, backward looking measure. ROE, on the other hand, forecasts market based expected equity returns negatively, indicating that it is a countercyclical variable.

[Table **??** about here]

[Figure 9 about here]

While the finding that the market derived expected equity return differs markedly from ROE is not surprising, it does represent a puzzle relative to the widespread practice in the financial sector to use ROE as a tool for capital allocation. Setting ROE targets, and managing the expansion, contraction, and possibly closure of business lines according to ROE is widespread practice among the largest, most sophisticated financial institutions.[7]

There are at least two potential explanations to resolve this puzzle:

1. financial institutions view market prices as being set irrationally, or
2. financial institutions suffer from debt overhang.

When market prices are—or are perceived to be—irrational, Stein (1996) argues that capital budgeting should rely on accounting based hurdle rates instead of market derived measures of the cost of capital. While Stein (1996) suggests to employ cash flow betas, an extensive accounting literature is advocating cost of capital calculations that are transformations of ROE and expected ROE. In particular, Gebhardt, Lee, and Swaminathan (2001) compute the cost of capital from ROE and expected ROE using a standard present value formula. Tang, Wu, and Zhang (2014) show that such an ROE based calculation of the cost of capital differ significantly from market based expected return calculations.

[7]See the annual reports of the largest banking organizations.

The observation that major financial firms use accounting based ROE measures for capital budgeting instead of market derived expected return measures might instead reflect debt overhang, as well as institutions' incentives to maximize pricing distortions of debt due to government guarantees or liquidity premia in short term wholesale funding markets. The debt overhang problem means that institutions take existing long term debt as given and take on leverage to maximize shareholder value, thus shifting risk to the long term debt holders. Distorted pricing of leverage due to government guarantees also generates risk shifting, to the public backstop.

Admati, DeMarzo, Hellwig, and Pfleiderer (2015) argue that risk shifting is a first order force in the leverage behavior of financial institutions, and hence impacts cost of capital of those institutions. Debt overhang, together with government backstops, drive a wedge between the market price of equity and the cost of capital of the financial institution. Consistent with that logic, Gandhi and Lustig (2015) show that government guarantees impact the market price of equity capital for financial institutions. If liabilities such as insurance liabilities or deposits receive a mispriced government guarantee, then there might be a wedge between the internal and the external cost of capital which might in fact make accounting based capital budgeting the right thing to do for financial firms.

V. Conclusion

We present a model for the cross section and time series of the cost of capital of financial intermediaries. We show that a five factor model that augments the Fama and French (1993) three factor model with a financial sector ROE factor (FROE), and with a financial sector minus market return SPREAD factor absorbs the common variation of financial sector equity returns and prices portfolios formed within the financial sector on these characteristics. The FROE and SPREAD factors have surprisingly low correlations with the pricing factors of the Fama and French (2014) and the Hou, Xue, and Zhang (2014) models.

When we calculate the time varying expected return to the pricing factors using the Kelly and Pruitt (2013) partial least squares estimator and document that expected returns to the financial sector correlates negatively with financial sector ROE over time. In contrast, in the cross-section, our regressions show a positive association between ROE and returns. Our interpretation of these findings is that risk taking by individual banks will increase ROE (by boosting profits or shrinking equity) but risk appetite in aggregate reduces the price of risk and compresses expected returns. Financial institution's competition on ROE might thus be one source of the procyclcial behavior documented by Adrian and Shin (2010, 2014).

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Figure 1. Financial Sector Characteristics. This figure plots the five characteristics used in the panel regressions. The upper left panel shows the value-weighted average quarter-by-quarter leverage change. The upper right panel shows the value-weighted average return on equity. The middle left plot shows the total size of the financial sector in Trillions \$. The middle right panel shows the value-weighted average of the log-book-to-market ratio. The lower left chart shows the cumulative value-weighted financial sector equity return since 1980Q1.

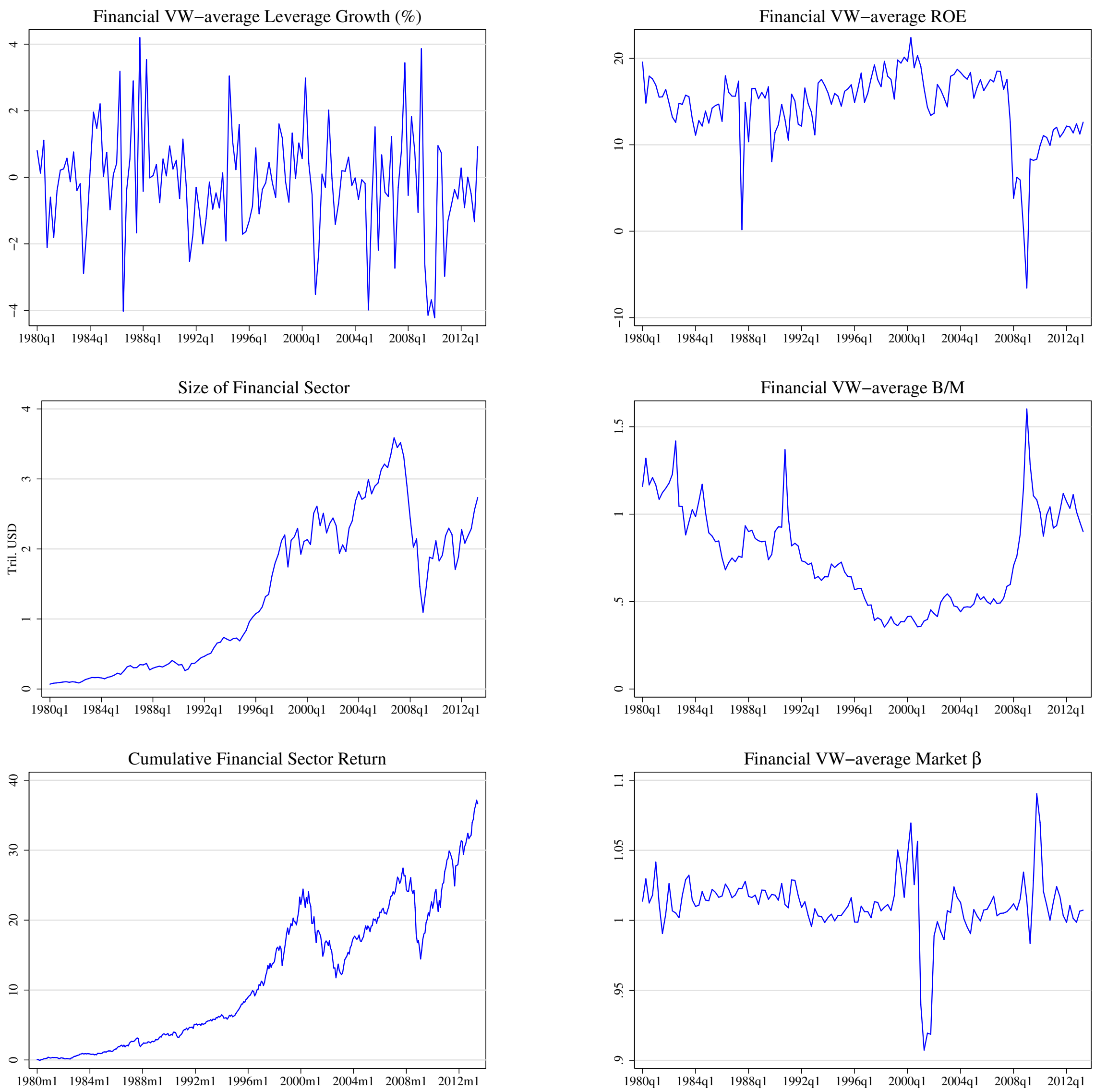


Figure 2. Correlations Among Characteristics. This figure plots cross sectional correlations among the characteristics over time. In each figure, correlations are computed cross sectional each quarter, and significance at the five percent level is indicated with a bolded circle. The upper left panel shows the correlation between leverage growth and asset growth. The upper left panels shows the correlation between leverage growth and book equity growth. The lower left panel shows the contemporaneous correlation between leverage growth and ROE. The lower right panel shows the correlation between leverage growth and future ROE changes.

