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# Financial Intermediaries and the Cross-Section of Asset Returns

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## Abstract

We document that risky asset returns can largely be explained by their covariances with shocks to the aggregate leverage of security broker-dealers. Our single-factor leverage model compares favorably with existing asset pricing benchmarks, including multi-factor equity models tested in the cross-sections sorted by size and book-to-market, momentum, and industries. The model also performs well in the cross section of Treasury bond portfolios sorted by maturity. Our findings indicate that broker dealer leverage is a valid representation of the stochastic discount factor, an interpretation consistent with recent intermediary asset pricing theories.



Key words: cross-sectional asset pricing, financial intermediaries


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# 1 Introduction

Modern finance theory asserts that asset prices are determined by their covariances with the stochastic discount factor (SDF), which is usually linked to the marginal value of aggregate wealth. Assets that are expected to pay off in future states with high marginal value of wealth are worth more today, as dictated by investors' first order conditions. Following this theory, much of the empirical asset pricing literature centers around measuring the marginal value of wealth of a representative investor, typically the average household. Specifically, the SDF is represented by the marginal value of wealth aggregated over all households. However, the logic that leads to this SDF relies on strong assumptions: all households must participate in all markets, there cannot be transactions costs, households are assumed to execute complicated trading strategies, the moments of asset returns are known, and investment strategies are continuously optimized based on forward-looking information. If these assumptions are violated for some agents, it can no longer be assumed that the marginal value of wealth of the average household prices all assets. For example, if some investors trade only in (say) value stocks, their marginal value of wealth can only be expected to correctly price those stocks. In contrast, should there exist a single class of investors that fits the assumptions of modern finance theory, their marginal value of wealth can be expected to price all assets.

Guided by modern finance theory, this paper shifts attention from measuring the SDF of the average household to measuring a "financial intermediary SDF." This approach takes us to a new place in the field of empirical asset pricing: rather than emphasizing average household behavior, the assumptions of frictionless markets and intertemporally optimizing behavior suggest to elevate financial intermediaries to the center stage of asset pricing. Indeed, financial intermediaries do fit the assumptions of modern finance theory nicely: They trade in many asset classes following often complex investment strategies. They face low transaction costs, which allows trading at high frequencies. Moreover, intermediaries use sophisticated, continuously updated models and extensive data to form forward-looking expectations of asset returns. Therefore, if we can measure the marginal value of wealth for these active investors, we can expect to price a broader class of assets (an insight due to He and Krishnamurthy, 2009). In other words, the marginal value of wealth of intermediaries can be expected to provide a more informative SDF.

Backed by a number of recent theories that give financial intermediaries a central role in asset pricing, we argue that the leverage of security broker-dealers is a good empirical proxy for the marginal value of wealth of financial intermediaries and it can thereby be used as a representation of the intermediary SDF. We find remarkably strong empirical support for this hypothesis: Exposures to broker-dealer leverage shocks can *alone* explain the average excess returns on a wide variety of test assets, including equity portfolios sorted by size, book-to-market, momentum, and industries, as well as the cross-section of Treasury bond portfolios sorted by maturity. The broker-dealer leverage factor is successful across all cross-sections in terms of high adjusted $R$-squared statistics, low cross-sectional pricing errors (alphas), and prices of risk that are significant and remarkably consistent across portfolios.[1] When taking all these criteria into account, our single factor outperforms standard multi-factor models tailored to price these cross-sections, including the Fama-French three-factor model and a four-factor model that includes the momentum factor. Figure 1 provides an example of the leverage factor's pricing performance in a cross-section that spans 65 common equity portfolios sorted on size, book-to-market, momentum, and industry and 6 Treaury bond portfolios sorted by maturity.

We provide a number of robustness checks that confirm the strong pricing ability of the leverage factor across a variety of equity and bond portfolios. Most importantly, we

[1] The returns on industry and momentum portfolios have thus far been particularly difficult to connect to risk. To the best of our knowledge, our leverage factor provides the first risk-based explanation for the returns on these portfolios. We regard the strong pricing performance across transaction cost intensive momentum and bond portfolios as and indication that these portfolios are better priced by the SDF of a sophisticated intermediary.

construct a tradeable leverage mimicking portfolio (LMP), which allows us to conduct pricing exercises at a higher frequency and over a longer time period. In cross-sectional and time-series tests using monthly data, we show that the single factor mimicking portfolio performs well going back to the 1930's. We also conduct mean-variance analysis and find the LMP to have the highest Sharpe ratio among benchmark portfolio returns. In fact, the mean variance characteristics of the LMP are close to the tangency portfolio on the efficient frontier generated by combinations of the three Fama-French factors and the momentum factor. As a further robustness check, we use the entire cross-section of stock returns to construct decile portfolios based on covariance with the LMP and find substantial dispersion in average returns that line up well with the post-formation LMP betas. Finally, we provide simulation evidence showing that our results are almost certainly not due to chance: The high $R$-squared statistics and low alphas that we obtain in our main tests occur only once in 100,000 simulations drawn at random from the empirical distribution of our leverage factor.

Our empirical results are consistent with a growing theoretical literature on the links between financial institutions and asset prices. First, shocks to leverage may capture the time-varying balance sheet capacity of financial intermediaries. Second, our results can be interpreted in light of intermediary asset pricing models. Third, our findings are consistent with intertemporal, heterogenous agent models where intermediary leverage is driven by economy-wide investment opportunities. Taken together, these three strands of theory imply that leverage will capture aspects of the intermediary SDF that other measures (such as aggregate consumption growth or the return on the market portfolio) do not capture. A common thread in these three strands of theories is the *procyclical* evolution of broker-dealer leverage, which suggests a negative relationship between broker-dealer leverage and the marginal value of wealth of investors. By implication, investors are expected to require higher compensation for holding assets whose returns exhibit greater comovement with broker-dealer leverage shocks. In the language of the arbitrage pricing theory, the cross-sectional price of risk associated with broker-dealer leverage shocks should be positive. To the best of our knowledge, we are the first to conduct cross-sectional asset pricing tests with financial intermediary balance sheet components in the pricing kernel.

The remainder of the paper is organized as follows. Section 2 provides a discussion of the related literature, reviewing a number of theoretical rationalizations for the link between financial intermediary leverage and aggregate asset prices. Section 3 describes the data and section 4 conducts a number of asset pricing tests in the cross-section of stock and bond returns. Section 5 analyzes the properties of the leverage mimicking portfolio, providing a variety of robustness checks. Section 6 discusses directions and challenges for existing theories. Section 7 concludes.

# 2 Financial Intermediary Asset Pricing

Three strands of theoretical research conceptually motivate our financial intermediary pricing kernel. While none of them yield direct empirical implications in terms of observable balance sheet components, they are broadly consistent with our finding that low leverage states are characterized by high marginal utility of wealth and therefore assets that covary positively with leverage earn higher average returns.

The first motivation for the intermediary pricing kernel arises if the balance sheet capacity of intermediaries can directly impact asset price dynamics, as is the case in the literature on limits to arbitrage. In such frameworks, the leverage of financial intermediaries measures the tightness of intermediary risk constraints and therefore their marginal value of wealth. As risk constraints—such as those on intermediary funding—tighten, prices fall, and expected returns rise. Since these models feature risk-neutral investors, the marginal value of wealth is simply the expected return, making low leverage states ones with high marginal utility. Prominent examples of such theories include Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Geanokoplos (2009), and Shleifer and Vishny (1997, 2010). In Brunnermeier and Pedersen, the ex-ante time-zero expected returns are given by $E[R_1^e] = \lambda Cov(\phi_1, R_1^e)$, where $\phi_1$ is the Lagrange multiplier on the time-one margin constraint, which is monotonically decreasing in time-one leverage (see their equation 30). Along similar lines, Danielsson, Shin, and Zigrand (2010) consider risk-neutral financial intermediaries that are subject to a value at risk (VaR) constraint. The intermediaries' demand for risky assets depends on the Lagrange multiplier of the VaR constraint that reflects effective risk aversion. In equilibrium, asset prices depend on the level of effective risk aversion, and hence on the leverage of the intermediaries—times of low intermediary leverage are times when effective risk aversion is high. As a result, financial intermediary leverage directly enters the equilibrium SDF. Importantly, leverage—not wealth—is the key measure of marginal value of wealth in these models.

The second strand of theories asserts that financial intermediaries are the marginal investor, and as a result the stochastic discount factor is given by the marginal value of wealth of the intermediary sector (e.g. He and Krishnamurthy, 2010). In this framework, only financial intermediaries possess the technology to invest in all risky asset classes. As a result, the stochastic discount factor is directly related to the functioning of the financial intermediary sector, and to the preferences that the owners of financial intermediaries have. In the simple setting of log preferences, the stochastic discount factor is proportional to the aggregate wealth of the intermediary sector, giving an intermediary CAPM. Acting as market makers, broker-dealers facilitate the trades of active investors such as hedge funds and asset managers. As substabtial inventory is required to meet the demand for such trades, and holding more inventory requires higher leverage, the leverage of broker-dealers may reflect the level of trading activity and wealth within the entire financial sector.[2] Indeed, Cheng,

[2]For example, consider a hedge fund trading a momentum strategy that requires turning over a dollar volume of shares each period proportional to its assets under management. In order to facilitate this volume, the market-making broker-dealer must carry more inventory—requiring it to increase leverage when hedge funds have more assets under management. Broker-dealer leverage can therefore be expected to mirror the wealth of the broader financial intermediary sector, which is otherwise difficult to measure.

Hong and Scheinkman (2010) find that leverage and risk taking by managers in the financial sector is empirically correlated with current compensation, particularly for broker-dealers, suggesting that times of high leverage are associated with high financial sector wealth. Conversely, low leverage states are associated with low wealth states, when the marginal value of wealth is high. Brunnermeier and Sannikov (2010) derive a closely related equilibrium asset pricing model with financial intermediaries where intermediation arises as an outcome of principal agent problems. In their model, the equilibrium is characterized by the dynamic evolution of a single state variable that maps directly onto financial intermediary leverage. As a result, leverage is the relevant state variable in the pricing kernel.

Third, it is possible that financial intermediary balance sheet variables contain information about developments elsewhere in the economy. This is the case in intertemporal settings with time-varying stochastic investment opportunities, which determine the intermediaries' portfolio choice. Consequently, leverage tracks the investment opportunity set, and shocks to leverage mirror shocks to the relevant state variables that in turn determine expected asset returns. When opportunities are good, arbitrageurs will lever up to take advantage of such opportunities. Higher leverage is thus associated with higher expected future wealth via greater risk-taking. Such theories build on heterogeneous-agent extensions of the Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1973) where leverage arises as a reduced-form representation of relevant state variables, capturing shifts in the marginal value of wealth. Examples include Chabakauri (2010), Prieto (2010) and Rytchkov (2009).

While a number of theoretical linkages between financial intermediaries and economy-wide risk have been proposed, the insight that financial institutions' balance sheets contain information about the real economy and expected asset returns has received less empirical attention. Adrian and Shin (2010) document that security broker-dealers adjust their financial leverage aggressively in response to changing economic conditions. Broker-dealers' balance sheet management practices result in high leverage in economic booms and low leverage in economic downturns. That is, broker-dealer leverage is pro-cyclical. In Table 1, we document the pro-cyclicality of leverage relative to the broker-dealers' own asset growth, and relative to aggregate variables including the market return, financial sector profit growth, and financial sector equity return. Recently, Adrian, Moench and Shin (2010) and Etula (2010) show that broker-dealer leverage contains strong predictive power for asset prices. The predictive power of leverage for stock and bond returns suggests that leverage contains valuable information about the evolution of risk premia over time. In this paper, we show that broker-dealer leverage can *price* assets by connecting the cross-section of returns to exposures to broker-dealer leverage shocks.

# 3 Data and Empirical Approach

Motivated by the theories on financial intermediaries and aggregate asset prices, we identify shocks to the leverage of security broker-dealers as a proxy for shocks to the pricing kernel. We use the following measure of broker-dealer ($BD$) leverage:

$$\text{Leverage}_t^{\text{BD}} = \frac{\text{Total Financial Assets}_t^{\text{BD}}}{\text{Total Financial Assets}_t^{\text{BD}} - \text{Total Financial Liabilities}_t^{\text{BD}}}. \tag{1}$$

We construct this variable using aggregate quarterly data on the levels of total financial assets and total financial liabilities of security broker-dealers as captured in Table L.129 of the Federal Reserve Flow of Funds. Table 2 provides the breakdown of assets and liabilities of security brokers and dealers as of the end of 2009.

**Broker-Dealer Aggregate Balance Sheet**. The total financial assets of $2080 billion in 2009 are divided in five main categories: (1) cash, (2) credit market instruments, (3) equities, (4) security credit, and (5) miscellaneous assets. The flow of funds further report finer categories of credit market instruments. According to the "Guide to the Flow of Funds" publication that accompanies the data, miscellaneous assets consist of three subcategories: direct investment of broker-dealers abroad, the net of receivables versus payables vis-a-vis other broker-dealers or clearing corporations, and tangible assets. Note that the net of receivables consists primarily of cash collateral associated with securities lending transactions. Miscellaneous assets represent over half of total assets, while credit market instruments represent slightly over one fourth. While the credit market instruments and the equities on the asset side of the balance sheet are informative about the investment strategies of broker dealers, the miscellaneous assets provide a proxy for investments by broker-dealer clients via their cash collateral positions.

On the liability side of Table 2, the largest items are (1) net repos, (2) security credit, and (3) miscellaneous liabilities. Net repos are the difference between repos and reverse repos, in addition to the difference between securities lent and securities borrowed. Security credit items are payables to either households or to commercial banks. Miscellaneous liabilities consist of three items: foreign direct investment in the broker-dealers, investment in the broker-dealer by the parent company, and unidentified liabilities ("other"). At the end of 2009, these unidentified liabilities were negative, reflecting pecularities in the accounting of the flow of funds (related to derivatives positions and other items that broker-dealers report but that do not have a corresponding Flow of Funds category).

One should note that the balance sheet data reported in the Flow of Funds are aggregated at the subsidiary level. This is important because security broker-dealers are usually subsidiaries of larger bank or financial holding companies.[3] For example, a bank holding company might own a commercial bank, a broker-dealer, a finance company, and perhaps a wealth management unit. In the Flow of Funds, all of these subsidiary balance sheets are reported separately. The balance sheet information for the security broker-dealers is aggregated primarily from the SEC's FOCUS and FOGS reports.

In sum, the asset side of broker-dealer balance sheets consists largely of risky assets, while a substantial portion of the liability side consists of short-term risk-free borrowing (net repos

[3] The item "investment into broker-dealer by parent company" on the liability side of the broker-dealer table reflects the interaction of the subsidiary with the parent company.

make up roughly 25-30% of liabilities). Increases in broker-dealer leverage as captured by the Flow of Funds thus correspond primarily to increases in risk-taking. Moreover, since the leverage of broker-dealers computed from the Flow of Funds is a net number, we do not emphasize the *level* of broker-dealer leverage but instead focus on the *shocks* to broker-dealer leverage.[4]

**Time-Series of Broker-Dealer Leverage.** While the Flow of Funds data begins in the first quarter of 1952, the data from the broker-dealer sector prior to 1968 raises suspicions: broker-dealer equity is *negative* over the period Q1/1952-Q4/1960 and extremely low for most of the 1960s, resulting in unreasonably high leverage ratios. As a result, we begin our sample in the first quarter of 1968.[5] A plot of broker-dealer leverage is displayed in Figure 2. The plot demonstrates that large decreases in broker-dealer leverage are indeed associated with times of macroeconomic and financial sector turmoil, further supporting the idea that sharp decreases in leverage represent "hard times" where the marginal value of intermediary wealth is high.

In order to capture risk that stems from unexpected changes in broker-dealer leverage, we construct shocks to log broker-dealer leverage as innovations over two quarters computed from an autoregression. We use innovations over two quarters (vs. one quarter) to reduce the impact of measurement error in broker-dealer leverage data on our estimates. The procedure leads to stronger time-series correlations between leverage shocks and returns, something non-traded factors often struggle with.[6] Note that due to the high persistence of the leverage series, using the *growth* in leverage (over two-quarters) is virtually identical to using log innovations. Hence, our results are not sensitive to the choice of growth versus

[4]Several items on the balance sheet are netted, particularly repos and receivables.

[5]This choice of start date also lends direct comparison to the liquidity factor of Pastor and Stambaugh (2003), the traded version of which is available on Robert Stambaugh's website since 1968.

[6]Using one-quarter innovations makes the time-series betas less significant, as does the lag of one-quarter innovations. As a further test, we repeat our empirical exercises using two-quarter leverage innovations contemporaneously with *asset returns* measured over two quarters and find that our empirical results strengthen further. This provides additional evidence to the presence of measurement errors in the broker-dealer balance sheet data.

innovations.[7] A plot of broker-dealer leverage shocks is displayed in Figure 2.

**Empirical Strategy**. We test our leverage factor model in the cross-section of asset returns via a linear factor model. That is, we propose a stochastic discount factor (SDF) for excess returns that is affine in financial intermediary leverage shocks:

$$SDF_t = 1 - bLevShock_t.$$

The no-arbitrage condition for asset $i$'s return in excess of the risk-free rate states:

$$\begin{aligned} 0 &= E[R^e_{i,t} SDF_t] \\ &= E[R^e_{i,t}(1 - bLevShock_t)]. \end{aligned}$$

Rearranging and using the definition of covariance, we obtain the factor model:

$$E[R^e_{i,t}] = bCov(R^e_{i,t}, LevShock_t) \tag{2}$$

$$= \lambda_{Lev}\beta_{i,Lev}, \tag{3}$$

where $\beta_{i,Lev} = Cov(R^e_{i,t}, LevShock_t)/Var(LevShock_t)$ denotes the exposure of asset $i$ to broker-dealer leverage shocks and $\lambda_{Lev}$ is the cross-sectional price of risk associated with leverage shocks.

For each asset $i$, we estimate the risk exposures from the time-series regression:

$$R^e_{i,t} = a_i + \beta'_{i,f}\mathbf{f}_t + \epsilon^i_t, \tag{4}$$

where $\mathbf{f}$ represents a vector of risk factors. In order to estimate the cross-sectional price of risk associated with the factors $\mathbf{f}$, we run the Fama and MacBeth (1973) cross-sectional regression of time-series average excess returns, $E\left[\mathbf{R}^e_t\right]$, on risk factor exposures:

$$E\left[\mathbf{R}^e_t\right] = \alpha + \beta'_f\lambda_f + \xi. \tag{5}$$

[7] Our results are also insensitive to using a two-quarter moving average of leverage growth, $\frac{Lev_t + Lev_{t-1}}{Lev_{t-1} + Lev_{t-2}}$.

This approach yields estimates of the cross-sectional prices of risk $\lambda_f$ and the average cross-sectional pricing error $\alpha$.

We compare our single leverage factor ($\mathbf{f} = LevShock$) to standard benchmark factor models, such as the Fama-French (1993) model ($\mathbf{f} = [R_{mkt}, R_{SMB}, R_{HML}]$), where the comparison benchmark will depend on the cross-section of test assets under consideration. We obtain factor data from Kenneth French's data library, Robert Stambaugh's website, and the Federal Reserve Board's Data Releases. The data on equity returns and U.S. Treasury returns are obtained from Kenneth French's data library and CRSP, respectively.

# 4 Empirical Results

We test specifications of the linear factor model (5) in the cross-section of asset returns. The model predicts that the average cross-sectional pricing error ($\alpha$) is zero, so that all returns in excess of the risk-free rate are compensation for systematic risk. As test assets, we consider the following portfolios that address well-known shortcomings of the CAPM: 25 size and book-to-market portfolios, 25 size and momentum portfolios, and 30 industry portfolios. We also consider the cross-section of bond returns, using returns on Treasury portfolios sorted by maturity as test assets.

We compare the performance of our leverage factor to existing benchmark models in each cross-section of test assets. Whenever a factor is a return, we include it also as a test asset since the model should apply to it as well. For instance, when pricing the portfolios sorted on size and book-to-market, we include the Fama-French factors market, SMB and HML as test assets. This forces traded factors to "price themselves" and also allows us to evaluate how our single leverage factor prices these important benchmark factors. A good pricing model features an economically small and statistically insignificant alpha, statistically significant and stable prices of risk across different cross-sections of test assets, and high explanatory power as measured by the adjusted $R$-squared statistic. In order to correct the standard errors for the pre-estimation of betas, we report $t$-statistics of Jagannathan and Wang (1998) in addition to the $t$-statistics of Fama and MacBeth (1973). We also provide confidence intervals for the $R$-squared statistic using 100,000 replications as the sample $R$-squared can be misleading or unstable.

Following the above evaluation criteria, and by applying our single-factor model to a wide range of test assets, we seek to sidestep the criticism of traditional asset pricing tests of Lewellen, Nagel and Shanken (2010). Importantly, we show that the model succeeds beyond the highly correlated size and book-to-market portfolios: Since the three Fama-French factors explain almost all time-series variation in these returns, the 25 portfolios essentially have only 3 degrees of freedom. As Lewellen, Nagel and Shanken point out, choosing factors that are even weakly correlated with the three Fama-French factors can give success in this cross-section and many existing models that show success in this cross-section have little or no power when other test portfolios are considered. We avoid this pitfall by including the more challenging momentum portfolios and industry portfolios as test assets. We also show strong pricing performance across bond portfolios of various U.S. Treasury maturities. This further strengthens our results since the model should apply to *all* risky assets, yet most existing tests only focus on stocks. The single-factor model we propose also avoids many of the criticisms that plague traditional tests, as fitting these cross-sections with many factors is substantially easier. Our simulations show the odds of a random "noise" factor that replicates our results to be only 1 in 100,000.

The sample considered in the main text is Q1/1968-Q4/2009. We display the results for the subsample that excludes the recent financial crisis in the Appendix.[8] The results over the pre-crisis subsample, Q1/1968-Q4/2005, are marginally weaker than the results for the full sample, which suggests that the financial crisis was an important event in revealing the inherent riskiness of some assets. However, the performance comparisons between our

[8]See Tables A1-A2.

leverage model and the existing benchmark models remain qualitatively unaffected across these subsamples. Using the pre-crisis sample, we also show that the Pastor and Stambaugh (2003) liquidity factor does not affect our comparisons.[9]

## 4.1 Size and Book-to-Market Portfolios

We begin our asset pricing exercises with the cross-section of 25 size and book-to-market sorted portfolios, which—since the seminal work of Fama and French (1993)—has become a standard benchmark for factor models. This cross-section highlights the inability of the CAPM to account for the over-performance of small and value stocks, a result that we confirm in column (i) of Table 3: The market factor has no explanatory power for the average returns, with a negative adjusted $R$-squared, and yields a large, highly statistically significant cross-sectional alpha of 1.54% per quarter. The cross-sectional price of risk associated with the market factor is economically small and statistically insignificant. We contrast this failure of the CAPM with the performance of our single factor financial intermediary leverage model. Column (iii) shows that broker-dealer leverage is able to explain 55% of the cross-sectional variation in average returns as measured by the adjusted $R$-squared statistic. Moreover, the cross-sectional alpha is only 0.3% per quarter and statistically indistinguishable from zero. As expected, the price of risk associated with leverage is positive and statistically significant—assets that hedge against adverse leverage shocks earn lower average returns. The 95% confidence interval of the $R$-squared demonstrates how looking at the point estimate may be misleading, as it is indeed wide, from 37% to 89%. Nonetheless, the lower bound is reassuringly high.

Column (ii) demonstrates that the Fama-French model—tailored to price this cross-section—produces an adjusted R-squared of 57%. Yet, this is only *two* percentage points greater than the explanatory power of our leverage model. Moreover, the confidence interval

[9]The Pastor-Stambaugh factor is included only in the shorter sample because it is not available beyond 2008.

of the $R$-squared statistic shows that both the lower and the upper bound are actually lower than the corresponding bounds for the leverage factor model (34% and 82% respectively). Note also that only the market factor and the HML factor have statistically significant prices of risk. To complete the picture, column (iv) combines our leverage factor with the three Fama-French factors in a four-factor specification. Remarkably, our leverage factor drives out the value factor: the price of risk associated with HML nearly halves and the factor is no longer significant at the 5% level. The additional explanatory power of the combined model is limited to about ten percentage points and the alpha remains small and statistically insignificant. These observations suggest that the information content of leverage shocks largely overlaps the information content of the Fama-French factors. The four panels of Figure 6 provide a graphical illustration of the performance of our financial intermediary leverage models relative to the single and multi-factor benchmarks.

## 4.2 Size and Momentum Portfolios

Table 4 and Figure 7 report the pricing results for the 25 size and momentum sorted portfolios. The format follows that of Table 3, but now the momentum factor of Carhart (1997) replaces the HML factor in the three-factor benchmark specification.

Column (i) again confirms that the market model has no explanatory power in this cross-section. This is contrasted with column (iii), which shows that the broker-dealer leverage factor is alone capable of explaining as much as 75% of the cross-sectional returns with a small and statistically *insignificant* alpha of 0.35%. As before, the price of risk associated with leverage shocks is positive and statistically significant. The three-factor benchmark model in column (ii) explains 77% of the cross-sectional returns but produces a statistically significant alpha of 0.36%. Thus, our leverage model again rivals the multi-factor benchmark on its own turf. Moreover, the $R$-squared confidence interval of our leverage factor $[67\%, 93\%]$ is much higher and tighter than that of the benchmark model $[36\%, 86\%]$.

Combining our leverage factor with the three-factor benchmark in column (iv) increases the explanatory power of the model to 87% and further decreases the magnitude of the alpha. In this combined specification, the magnitude of our leverage factor decreases, suggesting that its information content overlaps somewhat with that of the momentum factor.

The strong performance of our leverage factor for the momentum portfolios is particularly impressive as these portfolios have not been associated with any concrete source of macroeconomic risk. We offer a risk-based explanation for the momentum phenomenon: Stocks with high past returns tend to lose their positive momentum when broker-dealers unexpectedly reduce leverage, which can occur as a result of worsening funding conditions, eroding financial sector wealth, or a deterioration in investment opportunities. Our results suggest that momentum is not an asset pricing anomaly, but represents compensation for systematic risk.

## 4.3 Industry Portfolios

Table 5 and Figure 8 display our pricing results for the 30 industry portfolios, which have posed a challenge to existing asset pricing models. Column (i) once again confirms the well-known result that the CAPM cannot price this simple cross-section, leaving an average quarterly return of as much as 1.44% unexplained. The results for our leverage factor in column (iii) tell a different story: Our leverage model is able to explain 24% of the cross-sectional variation with an economically smaller and statistically insignificant alpha of 1.01%. The 95% confidence interval for the $R$-squared statistic is $[11\%, 78\%]$.

As a multi-factor benchmark, we use the Fama-French model. The results in column (ii) show that the three Fama-French factors are able to explain only 6% of the industry cross-section (which is well outside the confidence interval for the leverage factor $R$-squared) with a larger and statistically significant alpha of $-1.39\%$. The 95% confidence interval for the $R$-squared is $[0\%, 32\%]$, showing the limited explanatory power of the multi-factor benchmark in this cross-section. Also, the prices of risk associated with the market, SMB and HML factors are statistically insignificant. Thus, our single leverage factor greatly outperforms the three-factor benchmark in this cross-section. While the explanatory power of our leverage factor in this cross-section is admittedly low, it is nevertheless a significant improvement over the standard benchmark. The specification in column (vi) combines our leverage factor with this benchmark to show that the price of risk associated with shocks to leverage is hardly affected by the Fama-French factors. The adjusted $R$-squared only increases by a few percentage points to 27% but the alpha becomes statistically significant, suggesting that the Fama-French factors may add more harm than good to our single-factor broker-dealer specification.

## 4.4 Simultaneous Testing of Portfolios

We have shown that our leverage factor has broad explanatory power with consistent prices of risk over a number of cross-sections. To further illustrate this property, we next conduct an exercise where the 25 size and book-to-market portfolios, 10 momentum portfolios, and 30 industry portfolios are included *simultaneously* as test assets,[10] forcing the estimated prices of risk to be equal across different cross-sections. The results are reported in Table 6 with graphical illustrations in Figure 9. This set of 65 test assets presents a fair test of a model's ability to fit the cross-section of average returns, avoiding the critiques of Lewellen, Nagel, and Shanken (2010), and captures simultaneously four well-known CAPM asset pricing anomalies: size, book-to-market, momentum, and industry.