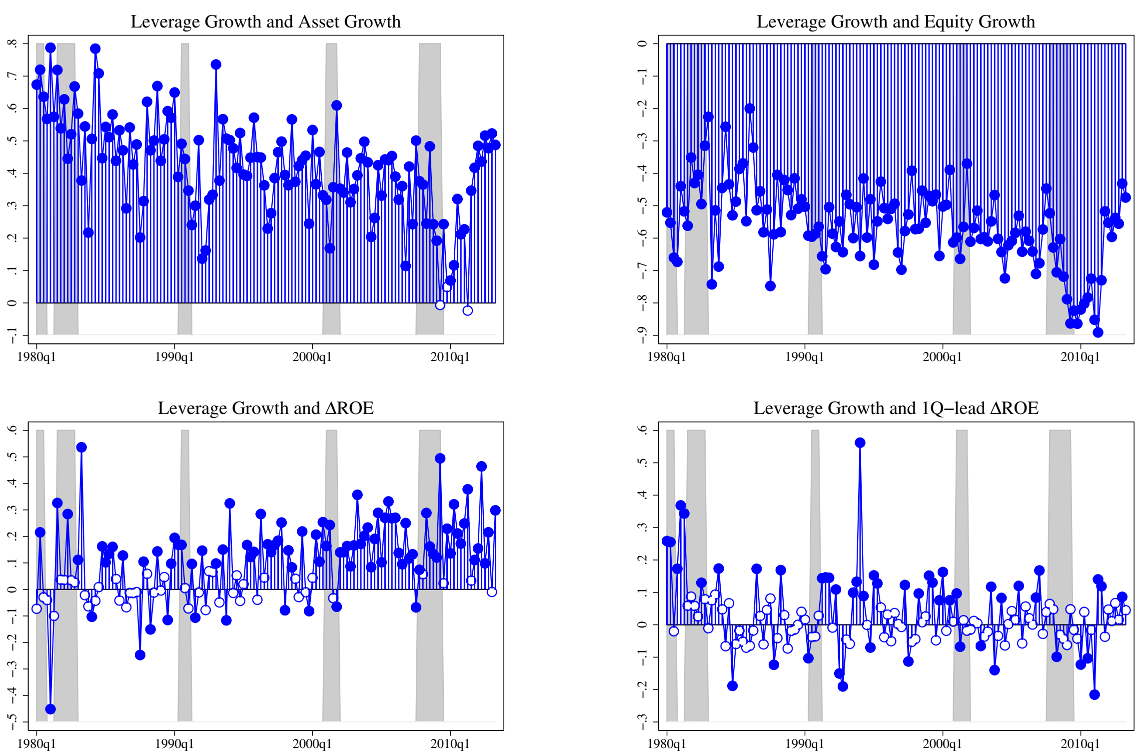


Figure 3. Panel VAR. The figure is generated from the panel VAR estimates reported in Table 2. Identification is recursively using a Cholesky decomposition with book equity being most exogenous, followed by book-to-market, leverage, and ROE. Standard errors are computed via bootstrap using 500 draws. The panel VAR methodology is based on Holtz-Eakin, Newey, and Rosen (1988).

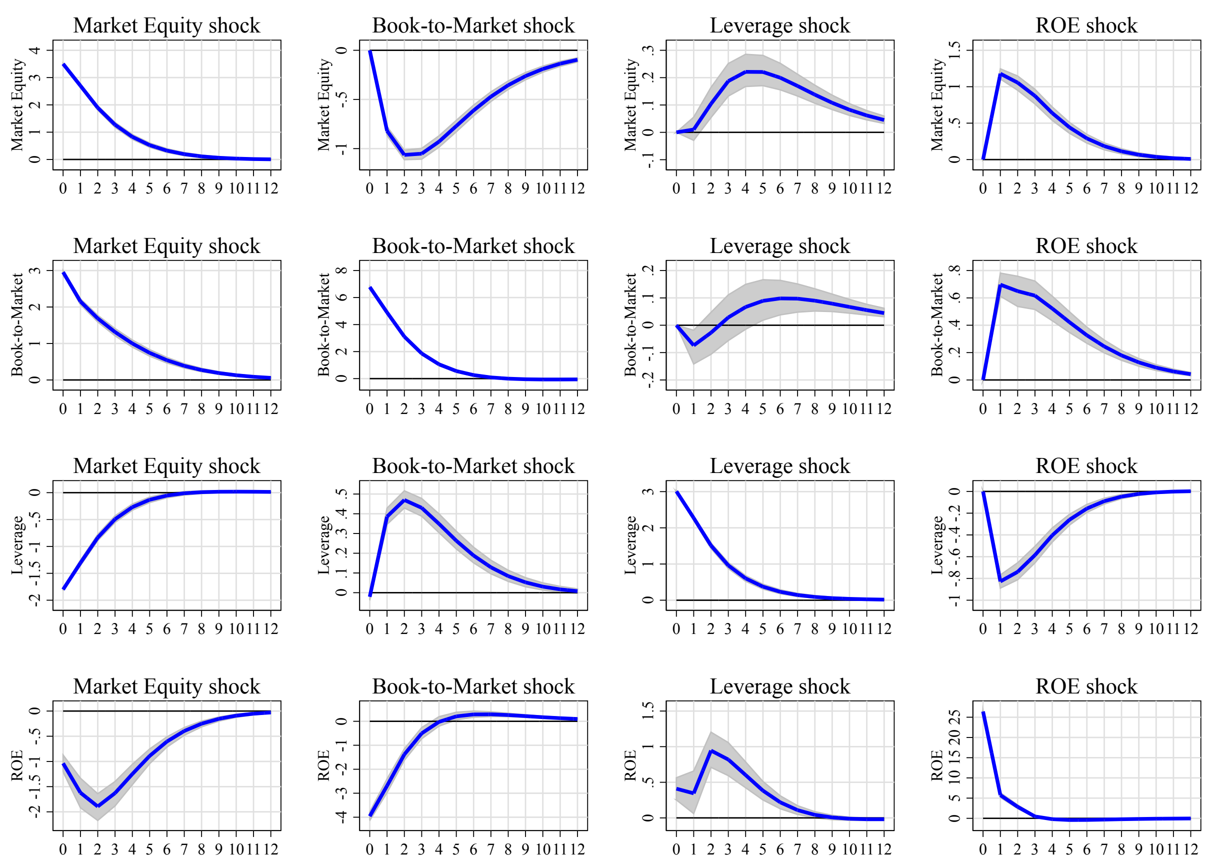


Figure 4. Pricing Factors. This figure plots the monthly holding period returns of the five pricing factors together with NBER recession shadings. The upper left panel shows returns to the financial sector low minus high leverage growth portfolio formed as the difference between the first and fifth quintiles; the upper right panel shows returns to the financial sector high minus low ROE portfolio formed as the difference between the fifth and first quintiles; the middle left panel shows the returns to the financial sector small minus big size sorted portfolio, formed as the average across double sorts on size and book-to-market as in Fama and French; the middle right panel shows the returns to the financial sector high minus low book-to-market sorted portfolio, formed as the average across double sorts on size and book-to-market as in Fama and French; and the lower left panel shows the excess return to the value-weighted financial sector. All returns are annualized by multiplying monthly returns by twelve.

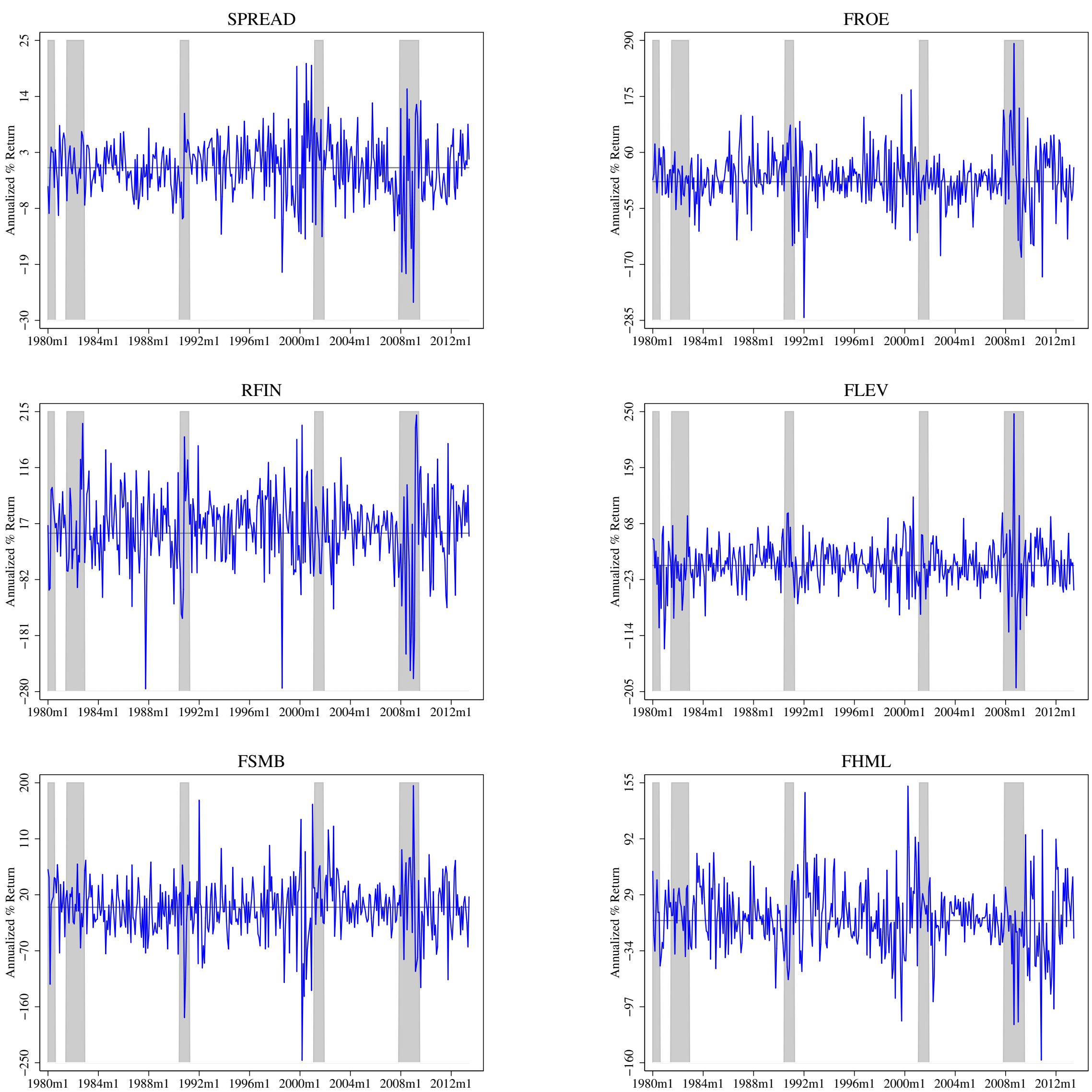
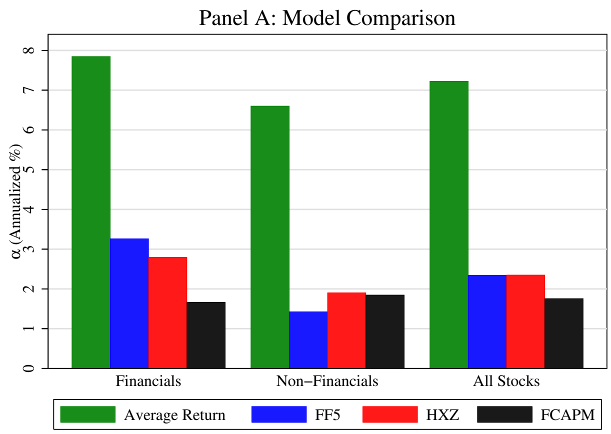
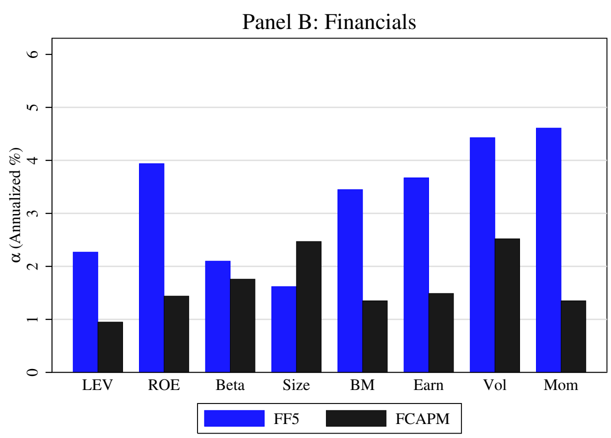


Figure 5. Pricing Performance: Pricing Errors. This figure shows the average absolute pricing errors (αs) for each model. HXZ refers to the model of Hou, Xue, and Zhang (2014), FF5 is the model of Fama and French (2014), and FCAPM is our financial sector model. Panel A computes the average absolute value of alphas for various models for all portfolios sorted within financials, non-financials, and the average across both. Panels B and C show the absolute αs for each individual sorted cross-section both for financial and non-financials. Here we only show the comparison of our FCAPM to the FF 5 factor model.





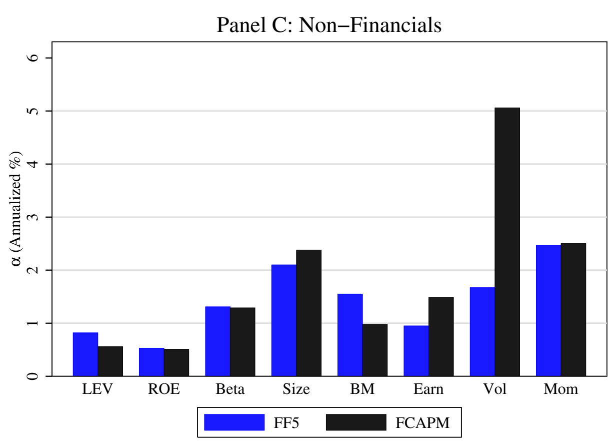


Figure 6. Principal Components This figure plots the fraction of the variance of time-series pricing errors explained by the first 10 principal components under different models and different cross-sections of assets. The upper left panel refers to a cross-section of 25 ROE and leverage growth sorted financial sector portfolios; the upper right panel refers to a cross-section of 25 size and book-to-market sorted financial sector portfolios; the lower left panel refers to a cross-section of 25 ROE and leverage growth sorted non-financial portfolios; and the lower right panel refers to a cross-section of 25 size and book-to-market sorted non-financial portfolios taken from Ken French's website. Each cross-section is the result of 5x5 independent sorts. Each panel shows the fraction of variance explained of 1) pricing errors of the CAPM, 2) pricing errors of the 3-factor Fama-French model, 3) pricing errors of the 5-factor FCAPM, 4) excess returns, and 5) pricing errors from a model of the first 5 principal components of the asset returns themselves.