Column (ii) shows that the Fama-French three-factor model has no explanatory power in this cross-section, with a negative adjusted $R$-squared statistic and an upper bound of the $R$-square confidence interval of only 5%. The four-factor benchmark in column (iii)—

[10]Note we use the 10 momentum portfolios here, instead of the 25 size and momentum portfolios used earlier, since size is already accounted for using the 25 size and book-to-market portfolios. The goal here is to simultaneously account for the size, book-to-market, industry, and momentum characteristics, which this test achieves.

which appends the Fama-French model with the momentum factor—explains 39% of the cross-sectional variation in average returns but produces an alpha of 0.80% per quarter that is highly statistically significant. We contrast this result with column (iv), which demonstrates that our leverage factor *alone* outperforms the four-factor benchmark with an adjusted R-squared of 46%. Importantly, the alpha of this single-factor specification is 0.67% and statistically insignificant while the price of risk associated with shocks to broker-dealer leverage is 0.23% and highly statistically significant. The 95% confidence intervals on the $R$-squared statistic are even more telling. The lower confidence bound of the leverage factor of 43% is barely lower than the sample R-squared, and it is actually *above* the four factor benchmark R-squared. These results for the combined cross-section reflect the consistent price of risk that shocks to broker-dealer leverage bear across different cross-sections of test portfolios.

In order to understand the successes and failures of the above models at a portfolio level, Figures 3, 4, and 5 plot the realized average excess returns against predicted average excess returns with individual portfolios labeled in the figures. Figure 3 shows that the strong performance of the leverage factor stems largely from the correct pricing of the industry portfolios and the momentum portfolios, except for the lowest momentum portfolio (Mom1) where even the four-factor model fails (see Fig. 5). The value/size cross-section is also priced well apart from the extreme small growth and extreme small value portfolios (S1B1 and S1B5). Yet, and perhaps most notably, the leverage factor is able to correctly price the value factor (HML) and size factor (SMB)—a dimension where the Fama-French model itself performs quite poorly (see Fig. 4).

## 4.5 Bond Portfolios

We now examine the pricing ability of our leverage factor in the cross-section of bonds, using various maturities of returns on Treasury bond portfolios. We consider average portfolio returns with maturities 0-1, 2-3, 3-4, 4-5, and 5-10 years, as reported in the CRSP database. We compare our leverage factor to the standard bond pricing factor—the level of the yield curve.[11] We compute this factor as the first principal component from yields of 1-10 year maturites by month (making 108 series total) from the Federal Reserve, cumulating the monthly yields to quarterly yields. We then compute shocks to the level factor as the residuals from a first-order autoregression.

Since there are only 6 bond portfolios, with little spread in average returns and low variances, we report several pricing diagnostics. We begin by conducting the standard cross-sectional pricing test for each factor with and without an intercept, presented in Table 7. Columns (i) and (iii) give the results for the yield curve level and the leverage factor, respectively, with an intercept included. Our leverage factor explains 94% of the cross-sectional variation in Treasury returns—higher maturity excess Treasury returns have systematically larger leverage betas. Indeed, Figure 10 shows that leverage betas line up with average excess returns quite nicely. However, the estimated alpha of 0.17% (about 0.67% annually) is statistically significant. The results for the level shock are similar, with a statistically significant intercept of 0.14% and an $R$-squared of 97%. Columns (ii) and (iv) repeat the results but impose the intercept to be zero. In this case, the level shock explains 97% of the cross-sectional variation, while the leverage factor explains 96% in terms of adjusted R-squared.[12] The price of leverage risk is significant and, at 0.14, is roughly consistent with our earlier estimates.

Next, we analyze the pricing errors for the individual test portfolios. Column (i) of Table 8 reports the realized mean returns for each portfolio. For each specification, we report the individual pricing errors, along with the mean absolute pricing error (MAPE) across portfolios. For multi-factor benchmark return models, we report time-series alphas

[11] Cochrane and Piazzesi (2008) show that level shocks are sufficient as a single bond pricing factor, and that level shocks are substantially better than the other principal components in terms of explaining the expected returns in this cross-section.

[12] We define the $R$-squared in a regression $y = \beta\lambda + \varepsilon$ with no intercept as $R^2 = 1 - \frac{\sum \varepsilon^2}{\sum y^2}$.

($\alpha = E[R^e] - \beta' E[R^e_{\text{factors}}]$), imposing the prices of risk to be the factor means, since these models would otherwise have too many degrees of freedom for only 6 test assets. Columns (i) and (ii) give the results for the Fama-French and Fama-French plus momentum factors (MAPE of 1.5%, and 0.9% respectively). Neither is able to explain even half of the average mean return of 1.7% per annum across maturities. Column (iii) gives the results for the level shock, where pricing errors are reported via a cross-sectional regression without an intercept ($\alpha = E[R^e] - \beta\lambda_{level}$). The MAPE falls to only 0.23% per annum. Column (iv) gives the corresponding results for our single leverage factor, which has a MAPE of 0.32% per annum. While this is somewhat higher than the MAPE of the level shock (only 0.08% higher annually), it is still substantially lower than the MAPE of the multi-factor models and is economically very small. To demonstrate the consistent prices of risk for our leverage factor across stocks and bonds, we also report the pricing errors where we impose the price of risk to be equal to the estimate from the large cross-section of stocks. We find the MAPE increases only slightly to 0.32% per annum, once again highlighting the ability of our model to price many test assets with consistent prices of risk.[13]

## 4.6 Discussion of Main Pricing Results and Robustness

The results in Tables 3-6 demonstrate that our single broker-dealer leverage factor does remarkably well in pricing well-known asset pricing anomalies. The single factor model exhibits consistently strong pricing performance across all cross-sections of test assets, as judged by the explanatory power, the pricing error, and the economic magnitude and significance of the prices of risk. The performance of our model rivals and in many cases even exceeds that of the portfolio-based "benchmarks" that were specifically tailored to explain each anomaly.

Yet, what we find most notable is that the prices of risk associated with our broker-dealer

[13] This also addresses the concern that we would be fitting the bond cross-section using an "unreasonable" price of risk.

leverage factor are not only statistically significant across different sets of test assets, but are also relatively stable in magnitude across cross-sections of stocks and bonds, which was confirmed above in the combined cross-section of 65 test assets. In the leverage model (column (iii) of Tables 3-5) the price of risk associated with shocks to broker-dealer leverage varies from 0.33% (size/book-to-market) to 0.36% (size/momentum) to 0.13% per quarter (industries) to 0.14% per quarter (bonds). Including many portfolios at once (size/book-to-market, momentum, and industries) gives a price of risk of 0.23%. This stability lends additional support to the broad-based performance of our broker-dealer leverage model.

To demonstrate the robustness of our results, and to highlight their strength, we show that they are almost certainly not due to chance. Specifically, we simulate a noisy factor by randomly drawing from the empirical distribution of the leverage factor with replacement. We construct this noise factor to have the same length as our original leverage factor (168 quarters) and use it in our cross-sectional pricing tests. Clearly, since this factor is drawn at random, it should not have any explanatory power in the cross-section of expected returns. We repeat this exercise 100,000 times, and ask how likely it is that a "random" factor would perform as well as our leverage factor in a cross-sectional test. The results in Table 14 show that, in 100,000 simulations, an absolute average pricing error as low or lower than we report is achieved only 10 times, an R-squared as high or higher than we report occurs 16 times, and the joint occurrence of a low alpha and high R-squared occurs only once. This makes it highly unlikely that our results are due to chance, since the p-value in each case is essentially zero.[14]

## 4.7 Understanding the Price of Leverage Risk

In order to better understand the commonality between our leverage factor and existing benchmarks, including both portfolio-based and macroeconomic models, we next examine

[14] We also construct a noisy factor using a normal dstribution where we match the autocorrelation of the leverage series. The results are very similar – with the p-values being essentially zero.

how the factor price of risk implied by our broker-dealer leverage model relates to the factor prices of risk implied by such benchmarks. Table 9 conducts this comparison for three benchmark specifications: the Fama-French three-factor model, the Lettau and Ludvigson (2001) conditional consumption CAPM model, and a three-factor macro model adapted from the specification of Chen, Roll and Ross (1986).[15] Specifically, we use the Fama-MacBeth procedure on the size and book-to-market portfolios to construct time-series of risk prices and then estimate the comovement of risk prices between models.

The results in the first panel show that the price of risk of the leverage factor is positively correlated with the price of HML risk, with a correlation parameter of 76%, which is statistically significant at the 1% level. This suggests that a high value premium is associated with a high price of financial intermediary leverage risk. While our tests certainly do not show that broker-dealers are driving the value premium, the findings are consistent with the notion that a common source of risk may be driving both the value premium and the fluctuations in intermediary leverage. The price of risk of the size factor, SMB, correlates positively with that of the leverage factor and is again significant at the 1% level.

In the second panel, we show that the price of risk of the leverage factor correlates negatively with the price of risk of Lettau and Ludvigson's *cay* factor, and significantly negatively with the interaction factor $cay \times \Delta c$. Recall that high *cay* corresponds to times of low risk premia—the price of risk of leverage thus correlates positively with risk premia over time. Note, however, that these results do not allow us to infer the relationship between the time series of leverage and the price of risk of leverage. The price of risk of consumption and leverage correlate significantly positively, indicating that the risk premium for positive exposure to consumption risk is the same sign as the risk premium for exposure to leverage risk. Note that the signs of the correlations of consumption growth, of *cay*, and of $cay \times \Delta c$ with the price of risk of broker-dealer leverage are the same as their correlations with the

[15] We thank Martin Lettau for making the factors used in Lettau and Ludvigson (2001) available on his website. All other macroeconomic data are obtained from Haver Analytics.

price of market risk.

Finally, the third panel shows that the price of risk associated with shocks to broker-dealer leverage is also highly negatively related to the compensation for shocks to industrial production and highly negatively related to the price of risk of inflation. Intuitively, adverse shocks to investment opportunities tend to coincide with lower-than-expected industrial production and higher unexpected inflation and default spreads. These signs are the same as the signs relative to the price of market risk.

Taken together, the economically meaningful and statistically significant correlations between the price of risk of our leverage factor and those of other common risk factors lend support to the view that shocks to broker-dealer leverage reflect unexpected changes in underlying economic and financial fundamentals. It is in this light that we interpret the robust pricing performance of our financial intermediary leverage model across a wide range of test assets.

# 5 The Leverage Factor Mimicking Portfolio

In order to conduct additional tests, we project our leverage factor onto the space of traded returns to form a "*L*everage factor *M*imicking *P*ortfolio" (LMP)—a traded portfolio that "mimicks" the leverage factor. This approach has several advantages and allows several new insights. First, since the LMP is a traded return, we can run tests using higher frequency data and a longer time series. This avoids the criticisms that our results rely on the post-1968 time period, or that our results may not hold at a higher frequency. Indeed, we confirm that our results hold at a monthly frequency going back to the 1930's. Second, we can run individual time-series alpha tests without having to estimate the cross-sectional price of risk, which is not unambiguously pinned down by the intermediary asset pricing theories discussed earlier. We confirm our strong pricing results using time-series alpha tests, including the ability of our factor to price the three Fama-French factors and momentum factor. Third, we can take a mean-variance approach to our results (see, e.g. Hansen and Jagannathan, 1991). We find that the LMP has the largest Sharpe ratio of any traded factor return and is close to the maximum possible Sharpe ratio using any combination of the Fama-French three factors and momentum factor. Finally, using the longer, higher frequency time series, we sort the entire cross-section of traded stocks by their LMP betas and document a large monotonically increasing spread in average returns.

## 5.1 Construction of the LMP

To construct the LMP, we project our non-traded broker-dealer leverage factor onto the space of excess returns. Specifically, we run the following regression:

$$LevShock_t = \alpha + [weights]'[BV, BN, BG, SV, SN, SG, Mom]_t + \epsilon_t, \tag{6}$$

where $[BV, BN, BG, SV, SN, SG, Mom]$ are the excess return of the six Fama-French benchmark portfolios on size ($S$mall and $B$ig) and book-to market ($V$alue, $N$eutral and $G$rowth) in excess of the risk-free rate and $Mom$ is the momentum factor. We choose these returns for their well-known ability to summarize a large amount of return space: Ideally, the error $\epsilon_t$ is orthogonal to the space of returns so that the covariance of any asset with leverage shocks is identical to its covariance with the LMP, defined as the fitted value of the regression. Normalizing the sum of $weights$ to one, the factor mimicking portfolio return is given by:

$$LMP_t = [normweights]'[BV, BN, BG, SV, SN, SG, Mom]_t,$$

where we estimate $normweights = [-0.39, 0.48, 0.13, -0.42, 1.19, -0.49, 0.50]$ via ordinary least squares over the sample 1968-2009.[16]

[16] Note that, by construction $Cov(LevShock_t, R_t^e) = Cov(LMP_t, R_t^e) + Cov(\epsilon_t, R_t^e) = Cov(LMP_t, R_t^e)$,for all $R_t^e \in span\{[BV, BN, BG, SV, SN, SG, Mom]_t\}$. Since the benchmark factors span a large amount of return space, the covariance of a return with the LMP is expected to be close to its covariance with leverage. However, we should acknowledge that some information may be lost in this procedure, particularly for portfolios such as industry for which the benchmark factors have little power compared to our leverage factor.

While the LMP loads strongly on momentum, the other style biases are less clear. On net, we do not see a higher emphasis on value as opposed to growth. Also, on net, there is no substantial difference between small and large loadings. Thus, the resulting factor is quite different from the three Fama-French factors.

## 5.2 Pricing Results Using the LMP

We investigate the pricing performance of the LMP using the stock and bond portfolios of the previous section as test assets. As before, we begin our tests using quarterly data from 1968-2009, but instead of conducting cross-sectional regressions, we record the time-series alphas for each portfolio. This avoids freely choosing the cross-sectional price of risk, since it imposes that the factor risk premium must equal the sample mean of the factor return.

We report these results for each individual test asset in Table 10. We also report two other meaningful diagnostics, the mean absolute pricing error (MAPE), and the mean squared pricing error (MSPE) over all test assets in Table 11. For comparison, we also report the annualized average absolute return to be explained in the first column. We further break these down into the individual cross-sections to compare the performance for each set of test assets. We see that the LMP has a comparative advantage on the industry, bond, and momentum cross-sections. In fact, for the 6 bond portfolios, the LMP's MAPE of 0.92% per annum is significantly lower than the corresponding MAPEs for the Fama-French benchmark (2.42%) and is slightly lower than the four-factor benchmark (0.94%), highlighting the ability of our factor to price the cross-section of bond returns. Similarly, the industry MAPE is only 1.93% for the LMP vs. 2.56% and 2.44% for the benchmarks. The total MAPE for the LMP is 1.85% per annum, vs. 1.71% for the four-factor benchmark and 2.32% for the Fama-French three factors, out of a total average return of 6.39% per annum to be explained, while the MSPE is 0.36 for the LMP vs. 0.39 for the four-factor benchmark and 0.72 for the Fama-French benchmark.