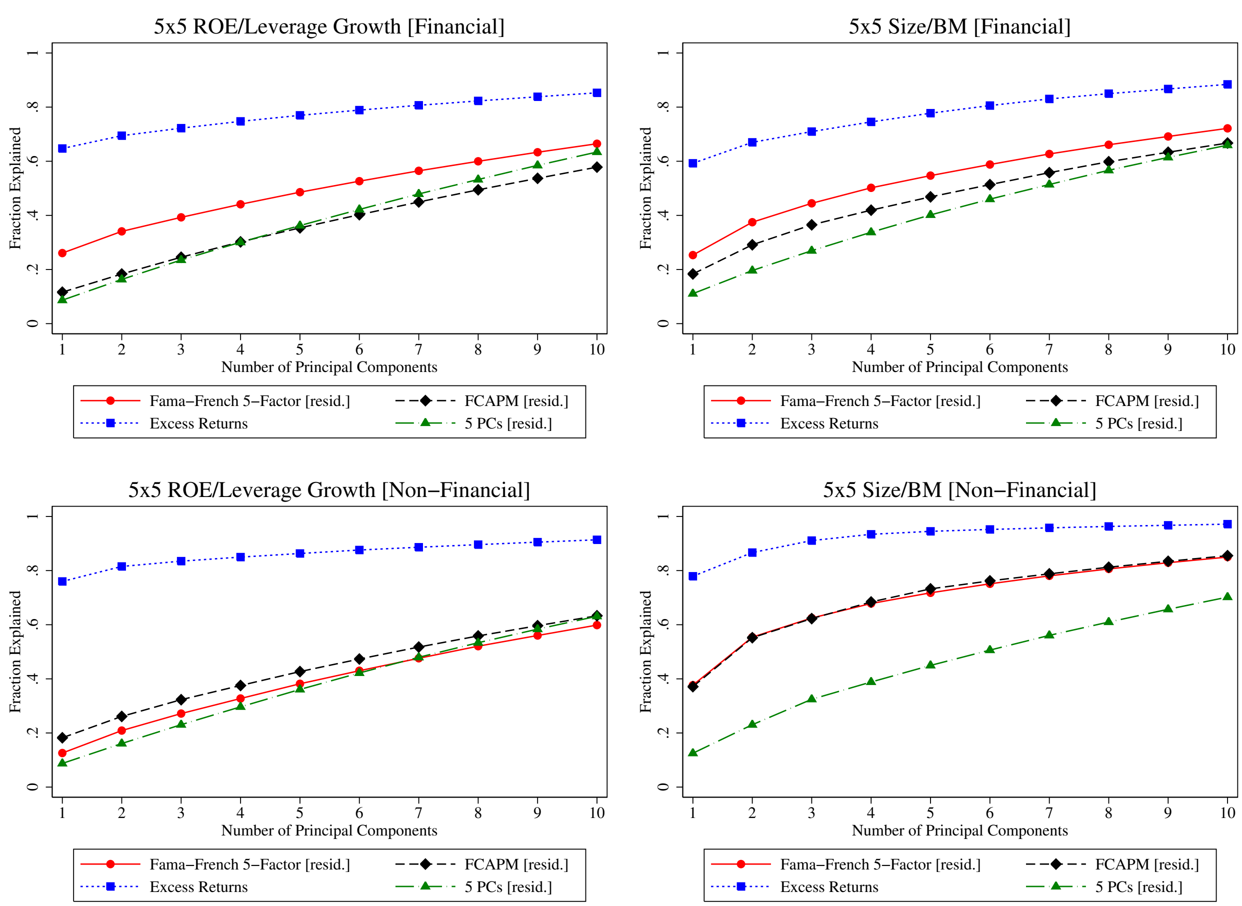


Figure 7. Long Horizon Panel Forecasting Slopes. This figure plots the panel regression forecasting slopes for cumulative, overlapping, annualized returns at 1-60 month horizons. The first five panels give univariate slopes with a 95% error band calculated with a Newey-West correction; the last panel gives the multivariate R^2 with all five characteristics included.

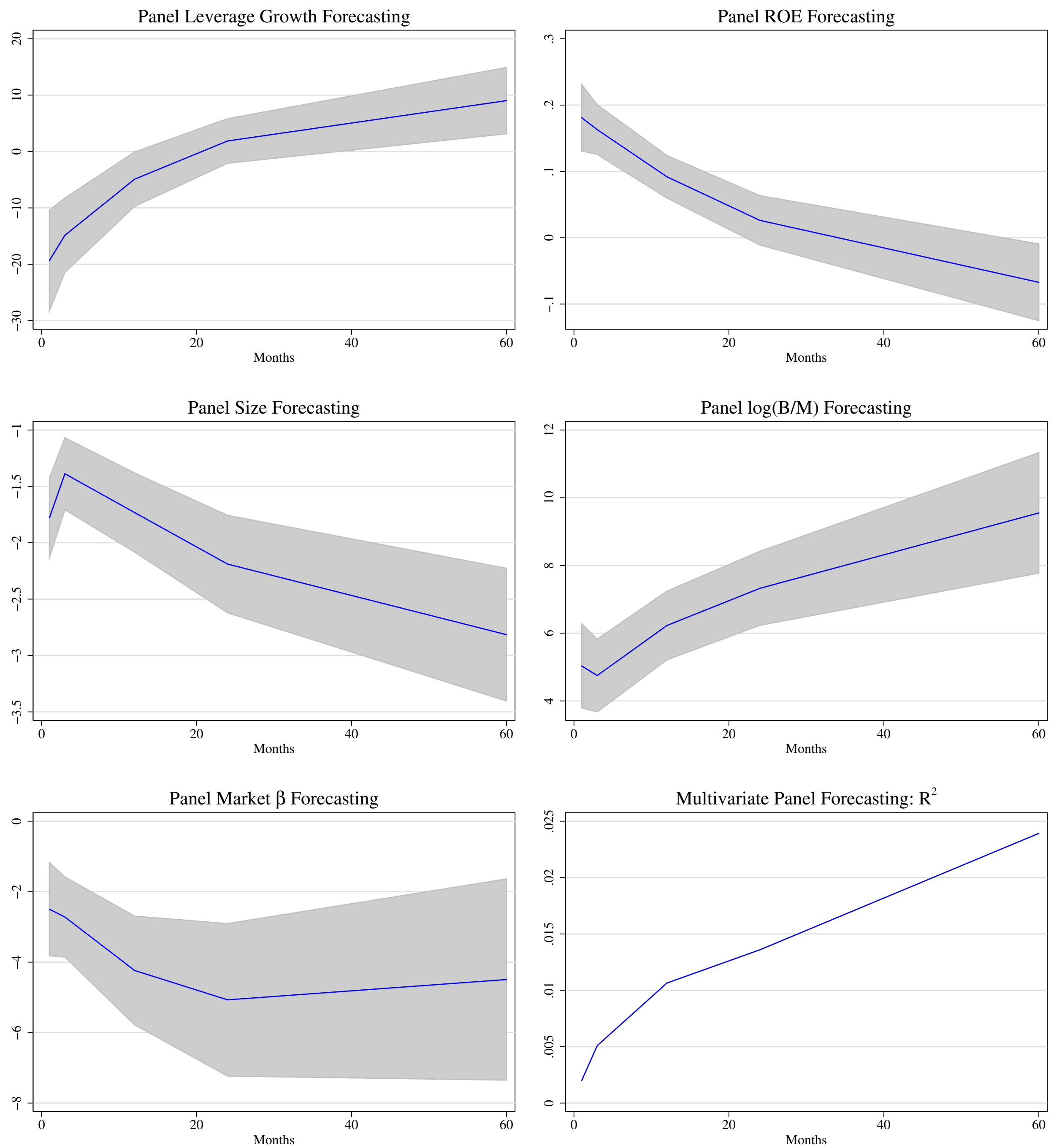


Figure 8. Conditional Expected Returns. This figure plots the conditional expected returns for the five pricing factors estimated using out-of-sample Kelly-Pruitt (2013) partial least squares regressions. Each panel plots the annual factor returns together with the expected return to the factor, and NBER recession shadings. Expected returns are computed with a four quarter lag.

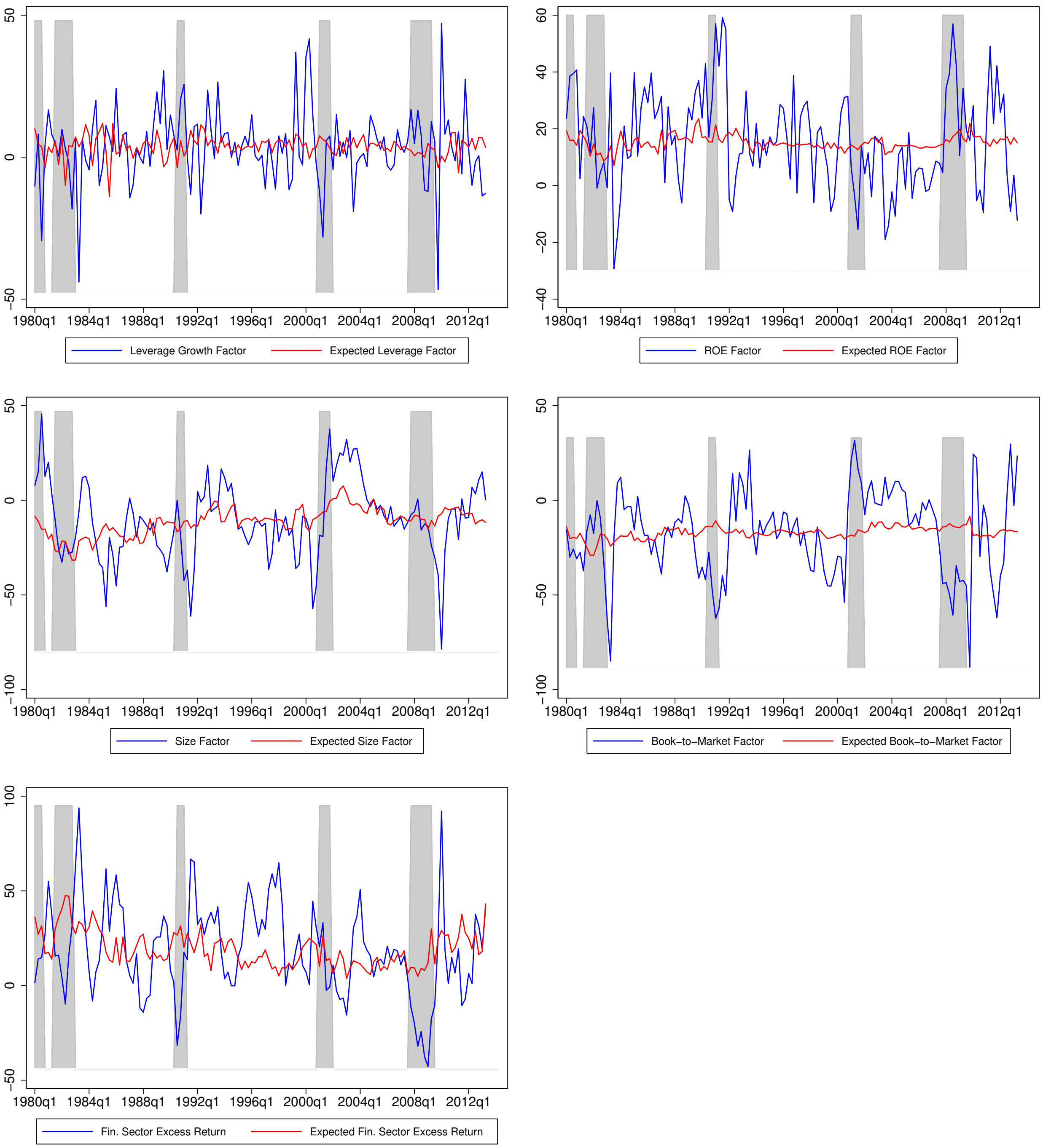


Figure 9. Alternative Estimates of the Cost of Capital. The first panel of this figure plots the value-weighted average ROE for the financial sector and the expected value-weighted equity return of the financial sector, together with NBER recession shadings. Both series are annualized by multiplying the quarterly series by four. The second panel plots the cross-correlogram of the expected equity return with respect to ROE.

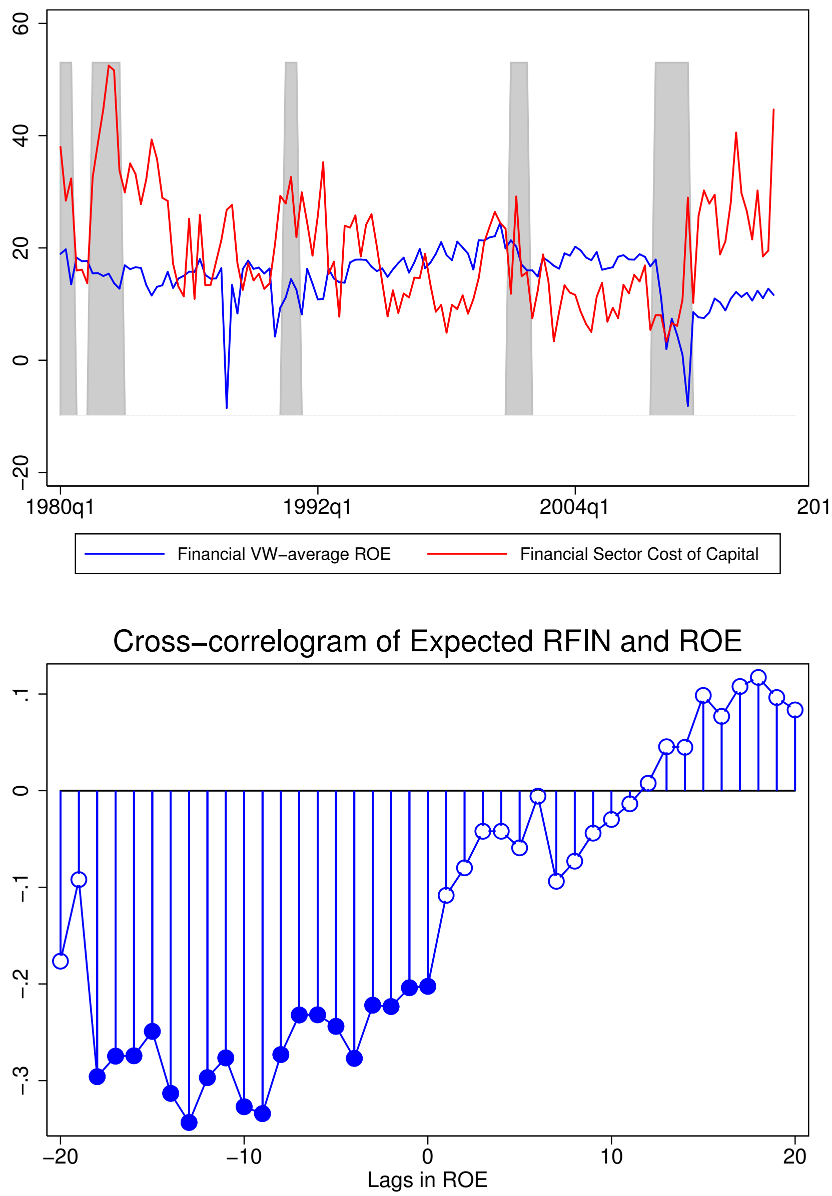


Table 1. Panel Regressions. This table shows the output from panel regressions of financial sector equity returns on the following characteristics: market beta, log-size as measured by the logarithm of market equity, log-book-to-market, quarter-to-quarter leverage growth, return-on-equity (ROE). Each characteristic is updated quarterly, while the excess returns are monthly. "F Ret" indicates that the panel regression is run only on financial sector equity returns (those with SIC code 6), while "NF Ret" represents non-financials. Equity returns are from CRSP, while characteristics are from Compustat. Standard errors are clustered by firm and month with corresponding t-stats in parenthesis. The sample is January 1980 - December 2013 in Panel A. Panel B excludes the years 2008 and 2009 for robustness as bank stocks experienced extreme returns in this period.