We also report the results from a standard cross-sectional test considered earlier, where we use all test assets simultaneously. To help ensure the factor prices of risk do not stray far from their means, we include the traded factors (Mkt, SMB, HML, Mom, LMP) also as test assets. The results are relegated to the appendix (Table A3) as they merely confirm the pricing ability of our leverage factor demonstrated earlier.

One may be concerned that, since the LMP is simply a linear combination of portfolio returns with strong pricing abilities, the mimicking portfolio will also mechanically inherit this ability. We show that this is not the case using two approaches: First, the LMP *alone* has stronger pricing power than a model with the three Fama-French factors and the momentum factor. Second, and more importantly, we simulate random weights from a uniform distribution and show that in 100,000 simulations, our low average pricing error (alpha) and high $R$-squared are achieved only 5 times, making it highly unlikely that our results are due to chance (individually, the low alpha is reached 65 times, the high $R$-squared 40 times). We find analogous results by projecting a simulated vector of random draws from the leverage factor, with replacement, onto the returns and recording the resulting weights. In this case, with 100,000 replications, we never once achieve the low absolute alpha and high $R$-squared we see in the data. We report these results in the previously mentioned Table 14.

As a further robustness check, we reproduce our pricing results using the LMP with monthly data going back to 1936. We use only stocks since the bond return data only begin in 1952. We look at both the individual time-series alphas, as well as the cross-sectional pricing errors and $R$-squared as in our main tests. We confirm the leverage factor's strong pricing ability using both time-series alphas and cross-sectional tests.[17] Our empirical results thus continue to hold over the longer time-span and at the higher monthly

[17] For the tests using monthly data and longer time-series, we save space by not reporting the time-series alphas of every test asset for every cross-section we consider. Instead, we only report the pricing of the Fama-French factors and momentum factors themselves (See Table 10). The results for the entire cross-section are similar to those using quarterly data and the shorter time-period.

frequency, providing further robustness for our results.

Finally, we show that our single leverage factor prices the three Fama-French factors and momentum factor *themselves*, using time-series alpha tests of these factors on the LMP. We report the results in Table 12. For robustness, we report the results using monthly data over the longer time-period (1936-2009), as well as the quarterly results used in our main sample (1968-2009). We find that the LMP correctly prices the market, SMB, and momentum factors, all of which have small and statistically insignificant pricing errors. However, we do find a statistically significant alpha of 2.45% per annum on the HML factor. These findings complement our cross-sectional results since we are not free to choose any parameters to fit the test assets—the price of risk is forced to be the mean of the LMP. The fact that the single LMP factor is able to price the four benchmark factors quite well further strengthens our results.

## 5.3 Mean-Variance Properties of LMP

We now turn to the mean-variance properties of our mimicking portfolio. Figure 11 plots the efficient frontier implied by the six Fama-French benchmark portfolios, the Fama-French three factors, and the momentum factor. We display the location of each benchmark factor in this space, as well as the line connecting each factor to the origin. Note that the slopes of the lines give the Sharpe ratios of the factors. Recall that a traded return is on the efficient frontier if and only if it is the projection of the stochastic discount factor onto the return space, which follows from the Hansen and Jagannathan (1991) bounds.

Figure 11 also plots the portfolio that gives the largest possible Sharpe ratio (0.35) of any linear combination of the three Fama-French factors and momentum factor, labeled $P$. Note that at 0.30, the Sharpe ratio of the leverage mimicking portfolio is much higher than those of the market (0.13), SMB (0.05), HML (0.15), or even the momentum (0.20) factor (see Table 13). In fact, the LMPs Sharpe ratio is comparable to the Sharpe ratio of $P$. Since the true mean-standard deviation space will in general be tighter than its sample counterpart, the proximity of the LMP to the sample mean-standard deviation frontier can be regarded as an additional piece of evidence that our leverage factor provides a good approximation to the stochastic discount factor.

### 5.4 LMP Decile Ranking Portfolios

As a final check, we use the traded LMP portfolio to construct portfolios from the entire cross-section of individual stock returns. We follow Fama and French (1993) and form portfolios based on pre-ranking betas, where betas are computed using past 10-year rolling window regressions. Specifically, we sort stocks into deciles based on pre-ranking betas in July of every year. We then document a large spread in average returns across the deciles and note that the returns are monotonically increasing in post-formation betas, which we estimate over the entire sample (1936-2009) and report in Table 15. Notably, the results hold using either equal or value-weighted portfolio returns, and do not seem to depend on size—the market capitalization shows no systematic difference across portfolios. The spread in returns is indeed large, with the largest LMP beta portfolio earning 1.8% monthly and the smallest earning 1.2% monthly, resulting in a spread of about 0.6%, which is approximately 7.2% annually.

In sum, the evidence from the cross-section of individual stock returns lends additional support to our finding that higher covariance with broker-dealer leverage is associated with higher expected return. Note that our goal here is not to obtain a 10-1 traded factor—we already have a traded factor that approximates leverage in the LMP. Rather, our goal is simply to give another diagnostic that covariances with leverage determine average returns. Using the entire universe of traded stocks avoids the criticism that leverage betas only explain the average returns across the portfolios we have analyzed.

# 6 Challenges and Directions for Theory

While we have demonstrated that our leverage factor possesses strong pricing ability across a wide variety of assets and asset classes, we have not provided a formal model that links leverage risk exposure to expected asset returns. A number of theories reviewed in Section 2 are broadly consistent with our results—but our empirical findings pose challenges to each of these theories. Of course, any theoretical model, when taken literally, cannot match *every* aspect of the data. Yet, it may be helpful to see where the limitations of the existing theories lie in light of our empirical findings. Thus, much like the theories guided our empirical tests in linking financial intermediaries to asset prices, we now hope that our empirical results will help guide future theoretical work in grappling with the facts. We analyze each theory in turn and discuss the potential clashes.

We noted that broker-dealer leverage may be a signal for the wealth of the financial system, consistent with models where the return on financial sector wealth determines expected returns (He and Krishnamurthy, 2009). As the wealth of the financial sector increases, demand for services from broker-dealers increases leading them to lever up capital. However, this intuition assumes that broker-dealer leverage is never constrained, which is inconsistent with our understanding of the events during the financial crisis. Moreover, direct measures for the financial sector wealth, such as the value-weighted equity return of financial institutions, do not seem to perform as well as leverage in explaining the cross-section of average returns.

Broker-dealer leverage may also measure the tightness of borrowing constraints or funding liquidity (Brunnermeier and Pedersen, 2009). This interpretation gives rise to pro-cyclical leverage ("the margin spiral") and is potentially an important source of macroeconomic risk, as witnessed by the deleveraging during the financial crisis. However, our findings present two challenges to the mechanics of the margin spiral. First, we find that leverage shocks are largely uncorrelated with the shocks to the Pastor-Stambaugh liquidity factor—

a measure of innovations to market liquidity—challenging the theoretical predictions that funding liquidity and market liquidity are intertwined. Second, our results hold well across different time periods, including both good times and crises. It seems less likely that broker-dealers are borrowing constrained when times are good; yet we pick up important risk exposures over these periods also.

Finally, in ICAPM approaches, where leverage arises as a reduced form representation of deeper state variables, the challenge is that our results strongly indicate that a *single* factor can serve as a close empirical approximation for the stochastic discount factor. In ICAPM frameworks, aggregate wealth is the most important risk factor while other systematic risks that arise from intertemporal hedging demands remain second-order. Therefore, our finding that broker-dealer leverage should be used in the pricing kernel instead of aggregate market return is not easily reconciled within ICAPM settings.

# 7 Conclusion

In this paper, we focus on measuring the SDF of a representative financial intermediary using the aggregate leverage of security broker-dealers. Our approach is motivated by a growing theoretical literature that has proposed a number of linkages between financial intermediaries and aggregate asset prices. Specifically, the leverage of the broker-dealers can be expected to reflect the marginal value of wealth of intermediaries because it may proxy for funding constraints, intermediary wealth, or investment opportunities. Since financial intermediaries trade in many markets, have low transactions costs, optimize frequently, and use extensive models to make investment decisions, these theories predict that the SDF based on a representative intermediary should have greater empirical success than its conventional counterparts.

Our empirical results are remarkably strong. We show that broker-dealer leverage as the *single* risk factor compares favorably to the Fama-French model in the cross-section of size and book-to-market sorted portfolios and rivals the benchmark tailored to explain the cross-section of size and momentum sorted portfolios. The single factor also does well in pricing the challenging cross-section of industry portfolios, clearly dominating benchmark models. Furthermore, the leverage factor prices the combined cross-section of all the above equity portfolios, a challenge where all benchmark models fail. Our factor also prices bond portfolios. The success of the leverage factor across all these cross-sections is measured in terms of high adjusted $R$-squared statistics, small and statistically insignificant cross-sectional pricing errors (alphas), and cross-sectional prices of risk that are significant and consistent across portfolios. When taking all these criteria into account, our single factor outperforms standard multi-factor models tailored to price the cross-sections considered. We also provide a battery of additional tests that confirm the robustness of our results.

Our study is a first step in exploring how the marginal value of wealth of intermediaries can be used as a pricing kernel. We see the search for additional measures of the intermediary SDF as a fruitful area for further reasearch. We also regard empirical tests that distinguish between competing theories, and, ultimately, a cohesive theory that can quantitatively match the empirical facts as particularly promising areas for future work.

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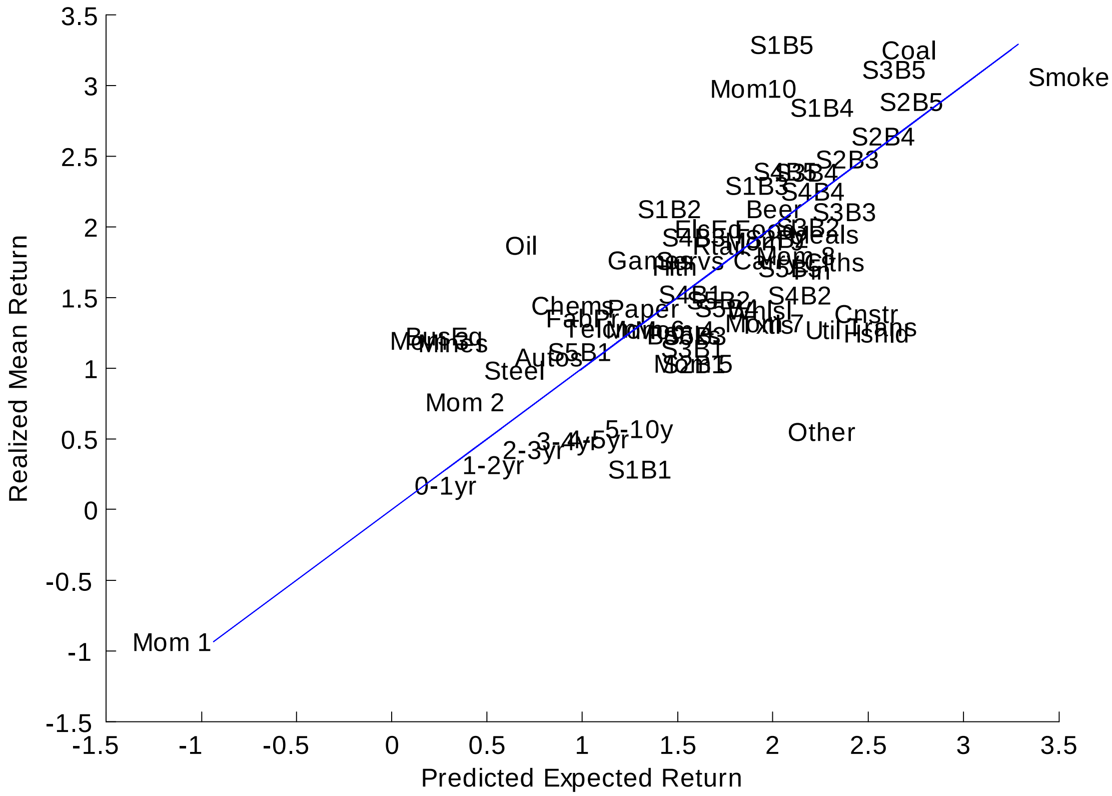


Figure 1: Realized vs. Predicted Mean Returns. We plot the realized mean excess returns of 65 equity portfolios (25 Size and Book-to-Market Sorted Portfolios, 30 Industry Portfolios, and 10 Momentum Sorted Portfolios) and 6 Treasury bond portfolios (sorted by maturity) against the mean excess returns predicted by a 1-factor financial intermediary leverage model, estimated without an intercept ($E[R^e] = \beta_{lev}\lambda_{lev}$). The sample period is Q1/1968-Q4/2009.