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	F Ret	F Ret	F Ret	F Ret	F Ret	F Ret	F Ret	F Ret	NF Ret
logSize	-0.80		-0.64		-1.10	-1.02	-9.80	-0.46	-0.81
	(-1.11)		(-0.92)		(-1.63)	(-1.52)	(-5.04)	(-0.73)	(-0.96)
logBM	4.98		5.38		6.33	6.52	8.35	4.12	5.75
	(2.41)		(2.43)		(2.88)	(2.96)	(2.00)	(3.10)	(3.06)
β	-0.15		-0.07		1.05	0.84	-2.69	2.32	-1.16
	(-0.04)		(-0.02)		(0.31)	(0.24)	(-0.74)	(0.84)	(-0.42)
ΔLeverage		-19.34	-21.36			-14.40	-10.95	-9.06	0.29
		(-2.62)	(-2.67)			(-2.19)	(-1.64)	(-1.85)	(0.06)
ROE				0.18	0.22	0.23	0.08	0.20	0.05
				(2.74)	(3.18)	(3.26)	(1.16)	(4.18)	(1.15)
Firm FE							Y		
Time FE								Y	
N	289,207	300,403	280,816	289,449	268,722	267,352	267,352	267,352	1,341,413
R-squared	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.12	0.00

Panel B	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	F Ret	F Ret	F Ret	F Ret	F Ret	F Ret	F Ret	F Ret	NF Ret
logSize	-0.66		-0.52		-1.01	-0.94	-7.71	-0.54	-0.69
	(-0.90)		(-0.72)		(-1.52)	(-1.40)	(-4.28)	(-0.84)	(-0.90)
logBM	5.29		5.68		6.48	6.67	10.15	4.64	4.86
	(2.57)		(2.56)		(2.93)	(3.01)	(2.40)	(3.63)	(2.56)
β	0.02		0.20		1.06	0.80	-2.72	1.08	-2.28
	(0.01)		(0.07)		(0.37)	(0.28)	(-0.89)	(0.46)	(-0.80)
ΔLeverage		-19.68	-21.18			-13.88	-11.54	-9.65	-4.12
		(-2.95)	(-3.02)			(-2.16)	(-1.76)	(-1.93)	(-1.11)
ROE				0.18	0.21	0.23	0.10	0.22	0.08
				(3.39)	(4.22)	(4.45)	(2.11)	(5.03)	(1.87)
Firm FE							Y		
Time FE								Y	
N	269,169	279,842	261,022	268,900	249,054	247,704	247,704	247,704	1,269,191
R-squared	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.11	0.00

Table 2. Correlations. This Table shows the correlations among firm characteristics. The sample is January 1980 - December 2013.

	ΔLEV	ROE	Asset growth	Equity growth	Earnings growth
Δ LEV	1				
ROE	-.12***	1			
Asset growth	.43***	.11***	1		
Equity growth	-.56***	.23***	.45***	1	
Earnings growth	-.02***	.01***	.01**	.04***	1
Net income growth	-.03***	.02***	.01***	.04***	.79***

Table 3. Panel Vector Autoregression. This Table shows estimates from the panel vector autoregression (VAR). The endogenous variables are book equity (annual log change), book-to-market (annual log change), leverage (annual log change), and ROE (annual change). The methodology for the VAR is based on Holtz-Eakin, Newey, and Rosen (1988). Panel A presents the output from the VAR regressions, while Panel B provides the correlation matrix of the error terms. The impulse response function is constructed from a Cholesky decomposition with the ordering book equity, book-to-market, leverage, ROE, where the book equity is the "most exogenous." Standard errors are computed via bootstrap with 500 draws. The sample is January 1980 - December 2013.

Panel A: Panel Vector Autoregression

	Book Equity	Book-to-Market	Leverage	ROE
Book equity (1Q lag)	0.86	-0.02	-0.03	0.13
	(74.68)	(-1.01)	(-2.58)	(1.95)
Book-to-market (1Q lag)	-0.09	0.74	0.04	-0.27
	(-24.12)	(112.54)	(11.85)	(-10.44)
Leverage (1Q lag)	-0.00	-0.03	0.76	0.08
	(-0.30)	(-2.08)	(64.11)	(-1.37)
ROE (1Q lag)	0.04	0.03	-0.03	0.22
	(26.72)	(12.50)	(-22.35)	(16.05)
Book equity (2Q lag)	-0.06	0.11	0.01	-0.10
	(-6.34)	(7.95)	(0.77)	(-1.73)
Book-to-market (2Q lag)	0.03	-0.06	-0.02	0.10
	(7.89)	(-10.63)	(-5.22)	(4.15)
Leverage (2Q lag)	0.03	0.03	-0.07	0.21
	(3.51)	(2.28)	(-7.13)	(3.42)
ROE (2Q lag)	0.01	0.00	0.00	0.08
	(-4.57)	(0.47)	(-2.40)	(7.77)

Panel B: Correlation of Residuals

	Book Equity	Book-to-Market	Leverage	ROE
Book Equity	1			
Book-to-Market	0.39	1		
Leverage	-0.52	-0.21	1	
ROE	-0.06	-0.13	0.06	1

Table 4. Summary Statistics of the Characteristics and Pricing Factors. The first panel gives summary statistics for the quarterly characteristics used in our financial sector panel regressions, given as the time-series average of cross-sectional statistics. The sample is 1980q1-2013q4. The second panel gives monthly, annualized time-series statistics for the five pricing factors of the FCAPM. The last three columns give the time-series correlation of the factors with the Fama French factors. The sample is January 1980 to December 2013.

Characteristics	Mean	Std Dev	Skew	Kurt
Leverage Growth	0.01	0.11	0.43	21.11
ROE	6.79	29.40	-2.18	37.87
Log(size)	4.82	1.92	0.37	2.95
Log(BM)	-0.26	0.70	-0.57	4.74

Factors	Mean	Std Dev	Skew	Kurt	Sharpe Ratio
FROE	6.92	16.52	-0.30	11.78	0.42
SPREAD	-0.01	1.75	-0.59	8.77	-0.01
MktRF	7.30	15.82	-1.70	9.77	0.46
HML	3.93	10.66	0.03	10.18	0.37
SMB	1.71	10.67	1.69	21.03	0.16

Factors	Corr Market	Corr SMB	Corr HML	Corr RMW	Corr CMA	Corr MKT	Corr rME	Corr rI/A	Corr rROE
FROE	-0.12	-0.29	-0.13	0.29	-0.11	-0.13	-0.22	-0.08	0.47
SPREAD	0.13	-0.02	0.44	0.12	0.18	0.12	-0.01	0.18	-0.03
MktRF	1	0.22	-0.34	-0.29	-0.41	1	0.14	-0.42	-0.27
HML	-0.34	-0.21	1	0.27	0.70	-0.33	-0.16	0.66	-0.02
SMB	0.24	0.99	-0.32	-0.51	-0.14	0.25	0.96	-0.21	-0.39

Table 5. This table provides comparisons of alphas across models. HXZ is the Hou, Xue, and Zhang (2014) 4 factor model, FF5 is the Fama and French (2014) 5 factor-model, and FCAPM is our financial sector model.