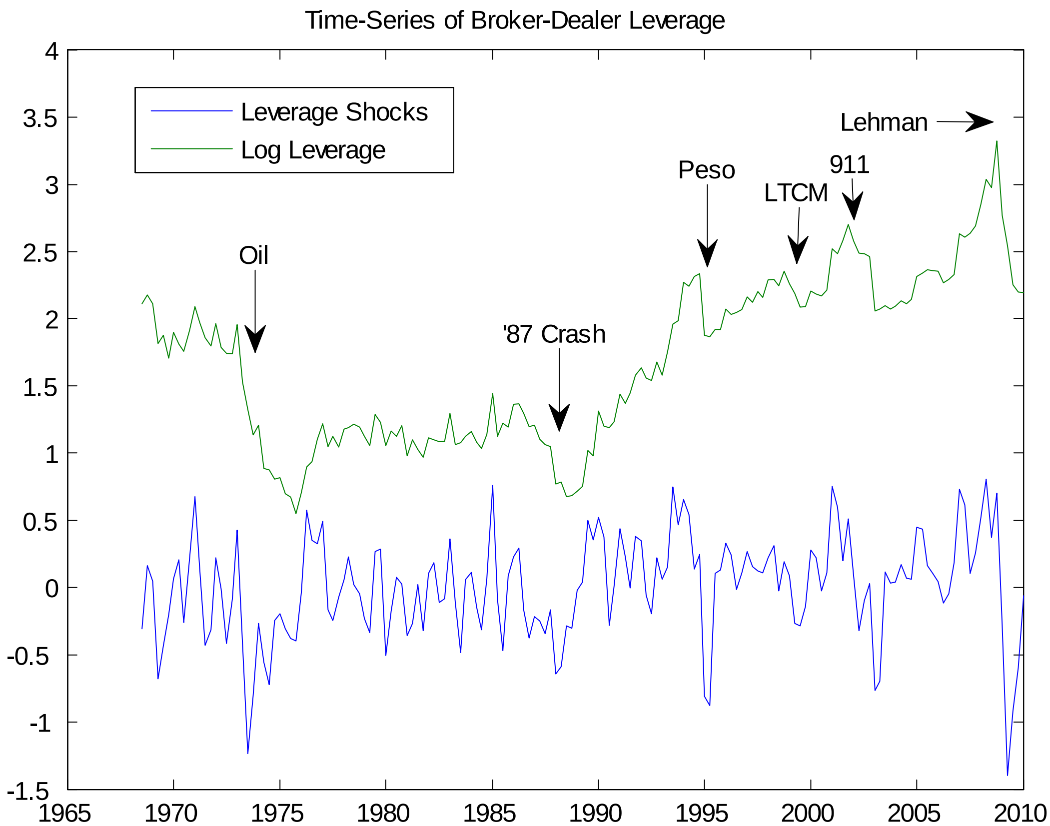


Figure 2: We plot the log leverage and the innovations in log leverage (the leverage factor) of security broker-dealers, Q1/1968-Q4/2009. The labels indicate macro / financial sector events associated with large changes in leverage and financial sector turmoil. "Oil" is the oil crisis of March 1973, "'87 Crash" is the stock market crash of 1987, "Peso" is the Peso currency crisis of December 1994, "LTCM" is the collapse of Long Term Capital Management in fall 1998, "911" represents the attacks on the world trade center in September 2001, and "Lehman" is the collapse of Lehman Brothers and the ensuing market turmoil in fall 2008.

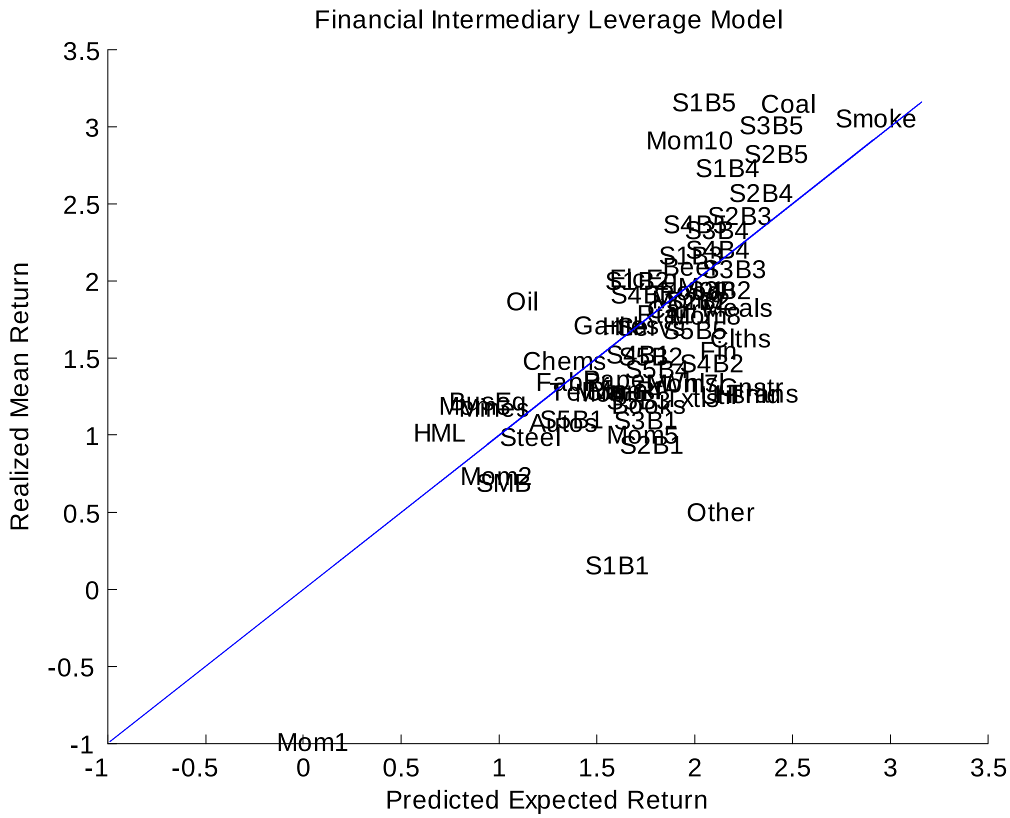


Figure 3: Realized vs. Predicted Mean Returns. We plot the realized mean excess returns of 65 portfolios (25 Size and Book-to-Market Sorted Portfolios, 30 Industry Portfolios, and 10 Momentum Sorted Portfolios) and 4 factors (market, SMB, HML, MOM) against the mean excess returns predicted by a 1-factor broker-dealer leverage model. The sample period is Q1/1968-Q4/2009.

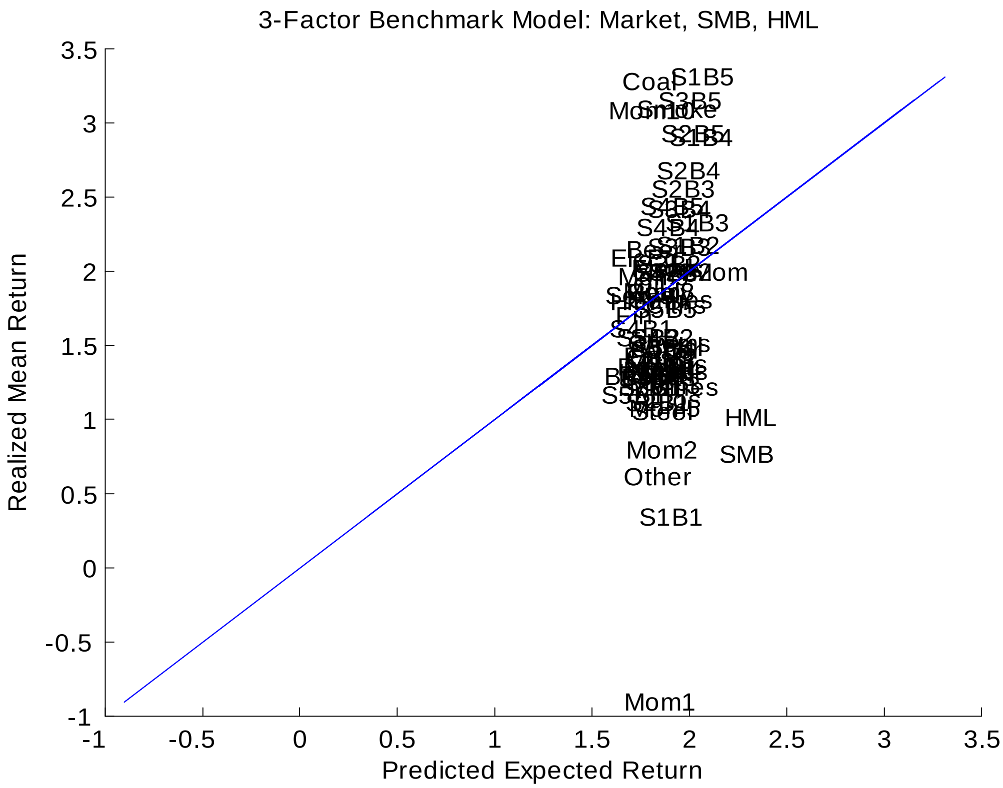


Figure 4: Realized vs. Predicted Mean Returns. We plot the realized mean excess returns of 65 portfolios (25 Size and Book-to-Market Sorted Portfolios, 30 Industry Portfolios, and 10 Momentum Sorted Portfolios) and 4 factors (market, SMB, HML, MOM) against the mean excess returns predicted by the Fama-French 3-factor benchmark (market, SMB, HML). The sample period is Q1/1968-Q4/2009.

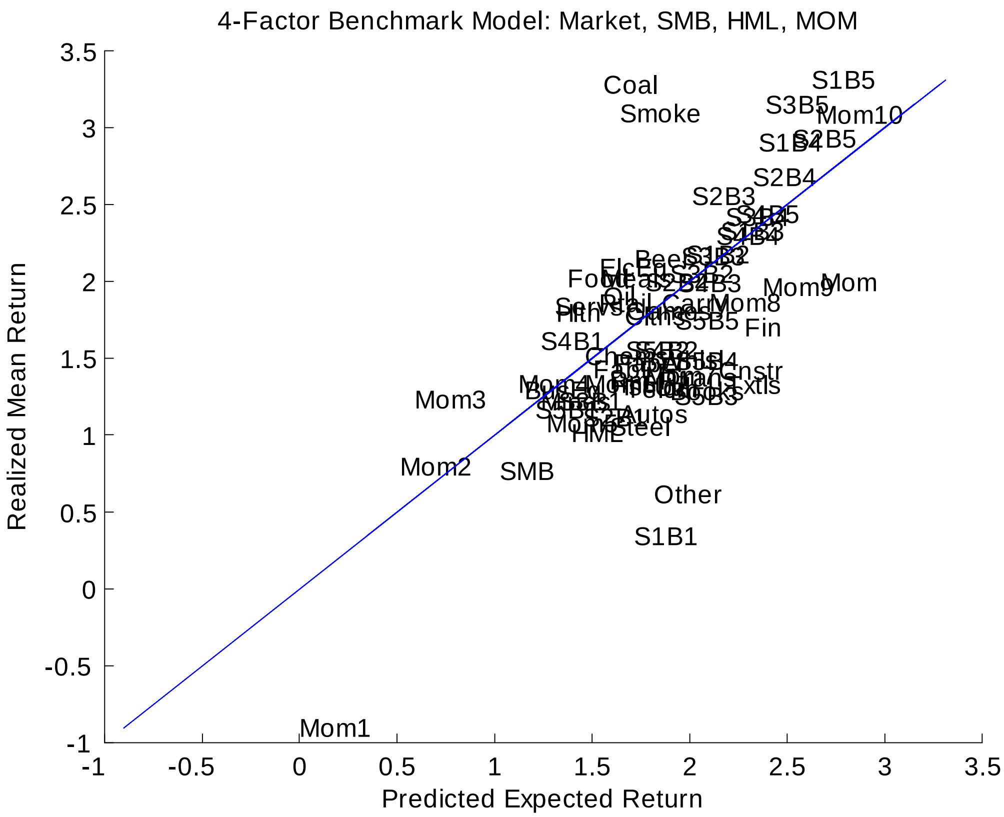


Figure 5: Realized vs. Predicted Mean Returns. We plot the realized mean excess returns of 65 portfolios (25 Size and Book-to-Market Sorted Portfolios, 30 Industry Portfolios, and 10 Momentum Sorted Portfolios) and 4 factors (market, SMB, HML, MOM) against the mean excess returns predicted by a 4-factor benchmark model (market, SMB, HML, MOM). The sample period is Q1/1968-Q4/2009.

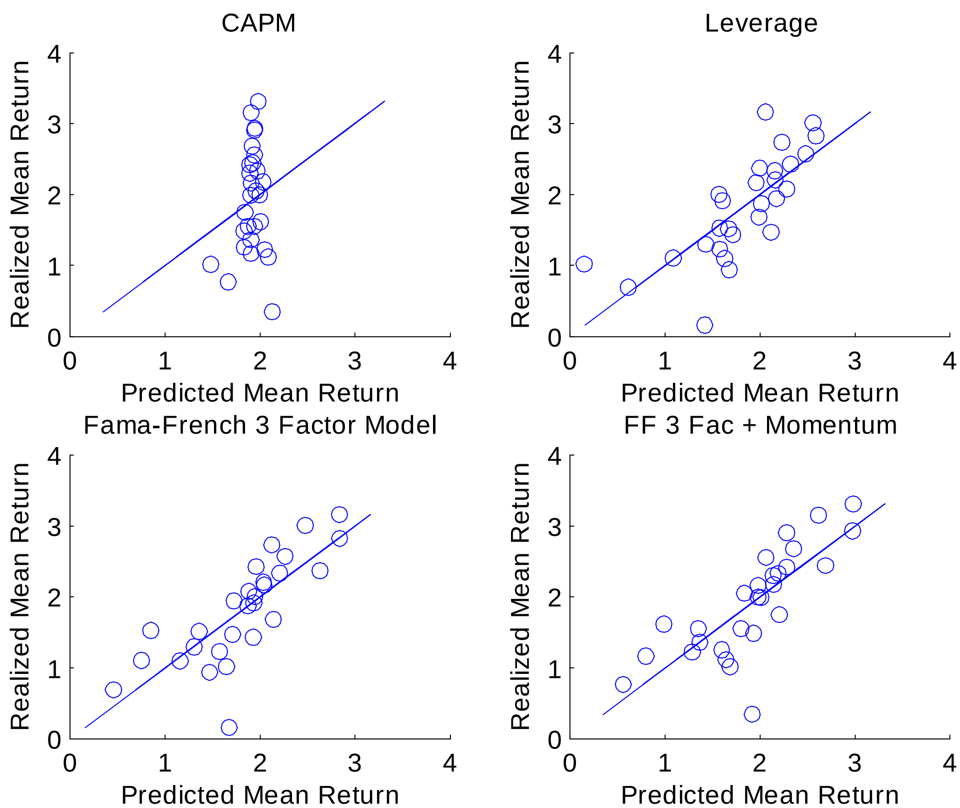


Figure 6: Realized vs. Predicted Mean Returns for 25 Size and Book-to-Market Sorted Portfolios. The sample period is Q1/1968-Q4/2009.

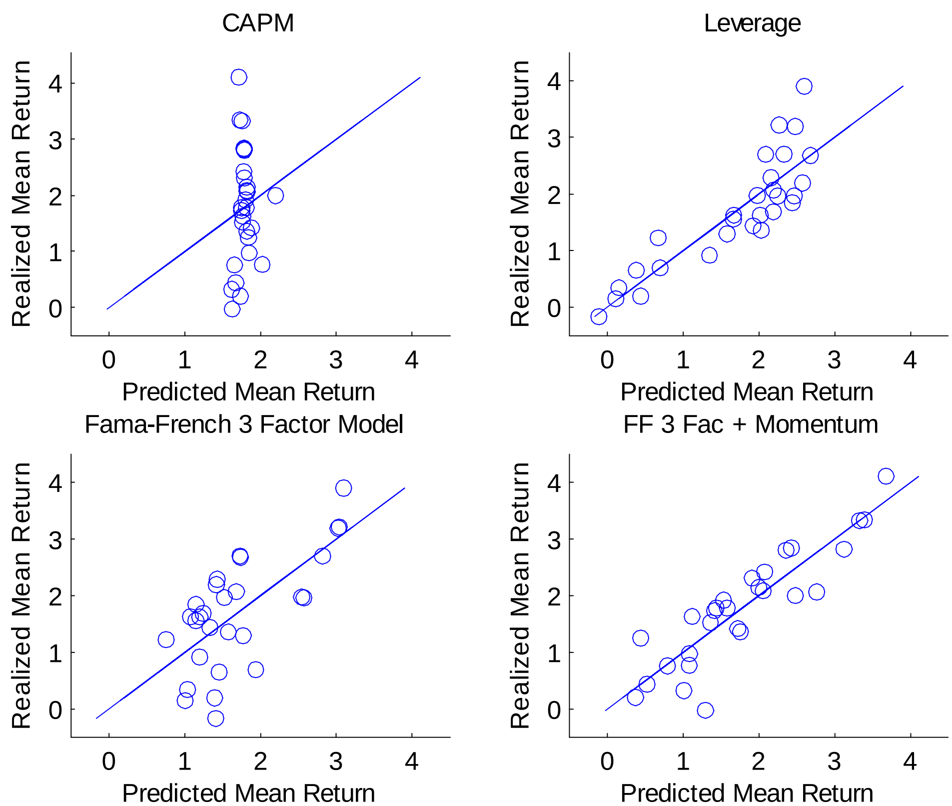


Figure 7: Realized vs. Predicted Mean Returns for 25 Size and Momentum Sorted Portfolios. The sample period is Q1/1968-Q4/2009.

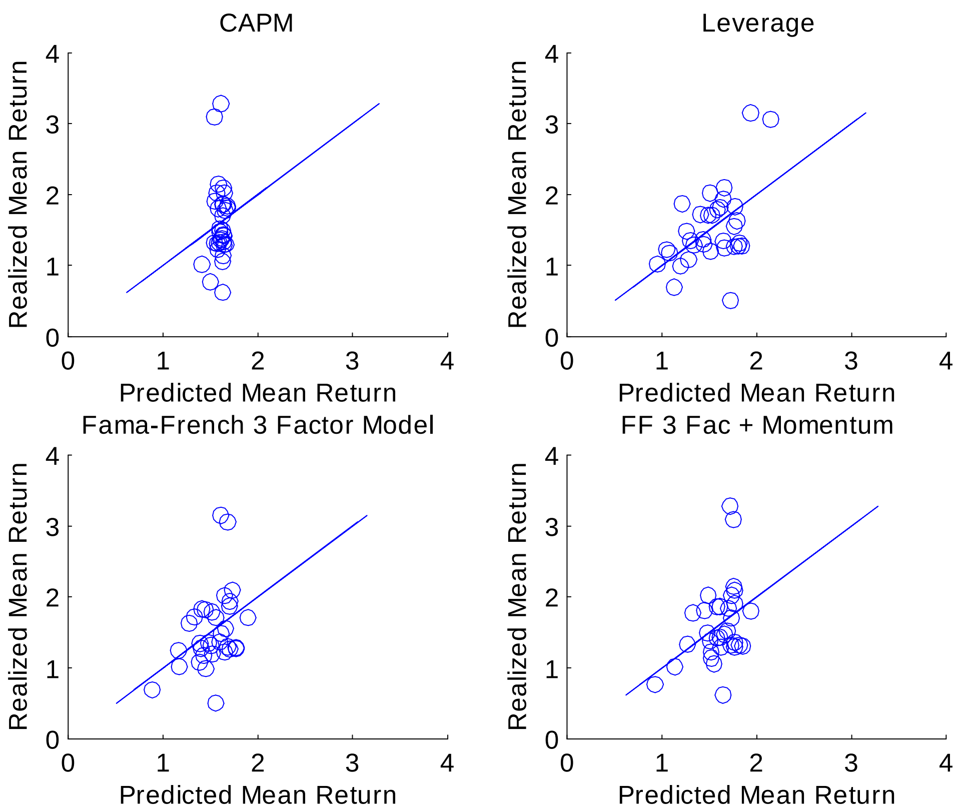


Figure 8: Realized vs. Predicted Mean Returns for 30 Industry Portfolios. The sample period is Q1/1968-Q4/2009.

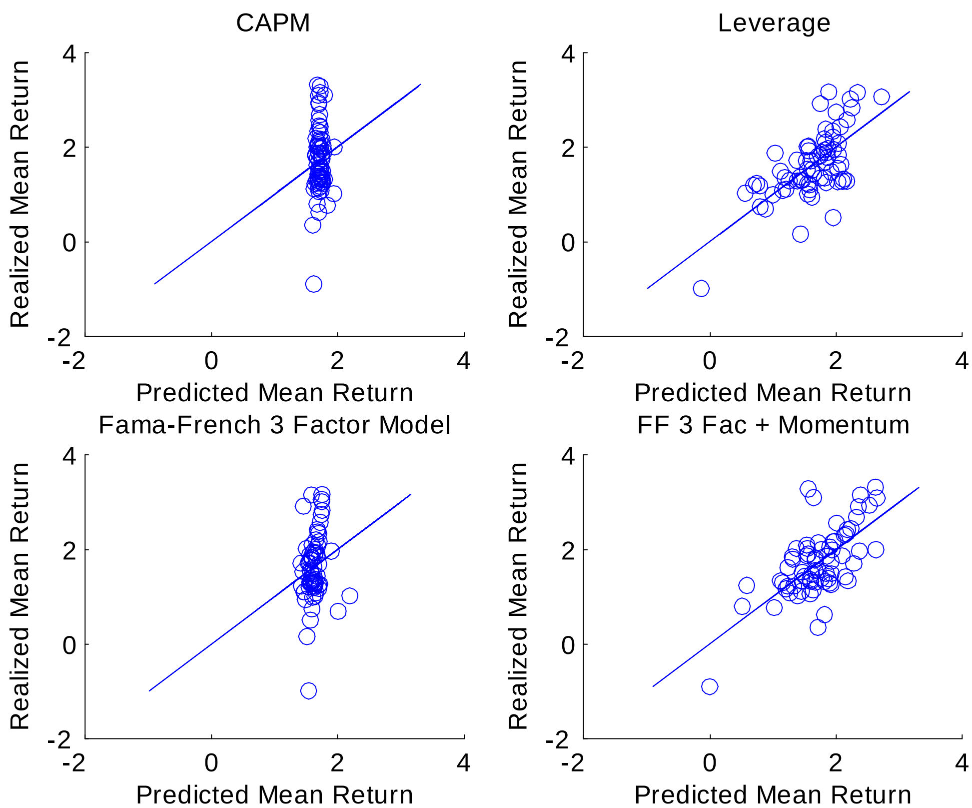


Figure 9: Realized vs. Predicted Mean Returns for 25 Size and Book-to-Market Sorted Portfolios, 30 Industry Portfolios, and 10 Momentum Sorted Portfolios. The sample period is Q1/1968-Q4/2009.

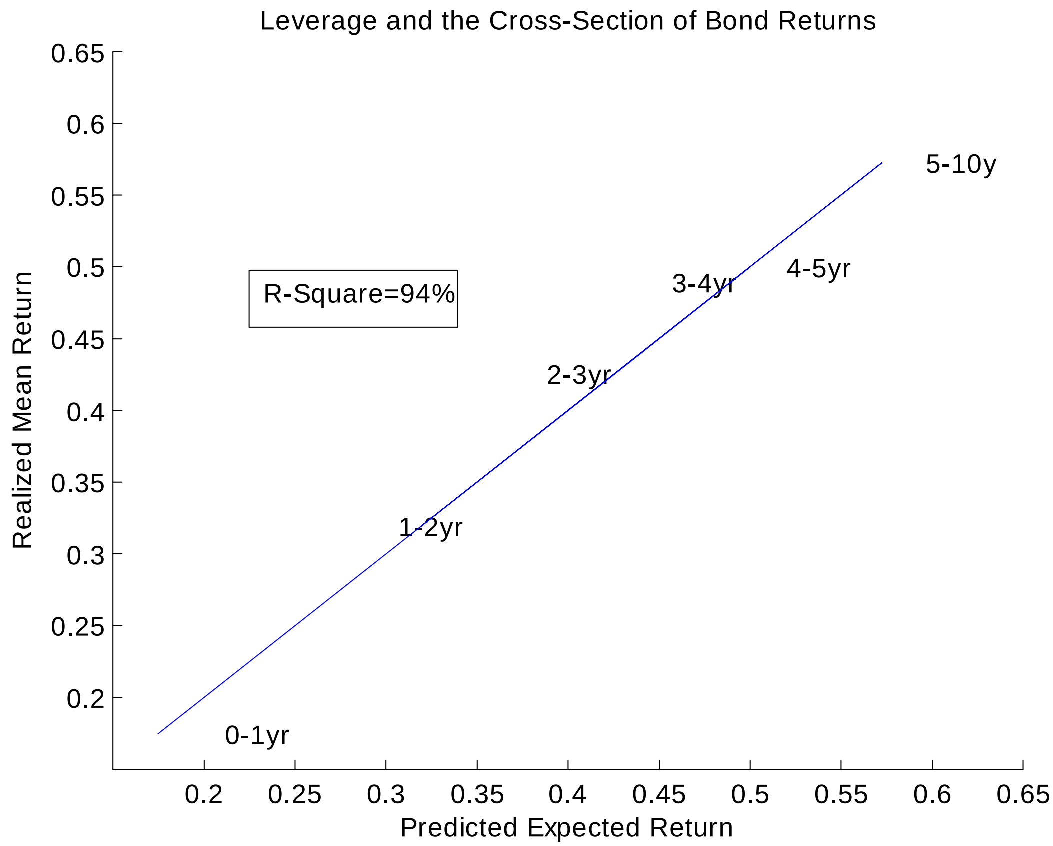


Figure 10: Realized vs. Predicted Mean Returns. We plot the realized mean excess returns of 6 U.S. Treasury bond portfolios sorted on maturity against the mean excess returns predicted by the single leverage factor. The sample period is Q1/1968-Q4/2009.

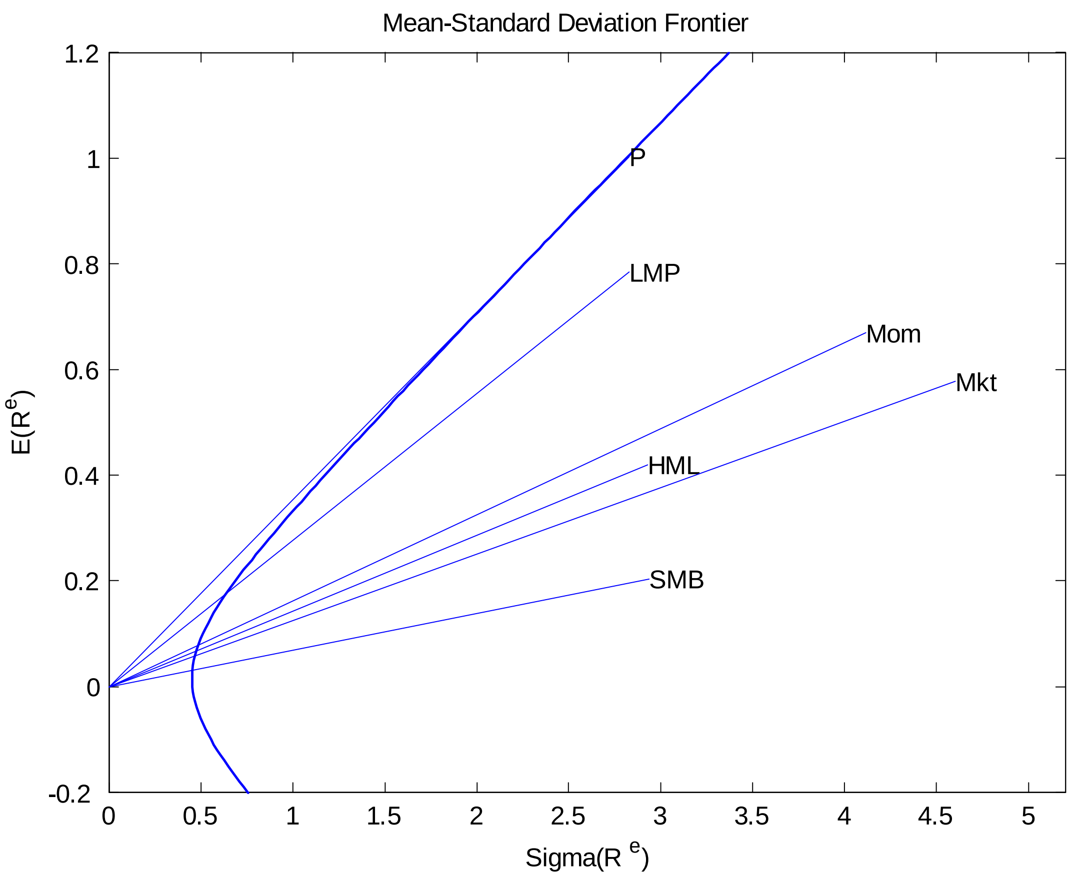


Figure 11: The hyperbola plots the sample mean-standard deviation frontier ("the efficient frontier") for the six Fama-French benchmark portfolios, the Fama-French factors (Mkt, SMB, HML), and the momentum factor. LMP is the leverage mimicking portfolio (see text for description), Mkt, SMB, HML are the Fama-French factors, Mom is the momentum factor, and P is the linear combination of Mkt, SMB, HML, and Mom that produces the highest possible Sharpe ratio in sample, P $= \underset{a,b,c,d}{max}\{\text{Sharpe}[a\text{Mkt}+b\text{SMB}+c\text{HML}+d\text{Mom}]\}$. Data are monthly from 1936-2009.