Panel A: Model Comparisons on Average Absolute Alphas

Cross-Section:	Avg Ret	HXZ	FF5	FCAPM
Financials	7.85	2.80	3.26	1.67
Non-Financials	6.60	1.90	1.42	1.85
All Stocks	7.22	2.35	2.34	1.76

Panel B: Absolute Alphas for Financials

Cross-Section:	Avg Ret	HXZ	FF5	FCAPM
Leverage	8.78	2.01	2.27	0.95
ROE	7.24	3.02	3.94	1.44
Market Beta	8.13	2.05	2.10	1.76
Size	9.15	1.70	1.62	2.47
Book-to-market	8.74	2.47	3.45	1.35
Earnings	7.52	3.38	3.67	1.49
Volatililty	6.20	4.13	4.43	2.52
Momentum	7.02	3.62	4.61	1.35

Panel C: Absolute Alphas for Non-Financials

Cross-Section:	Avg Ret	HXZ	FF5	FCAPM
Leverage	7.35	0.87	0.82	0.56
ROE	5.68	1.77	0.53	0.51
Market Beta	7.06	1.19	1.31	1.29
Size	8.10	3.56	2.10	2.38
Book-to-market	7.73	2.81	1.55	0.98
Earnings	7.18	0.78	0.95	1.49
Volatility	3.86	0.90	1.67	5.06
Momentum	5.84	3.33	2.47	2.50

Table 6. Explanatory Power of Factors. This table shows the partial R^2 s of adding each respective factor to the other factors, in different sorts, averaged across all of the test portfolios.

FCAPM		Total R^2	FROE	SPREAD	MktRF	SMB	HML
25 Leverage Growth/ROE	[Fin]	66.16	3.03	8.32	33.05	0.33	0.81
25 Size/BM	[Fin]	59.26	1.46	5.24	26.14	5.02	1.81
25 FF Size/BM	[NonFin]	90.81	0.09	0.10	56.13	9.81	4.73
25 FF Size/Mom.	[NonFin]	83.56	0.91	0.18	52.31	7.65	1.28

Fama-French		Total R^2	Market	SMB	HML	RMW	CMA
25 Leverage Growth/ROE	[Fin]	55.87	44.63	0.79	4.97	0.67	0.32
25 Size/BM	[Fin]	54.15	34.77	7.21	4.60	0.92	0.15
25 FF Size/BM	[NonFin]	91.50	57.21	9.58	3.11	0.60	0.09
25 FF Size/Mom.	[NonFin]	84.14	53.78	8.30	1.52	0.91	0.38

Hou-Xue-Zhang		Total R^2	MKT	rME	rI/A	rROE
25 Leverage Growth/ROE	[Fin]	49.30	41.71	0.31	2.15	1.07
25 Size/BM	[Fin]	47.70	32.46	4.75	2.38	1.17
25 FF Size/BM	[NonFin]	87.21	57.32	9.09	2.70	0.58
25 FF Size/Mom.	[NonFin]	84.33	53.30	7.48	0.70	3.21

Table 7. Panel Forecasting. This table gives univariate panel regression forecasting slopes for one month, three month, 12 month, and 60 month overlapping, annualized returns. Standard errors are Newey-West adjusted for autocorrelation.

	1M	3M	12M	24M	60M
Leverage Growth	-19.34***	-14.86***	-4.901**	1.876	9.029***
ROE	0.181***	0.163***	0.0919***	0.0262	-0.0672**
Log-size	-1.780***	-1.388***	-1.732***	-2.189***	-2.815***
Log-B/M	5.035***	4.750***	6.228***	7.326***	9.551***
Market beta	-2.498***	-2.719***	-4.236***	-5.070***	-4.493***

Table 7. Summary Statistics of Kelly-Pruitt Factors. This table reports the summary statistics for the Kelly-Pruitt Factors of book leverage growth, ROE, size, log book-to-market, and dividend yield. Each factor corresponds to a different characteristic and is reported as the fitted value of the regression of the high minus low portfolio return sorted on that characteristic regressed on that factor. Thus, the factors are converted to (annualized) expected returns.

	Mean	Std. Dev.	Skew	Kurt
book leverage growth	3.77	0.61	1.50	0.43
ROE	15.07	0.27	5.98	0.19
size	-11.08	1.76	-4.40	1.24
book-to-market	-17.08	0.20	-6.78	0.14
dividend yield	18.90	0.48	7.50	0.34

Table 8. Financial Sector Expected Return and ROE. This table reports the summary statistics for the expected return to the financial sector and the financial sector ROE.

	Mean	Std. Dev.	Skew	Kurt	Correlation
Expected return	19.66	5.17	7.80	3.65	-0.20
ROE	14.97	2.49	5.94	1.76	-0.20

Table A1. Pricing Performance. This table shows the time series properties of quintile sorts by size, book-to-market, leverage change, ROE, market beta, and volatility. All α s and returns are monthly and annualized by multiplying by twelve. The sample period is January 1980 to December 2013.

Leverage Growth Sorts	Q1	Q2	Q3	Q4	Q5	Q1-Q5
$R_t - R_f$	9.792	7.793	9.361	8.947	8.004	1.788
α CAPM	1.447	0.470	2.432	1.610	-0.519	1.965
α Fama-French	-1.190	-3.357*	-1.287	-2.035	-3.482*	2.292
α Zhang	-1.117	-4.113*	-1.314	-1.289	-2.223	1.106
α FCAPM	1.198	0.309	1.948	0.815	0.498	0.700
β MktRF	1.101***	0.981***	0.931***	0.993***	1.122***	-0.021
β FROE	0.015	0.035	0.049*	0.063**	-0.124***	0.139**
β SPREAD	4.990***	4.935***	5.204***	5.357***	5.086***	-0.096
R^2	0.006	-0.143	-0.118	-0.107	-0.112	0.118
ROE Sorts	Q1	Q2	Q3	Q4	Q5	Q5-Q1
$R_t - R_f$	2.943	5.196	8.500	9.705	9.868	6.924
α CAPM	-5.736*	-2.577	1.175	2.380	2.071	7.807***
α Fama-French	-8.093***	-6.762***	-3.048	-1.245	-0.576	7.517**
α Zhang	-5.259	-4.430	-2.445	-1.290	-1.667	3.592
α FCAPM	0.892	-3.425**	0.119	1.896*	0.892	0***
β MktRF	1.041***	1.071***	0.996***	0.992***	1.041***	0***
β FROE	-0.772***	-0.131**	0.017	0.024	0.228***	1***
β SPREAD	4.976***	4.664***	5.188***	5.285***	4.976***	0**
R^2	-0.096	0.053	-0.017	-0.136	-0.096	0
Size Sorts	Q1	Q2	Q3	Q4	Q5	Q5-Q1
$R_t - R_f$	9.820	7.981	9.528	10.664	7.755	-2.065
α CAPM	5.121	3.050	3.704	4.262*	-0.142	-5.263*
α Fama-French	2.578	-0.561	-1.193	-0.845	-2.911*	-5.489*
α Zhang	4.508	0.317	0.230	-0.889	-2.577	-7.085**
α FCAPM	5.626**	2.382	2.044	2.280	0.033	-5.593**
β MktRF	0.560***	0.622***	0.747***	0.827***	1.049***	0.489***
β FROE	-0.239***	-0.119***	-0.074**	-0.009	0.008	0.247***
β SPREAD	1.735***	2.102***	2.746***	3.137***	5.538***	3.803***
R^2	0.511	0.458	0.585	0.560	-0.162	-0.673

Table A1. Count'd.