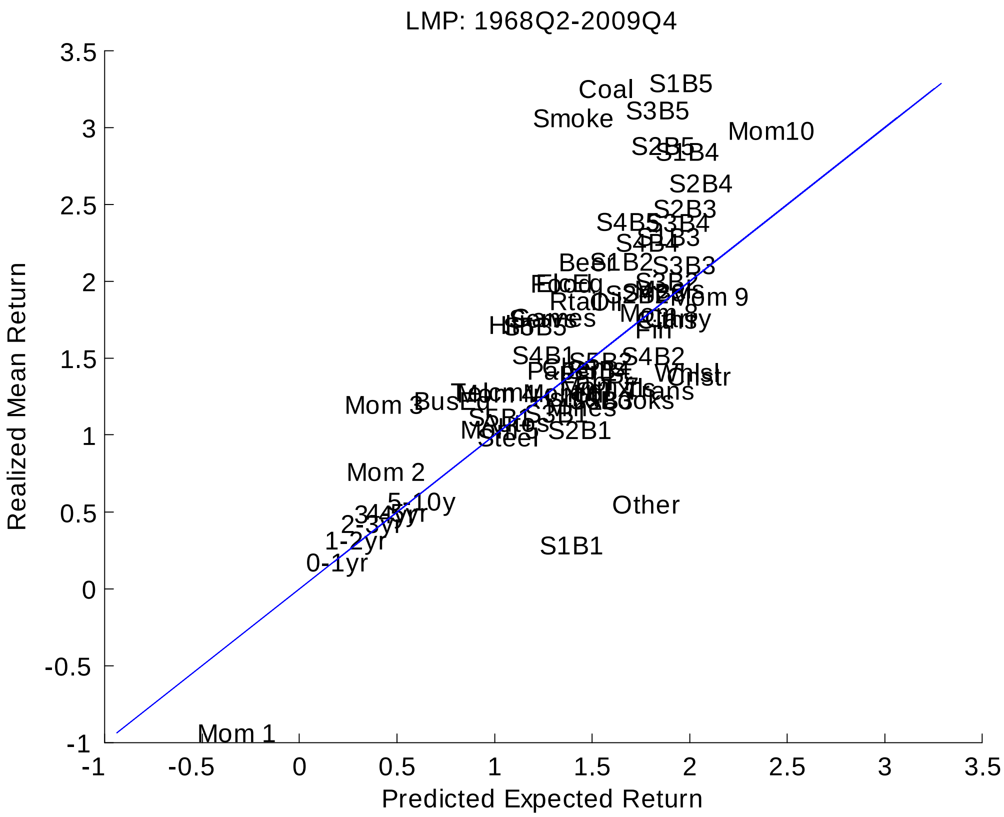


Figure 12: Realized vs. Predicted Mean Returns. We plot the realized mean excess returns of 71 portfolios (25 Size and Book-to-Market Sorted Portfolios, 30 Industry Portfolios, 10 Momentum Sorted Portfolios, 6 Maturity Sorted Treasury Returns) against the mean excess returns predicted by the LMP (leverage mimicking portfolio). We impose the theoretical restrictions of zero intercept and a price of risk equal to the mean of the LMP (i.e., we plot realized mean returns against mean returns less time-series alphas). The sample period is Q1/1968-Q4/2009.

Table 1: Broker-dealer leverage is pro-cyclical. We display the correlation of U.S. broker-dealer leverage growth with a selection of state variables, including the value-weighted return on the U.S. equity market, profit growth of the U.S. financial sector (source: Bureau of Economic Analysis), the value-weighted stock return of the U.S. financial sector, and the asset growth of U.S. broker-dealers. Positive correlation in each case shows that leverage growth is pro-cyclical and related to wealth, compensation, and investment opportunities. The sample is Q1/1968-Q4/2009.

| Correlation of Broker-Dealer Leverage Growth | | | |
|---|---|---|---|
| Market Return | Financials Profit Growth | Financials Stock Return | Broker-Dealer Asset Growth |
| 0.166 | 0.168 | 0.220 | 0.729 |

Table 2: Assets and Liabilities of Security Brokers and Dealers as of the end of Q4/2009. The amounts are in billions of dollars, not seasonally adjusted. (Source: U.S. Flow of Funds Release, March 11, 2010, Table L.129.)

| | |
|---|---|
| Total financial assets | 2080 |
| Checkable deposits and currency | 90.7 |
| Credit market instruments | 529.7 |
| Open market paper | 41.5 |
| Treasury securities | 128.8 |
| U.S. government agency securities | 110.9 |
| Municipal securities and loans | 35.4 |
| Corporate and foreign bonds | 146.1 |
| Other loans and advances (syndicated loans) | 67 |
| Corporate equities | 121.5 |
| Security credit | 203 |
| Miscellaneous assets | 1135.1 |
| | |
| Total financial liabilities | 1994.7 |
| Net security repos | 470.4 |
| Corporate bonds | 92.8 |
| Trade payables | 70 |
| Security credit | 887.8 |
| Taxes payable | 5.7 |
| Miscellaneous liabilities | 468 |
| Direct investment | 83.6 |
| Equity investment in subsidiaries | 1085.2 |
| Other | -700.8 |

Table 3: Pricing the Cross-Section of 25 Size and Book to Market Portfolios

We use Fama-MacBeth two-pass regressions to price the cross-section of 25 size and book-to-market sorted portfolios. The table reports estimated coefficients in quarterly percentage points with Fama-MacBeth and Jagannathan-Wang t-statistics in parentheses. We also report bootstrapped confidence intervals for the R-Squared statistic using 100,000 draws of size 168 (the total number of quarters in the sample) with replacement. The sample period is Q1/1968 - Q4/2009.

| | Benchmarks | | Leverage | |
|---|---|---|---|---|
| | | 3-Factor | 1-Factor | Leverage and |
| | CAPM | Benchmark | Leverage Model | 3-Factor Benchmark |
| | (i) | (ii) | (iii) | (iv) |
| Constant | 1.544 | -0.100 | 0.300 | 0.155 |
| | (3.418) | (-0.681) | (0.733) | (0.974) |
| | (3.408) | (-0.679) | (0.730) | (0.971) |
| Leverage | | | 0.333 | 0.259 |
| | | | (3.602) | (3.570) |
| | | | (3.591) | (3.560) |
| Market | 0.040 | 0.164 | | 0.112 |
| | (0.442) | (2.057) | | (1.402) |
| | (0.441) | (2.050) | | (1.398) |
| SMB | | 0.111 | | 0.093 |
| | | (1.395) | | (1.180) |
| | | (1.391) | | (1.177) |
| HML | | 0.262 | | 0.158 |
| | | (2.982) | | (1.815) |
| | | (2.973) | | (1.809) |
| R-Squared | 3% | 62% | 57% | 73% |
| Adj. R-Squared | -1% | 57% | 55% | 68% |
| R-Squared Confidence Interval | [0%, 22%] | [34%, 82%] | [37%, 89%] | [59%, 92%] |

Table 4: Pricing the Cross-Section of 25 Size and Momentum Portfolios

We use Fama-MacBeth two-pass regressions to price the cross-section of 25 size and momentum sorted portfolios. The table reports estimated coefficients in quarterly percentage points with Fama-MacBeth and Jagannathan-Wang t-statistics in parentheses. We also report bootstrapped confidence intervals for the R-Squared statistic using 100,000 draws of size 168 (the total number of quarters in the sample) with replacement. The sample period is Q1/1968 - Q4/2009.

| | Benchmarks | | Leverage | |
|---|---|---|---|---|
| | CAPM | 3-Factor Benchmark | 1-Factor Leverage Model | Leverage and 3-Factor Benchmark |
| | (i) | (ii) | (iii) | (iv) |
| Constant | 2.126 | 0.363 | 0.353 | -0.128 |
| | (4.368) | (1.942) | (0.355) | (-1.425) |
| | (4.355) | (1.936) | (0.354) | (-1.421) |
| Leverage | | | 0.362 | 0.220 |
| | | | (3.753) | (3.498) |
| | | | (3.742) | (3.487) |
| Market | -0.035 | 0.156 | | 0.189 |
| | (-0.343) | (1.967) | | (2.398) |
| | (-0.342) | (1.961) | | (2.391) |
| SMB | | 0.120 | | 0.127 |
| | | (1.471) | | (1.575) |
| | | (1.467) | | (1.571) |
| Momentum | | 0.253 | | 0.271 |
| | | (3.235) | | (3.448) |
| | | (3.225) | | (3.437) |
| R-Squared | 1% | 80% | 76% | 89% |
| Adj. R-Squared | -3% | 77% | 75% | 87% |
| R-Squared Confidence Interval | [0%, 1%] | [36%, 86%] | [67%, 93%] | [63%, 94%] |

## Table 5: Pricing the Cross-Section of 30 Industry Portfolios

We use Fama-MacBeth two-pass regressions to price the cross-section of 30 industry portfolios. The table reports estimated coefficients in quarterly percentage points with Fama-MacBeth and Jagannathan-Wang t-statistics in parentheses. We also report bootstrapped confidence intervals for the R-Squared statistic using 100,000 draws of size 168 (the total number of quarters in the sample) with replacement. The sample period is Q1/1968 - Q4/2009.

| | Benchmarks | | Leverage | |
|---|---|---|---|---|
| | CAPM | 3-Factor Benchmark | 1-Factor Leverage Model | Leverage and 3-Factor Benchmark |
| | (i) | (ii) | (iii) | (iv) |
| Constant | 1.44 | 1.39 | 1.01 | 1.20 |
| | (3.812) | (4.447) | (1.588) | (3.955) |
| | (3.800) | (4.433) | (1.584) | (3.943) |
| Leverage | | | 0.13 | 0.11 |
| | | | (1.674) | (1.477) |
| | | | (1.669) | (1.472) |
| Market | 0.02 | 0.04 | | 0.04 |
| | (0.219) | (0.507) | | (0.532) |
| | (0.218) | (0.506) | | (0.530) |
| SMB | | -0.08 | | -0.04 |
| | | (-0.866) | | (-0.486) |
| | | (-0.864) | | (-0.484) |
| HML | | -0.04 | | -0.05 |
| | | (-0.409) | | (-0.537) |
| | | (-0.408) | | (-0.536) |
| R-Squared | 1% | 15% | 27% | 36% |
| Adj. R-Squared | -2% | 6% | 24% | 27% |
| R-Squared Confidence Interval | [0%, 4%] | [0%, 32%] | [11%, 78%] | [8%, 68%] |

## Table 6: Pricing the Cross-Section of 65 Equity Portfolios

We use Fama-MacBeth two-pass regressions to price the cross-section of 25 size and book-to-market sorted portfolios, 10 momentum sorted portfolios, and 30 industry portfolios. The table reports estimated coefficients in quarterly percentage points with Fama-MacBeth and Jagannathan-Wang t-statistics in parentheses. We also report bootstrapped confidence intervals for the R-Squared statistic using 100,000 draws of size 168 (the total number of quarters in the sample) with replacement. The sample period is Q1/1968 - Q4/2009.

| | Benchmarks | | | Leverage | |
|---|---|---|---|---|---|
| | CAPM | Fama-French 3-Factor Benchmark | 4-Factor Benchmark | 1-Factor Leverage Model | Leverage and 3-Factor Benchmark |
| | (i) | (ii) | (iii) | (iv) | (v) |
| Constant | 1.904 | 2.023 | 0.795 | 0.666 | 0.673 |
| | (5.131) | (6.901) | (4.253) | (0.892) | (3.905) |
| | (5.116) | (6.88) | (4.240) | (0.889) | (3.893) |
| Leverage | | | | 0.230 | 0.153 |
| | | | | (4.172) | (2.364) |
| | | | | (4.159) | (2.357) |
| Market | -0.020 | -0.044 | 0.089 | | 0.085 |
| | (-0.227) | (-0.53) | (1.124) | | (1.075) |
| | (-0.226) | (-0.529) | (1.121) | | (1.071) |
| SMB | | 0.021 | 0.038 | | 0.047 |
| | | (0.267) | (0.478) | | (0.594) |
| | | (0.267) | (0.477) | | (0.592) |
| HML | | 0.023 | 0.087 | | 0.060 |
| | | (0.273) | (1.040) | | (0.720) |
| | | (0.272) | (1.037) | | (0.718) |
| Momentum | | | 0.219 | | 0.208 |
| | | | (2.804) | | (2.647) |
| | | | (2.796) | | (2.639) |
| R-Squared | 1% | 3% | 42% | 47% | 55% |
| Adj. R-Squared | -1% | -2% | 39% | 46% | 51% |
| R-Squared Confidence Interval | [0%, 2%] | [0%, 5%] | [19%, 66%] | [43%, 79%] | [35%, 78%] |

Table 7: Pricing the Cross-Section of 6 Bond Portfolios Sorted By Maturity

We use Fama-MacBeth two-pass regressions to price the cross-section of 6 treasury bond portfolios sorted on maturity. The table reports estimated coefficients in quarterly percentage points with Fama-MacBeth and Jagannathan-Wang t-statistics in parentheses. We compare our single leverage factor with shocks to the bond level factor (computed as principal components). We estimate each model with and without an intercept. For the no-intercept case, the R-Square is not well defined, hence we define R-Square as $R^2 = 1 - \sum \epsilon^2 / \sum y^2$ where $y = \beta\lambda + \epsilon$. The sample period is Q1/1968 - Q4/2009.

| | Benchmarks | | Leverage | |
|---|---|---|---|---|
| | Int | No-Int | Int | No-Int |
| | Level Shock | Level Shock | Leverage | Leverage |
| | (i) | (ii) | (iii) | (iv) |
| Constant | 0.138 | | 0.166 | |
| | (2.99) | | (3.59) | |
| | (2.89) | | (3.25) | |
| Leverage | | | 0.090 | 0.138 |
| | | | (1.53) | (2.25) |
| | | | (1.40) | (1.85) |
| Level Shock | 0.056 | 0.079 | | |
| | (1.55) | (2.23) | | |
| | (1.51) | (2.14) | | |
| R-Squared | 98% | 98% | 95% | 96% |
| Adj. R-Squared | 97% | 97% | 94% | 96% |
| R-Squared CI | [38%, 100%] | [59%, 100%] | [25%, 100%] | [60%, 100%] |

## Table 8: Pricing the Cross-Section of 6 Bond Portfolios Sorted By Maturity

We provide the pricing errors and mean absolute pricing error (MAPE) for the bond portfolios. The returns are an average of the maturities listed. We report two sets of pricing errors for the leverage factor. The first, (NRE), uses the estimate of the prices of risk for leverage from the 65 portfolio regression of stocks described earlier, while the second (RE) re-estimates the price of risk to fit the bond cross-section. Pricing errors are reported as $\alpha = E[R^e] - \beta\lambda$. For the benchmark factors, we use pricing errors from the time-series regressions, which impose that prices of risk are equal to factor means, so the pricing errors are $\alpha = E[R^e] - \beta' E[R_{fac}]$. We also include the level shocks factor, where we estimate the price of risk with no intercept. We impose the prices of risk in the multi-factor models, rather than estimate them, since three or four factor will by definition fit 6 portfolio returns. We report pricing errors in annual percentages. The sample period is Q1/1968 - Q4/2009.