BM Sorts	Q1	Q2	Q3	Q4	Q5	Q5-Q1
$R_t - R_f$	7.993	7.427	10.879	7.140	10.261	2.268
α CAPM	0.172	0.308	3.574	-0.872	1.463	1.291
α Fama-French	-2.851	-3.721**	-1.182	-4.710**	-4.762	-1.911
α Zhang	-3.291	-3.721	0.047	-3.322	-1.976	1.315
α FCAPM	-0.649	0.117	2.718**	0.001	3.245	3.894
β MktRF	1.040***	0.953***	0.983***	1.052***	1.177***	0.137*
β FROE	0.167***	0.081***	-0.010	-0.227***	-0.544***	-0.712***
β SPREAD	4.275***	5.446***	5.771***	5.923***	5.573***	1.298*
R^2	-0.053	-0.210	-0.004	-0.017	0.052	0.104
Market Beta Sorts	Q1	Q2	Q3	Q4	Q5	Q5-Q1
$R_t - R_f$	7.683	8.630	8.585	7.008	8.744	1.061
α CAPM	4.525*	4.525**	3.491*	0.864	-0.664	-5.189**
α Fama-French	0.575	1.074	-0.913	-4.715***	-3.224	-3.799
α Zhang	0.327	0.251	-2.103	-5.021**	-2.552	-2.880
α FCAPM	3.278*	3.250*	1.961	-0.252	-0.075	-3.353
β MktRF	0.420***	0.560***	0.706***	0.850***	1.265***	0.846***
β FROE	-0.049*	-0.012	0.042	0.019	-0.053**	-0.004
β SPREAD	1.428***	1.923***	2.829***	4.605***	5.949***	4.521***
R^2	0.378	0.275	0.175	0.023	-0.134	-0.512
Volatility Sorts	Q1	Q2	Q3	Q4	Q5	Q1-Q5
$R_t - R_f$	8.588	7.993	9.937	8.247	-3.764	12.352
α CAPM	2.985	1.067	1.898	-1.762	-15.229***	18.214***
α Fama-French	-1.686	-3.496*	-1.778	-3.371	-11.819***	10.133**
α Zhang	-2.907	-4.284*	-1.429	-1.928	-10.097**	7.190*
α FCAPM	1.676	0.054	1.037	0.506	-9.306***	10.982***
β MktRF	0.797***	0.961***	1.107***	1.255***	1.395***	-0.598***
β FROE	0.086***	0.077***	0.013	-0.205***	-0.642***	0.728***
β SPREAD	3.815***	5.232***	5.401***	5.890***	3.399***	0.416
R^2	-0.086	-0.110	-0.028	0.171	0.316	-0.401
Momentum Sorts	Q1	Q2	Q3	Q4	Q5	Q5-Q1
$R_t - R_f$	1.536	7.757	7.604	8.985	9.214	7.678
α CAPM	-8.143*	-0.036	0.359	2.460	1.757	9.900**
α Fama-French	-10.511**	-4.373*	-3.107	-2.399	-2.642	7.869
α Zhang	-4.905	-1.773	-2.472	-2.820	-6.152***	-1.247
α FCAPM	-4.392	0.569	-0.199	1.205	0.361	4.753
β MktRF	1.235***	1.034***	0.966***	0.888***	0.999***	-0.236**
β FROE	-0.582***	-0.144***	0.017	0.129***	0.160***	0.742***
β SPREAD	6.097***	6.026***	5.629***	5.054***	4.350***	-1.747*
R^2	-0.032	-0.115	-0.043	-0.096	0.034	0.066

Figure A1. Pricing Performance: Pricing Errors for Financials. This figure shows the average pricing errors for value-weighted portfolios sorted into quintiles. The upper left panel shows αs for leverage growth sorted portfolios; the upper right panel shows αs for ROE sorted portfolios; the middle left panel shows αs for size sorted portfolios; the middle right panel shows αs for book-to-market sorted portfolios; the lower left panel shows αs for market beta sorted portfolios; and the lower right panel shows αs for volatility sorted portfolios. All returns are annualized by multiplying monthly returns by twelve.

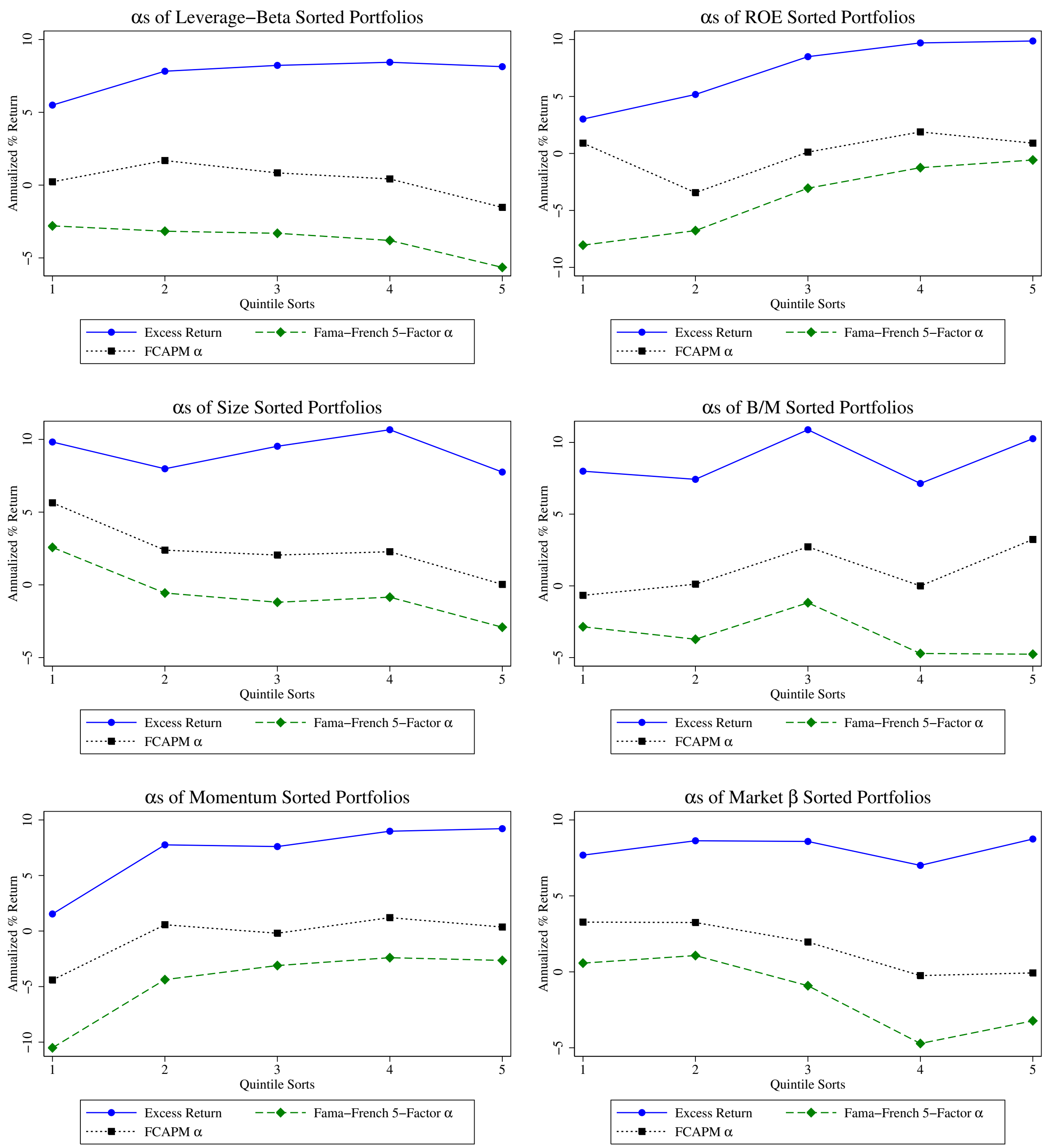


Figure A2. Pricing Performance: Pricing Errors for Non-Financials. This figure shows the average pricing errors for value-weighted portfolios sorted into quintiles. The upper left panel shows αs for leverage growth sorted portfolios; the upper right panel shows αs for ROE sorted portfolios; the middle left panel shows αs for size sorted portfolios; the middle right panel shows αs for book-to-market sorted portfolios; the lower left panel shows αs for market beta sorted portfolios; and the lower right panel shows αs for volatility sorted portfolios. All returns are annualized by multiplying monthly returns by twelve.