| | | Benchmarks | | | Leverage | |
|---|---|---|---|---|---|---|
| | | | Fama-French, | Level | NRE | RE |
| | Mean Ret | Fama-French | Mom | Shock | Leverage | Leverage |
| | | (i) | (ii) | (iii) | (iv) | (v) |
| 0-1yr | 0.699 | 0.612 | 0.583 | 0.360 | 0.398 | 0.418 |
| 1-2yr | 1.277 | 1.084 | 0.840 | 0.312 | 0.351 | 0.415 |
| 2-3yr | 1.702 | 1.467 | 1.037 | 0.219 | 0.241 | 0.342 |
| 3-4yr | 1.955 | 1.729 | 1.127 | 0.110 | 0.044 | 0.176 |
| 4-5yr | 1.998 | 1.849 | 1.030 | -0.127 | -0.327 | -0.167 |
| 5-10yr | 2.290 | 2.105 | 0.959 | -0.267 | -0.534 | -0.339 |
| MAPE | 1.653 | 1.475 | 0.929 | 0.233 | 0.316 | 0.309 |

## Table 9: Correlations of Cross-Sectional Prices of Risk

We investigate the correlations of the factor prices of risk implied by our three-factor funding liquidity model and three benchmark models, the Fama-French-Carhart model, the Lettau-Ludvigson CCAPM, and a Macro model adapted from the specification of Chen, Roll, and Ross (1986). The prices of risk are computed via Fama-MacBeth two-pass regressions applied to the cross-section of 25 size and book-to-market sorted portfolios. The table reports estimated correlation coefficients with p-values in parentheses. The sample period is Q1/1970 - Q3/2009, which is slightly restricted due to limited availability of the Chen, Roll, and Ross factors.

| | Broker-Dealer Model with Market | |
|---|---|---|
| | Market | Leverage |
| Fama-French-Carhart Model | | |
| Market | 0.908 | 0.128 |
| | (0.00) | (0.11) |
| SMB | 0.690 | 0.243 |
| | (0.00) | (0.00) |
| HML | -0.325 | 0.760 |
| | (0.00) | (0.00) |
| Lettau-Ludvigson CCAPM | | |
| $cay$ | -0.721 | -0.097 |
| | (0.00) | (0.23) |
| $\Delta c$ | 0.796 | 0.211 |
| | (0.00) | (0.01) |
| $cay \times \Delta c$ | -0.764 | -0.324 |
| | (0.00) | (0.00) |
| Macro Model | | |
| DEF | -0.061 | -0.063 |
| | (0.45) | (0.43) |
| CPI | 0.017 | 0.747 |
| | (0.83) | (0.00) |
| IP | -0.743 | -0.628 |
| | (0.00) | (0.00) |

## Table 10: Pricing the benchmark factors with LMP

We give the time-series alphas generated by each model (LMP, Fama-French, and Fama-French plus momentum). The sample period is Jan. 1968 - Dec. 2009.

| | LMP | | | | | FF+Mom | | | FF | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Alpha | T-Alpha | Beta | T-Beta | R2 | Alpha | T-Alpha | R2 | Alpha | T-Alpha | R2 |
| S1B1 | -0.929 | -0.659 | 0.568 | 2.308 | 0.031 | -1.820 | -4.779 | 0.936 | -1.937 | -5.621 | 0.935 |
| S1B2 | 0.596 | 0.515 | 0.704 | 3.479 | 0.068 | -0.294 | -1.117 | 0.956 | -0.098 | -0.408 | 0.956 |
| S1B3 | 0.485 | 0.481 | 0.822 | 4.662 | 0.116 | -0.361 | -1.398 | 0.947 | 0.109 | 0.443 | 0.942 |
| S1B4 | 0.950 | 1.006 | 0.871 | 5.278 | 0.144 | -0.053 | -0.199 | 0.939 | 0.685 | 2.564 | 0.924 |
| S1B5 | 1.295 | 1.195 | 0.898 | 4.743 | 0.119 | -0.205 | -0.703 | 0.942 | 0.569 | 1.948 | 0.929 |
| S2B1 | -0.170 | -0.138 | 0.573 | 2.660 | 0.041 | -0.461 | -1.680 | 0.957 | -0.865 | -3.372 | 0.954 |
| S2B2 | 0.359 | 0.354 | 0.729 | 4.124 | 0.093 | 0.051 | 0.208 | 0.951 | -0.085 | -0.381 | 0.951 |
| S2B3 | 0.639 | 0.745 | 0.854 | 5.699 | 0.164 | 0.261 | 1.066 | 0.938 | 0.536 | 2.377 | 0.936 |
| S2B4 | 0.618 | 0.751 | 0.918 | 6.385 | 0.197 | -0.029 | -0.108 | 0.921 | 0.526 | 2.016 | 0.910 |
| S2B5 | 1.004 | 1.042 | 0.858 | 5.091 | 0.135 | -0.232 | -0.821 | 0.932 | 0.332 | 1.222 | 0.924 |
| S3B1 | 0.099 | 0.088 | 0.501 | 2.542 | 0.038 | -0.025 | -0.103 | 0.958 | -0.437 | -1.872 | 0.954 |
| S3B2 | 0.233 | 0.268 | 0.809 | 5.322 | 0.146 | 0.016 | 0.062 | 0.933 | 0.198 | 0.852 | 0.932 |
| S3B3 | 0.226 | 0.297 | 0.862 | 6.473 | 0.202 | 0.076 | 0.254 | 0.889 | 0.307 | 1.128 | 0.887 |
| S3B4 | 0.456 | 0.601 | 0.875 | 6.604 | 0.208 | -0.011 | -0.035 | 0.884 | 0.403 | 1.419 | 0.876 |
| S3B5 | 1.275 | 1.462 | 0.835 | 5.481 | 0.153 | 0.359 | 0.971 | 0.862 | 0.867 | 2.519 | 0.853 |
| S4B1 | 0.567 | 0.558 | 0.467 | 2.632 | 0.040 | 0.634 | 2.605 | 0.950 | 0.284 | 1.249 | 0.946 |
| S4B2 | -0.215 | -0.262 | 0.788 | 5.473 | 0.153 | -0.129 | -0.420 | 0.893 | -0.203 | -0.728 | 0.892 |
| S4B3 | 0.187 | 0.249 | 0.803 | 6.111 | 0.184 | -0.018 | -0.060 | 0.883 | 0.171 | 0.632 | 0.882 |
| S4B4 | 0.503 | 0.679 | 0.800 | 6.171 | 0.187 | 0.061 | 0.208 | 0.884 | 0.425 | 1.562 | 0.878 |
| S4B5 | 0.689 | 0.783 | 0.780 | 5.075 | 0.134 | -0.120 | -0.341 | 0.875 | 0.136 | 0.426 | 0.873 |
| S5B1 | 0.327 | 0.416 | 0.374 | 2.723 | 0.043 | 0.487 | 2.434 | 0.944 | 0.203 | 1.089 | 0.940 |
| S5B2 | 0.081 | 0.121 | 0.656 | 5.594 | 0.159 | 0.130 | 0.554 | 0.907 | 0.256 | 1.204 | 0.906 |
| S5B3 | -0.301 | -0.496 | 0.693 | 6.544 | 0.205 | -0.454 | -1.741 | 0.866 | -0.114 | -0.469 | 0.859 |
| S5B4 | -0.063 | -0.101 | 0.690 | 6.299 | 0.193 | -0.323 | -1.345 | 0.893 | -0.125 | -0.570 | 0.890 |
| S5B5 | 0.494 | 0.681 | 0.558 | 4.402 | 0.105 | -0.102 | -0.291 | 0.811 | -0.016 | -0.051 | 0.811 |
| Food | 0.800 | 1.131 | 0.545 | 4.408 | 0.105 | 1.090 | 2.138 | 0.576 | 0.899 | 1.947 | 0.574 |
| Beer | 0.796 | 0.937 | 0.601 | 4.050 | 0.090 | 0.727 | 1.114 | 0.512 | 1.012 | 1.711 | 0.508 |
| Smoke | 1.775 | 1.746 | 0.587 | 3.306 | 0.062 | 1.970 | 2.087 | 0.264 | 1.769 | 2.072 | 0.263 |
| Games | 0.587 | 0.484 | 0.544 | 2.563 | 0.038 | -0.306 | -0.522 | 0.797 | -0.673 | -1.265 | 0.794 |
| Books | -0.360 | -0.370 | 0.734 | 4.316 | 0.101 | -0.803 | -1.676 | 0.802 | -0.651 | -1.501 | 0.801 |
| Hshld | 0.124 | 0.155 | 0.534 | 3.800 | 0.080 | 0.031 | 0.059 | 0.632 | 0.126 | 0.263 | 0.632 |
| Clths | -0.078 | -0.069 | 0.825 | 4.150 | 0.094 | -0.162 | -0.249 | 0.732 | -0.561 | -0.950 | 0.729 |
| Hlth | 0.888 | 1.142 | 0.406 | 2.989 | 0.051 | 1.134 | 2.331 | 0.662 | 1.062 | 2.415 | 0.662 |
| Chems | 0.178 | 0.223 | 0.596 | 4.267 | 0.099 | 0.165 | 0.350 | 0.713 | -0.002 | -0.004 | 0.712 |
| Txtls | -0.422 | -0.385 | 0.780 | 4.074 | 0.091 | -1.375 | -2.346 | 0.764 | -1.229 | -2.318 | 0.763 |
| Cnstr | -0.609 | -0.658 | 0.904 | 5.596 | 0.159 | -0.872 | -1.929 | 0.817 | -0.595 | -1.448 | 0.815 |
| Steel | 0.001 | 0.001 | 0.470 | 2.452 | 0.035 | -0.695 | -0.928 | 0.590 | -0.861 | -1.272 | 0.590 |
| FabPr | -0.003 | -0.003 | 0.639 | 3.784 | 0.079 | -0.130 | -0.257 | 0.772 | -0.380 | -0.831 | 0.770 |
| ElcEq | 0.861 | 0.928 | 0.547 | 3.377 | 0.064 | 0.568 | 1.342 | 0.823 | 0.594 | 1.554 | 0.823 |
| Autos | 0.016 | 0.014 | 0.500 | 2.603 | 0.039 | -0.798 | -1.228 | 0.695 | -1.253 | -2.117 | 0.690 |
| Carry | -0.039 | -0.038 | 0.846 | 4.783 | 0.121 | -0.239 | -0.372 | 0.677 | -0.121 | -0.208 | 0.677 |
| Mines | -0.142 | -0.131 | 0.608 | 3.208 | 0.058 | 0.062 | 0.064 | 0.308 | -0.048 | -0.055 | 0.308 |
| Coal | 1.708 | 1.047 | 0.700 | 2.455 | 0.035 | 2.056 | 1.321 | 0.201 | 1.988 | 1.414 | 0.201 |
| Oil | 0.276 | 0.392 | 0.725 | 5.885 | 0.173 | 0.642 | 1.033 | 0.414 | 1.004 | 1.777 | 0.407 |
| Util | -0.241 | -0.404 | 0.694 | 6.656 | 0.211 | -0.131 | -0.273 | 0.537 | 0.206 | 0.472 | 0.530 |
| Telcm | 0.401 | 0.545 | 0.402 | 3.132 | 0.056 | 0.087 | 0.184 | 0.651 | 0.107 | 0.253 | 0.651 |
| Servs | 0.793 | 0.698 | 0.466 | 2.346 | 0.032 | 0.777 | 2.008 | 0.898 | 0.285 | 0.794 | 0.892 |
| BusEq | 0.721 | 0.635 | 0.256 | 1.288 | 0.010 | 0.400 | 0.714 | 0.781 | -0.168 | -0.326 | 0.774 |
| Paper | 0.194 | 0.242 | 0.569 | 4.061 | 0.090 | -0.030 | -0.065 | 0.728 | -0.185 | -0.443 | 0.727 |
| Trans | -0.395 | -0.453 | 0.789 | 5.185 | 0.139 | -0.641 | -1.365 | 0.772 | -0.495 | -1.164 | 0.772 |
| Whlsl | -0.387 | -0.431 | 0.837 | 5.336 | 0.146 | -0.461 | -0.969 | 0.782 | -0.177 | -0.408 | 0.779 |
| Rtail | 0.534 | 0.571 | 0.591 | 3.616 | 0.073 | 0.492 | 0.983 | 0.758 | 0.292 | 0.643 | 0.757 |
| Meals | 0.268 | 0.245 | 0.781 | 4.091 | 0.092 | 0.357 | 0.521 | 0.674 | 0.093 | 0.150 | 0.672 |
| Fin | -0.218 | -0.258 | 0.855 | 5.790 | 0.168 | -0.656 | -1.752 | 0.851 | -0.262 | -0.759 | 0.846 |
| Other | -1.085 | -1.209 | 0.758 | 4.835 | 0.123 | -1.240 | -2.627 | 0.779 | -1.129 | -2.645 | 0.779 |
| Mom 1 | -0.532 | -0.380 | -0.165 | -0.674 | 0.003 | -0.829 | -2.036 | 0.923 | -3.832 | -6.239 | 0.786 |
| Mom 2 | 0.404 | 0.368 | 0.175 | 0.914 | 0.005 | 0.393 | 1.365 | 0.938 | -1.609 | -3.844 | 0.839 |
| Mom 3 | 0.901 | 0.988 | 0.149 | 0.937 | 0.005 | 0.971 | 3.519 | 0.917 | -0.704 | -1.899 | 0.817 |
| Mom 4 | 0.413 | 0.518 | 0.411 | 2.947 | 0.050 | 0.455 | 1.596 | 0.889 | -0.449 | -1.511 | 0.853 |
| Mom 5 | 0.140 | 0.193 | 0.418 | 3.301 | 0.062 | 0.068 | 0.264 | 0.892 | -0.499 | -1.988 | 0.875 |
| Mom 6 | 0.113 | 0.154 | 0.545 | 4.248 | 0.098 | 0.100 | 0.376 | 0.892 | -0.120 | -0.493 | 0.890 |
| Mom 7 | -0.006 | -0.010 | 0.622 | 5.741 | 0.166 | -0.118 | -0.469 | 0.876 | 0.214 | 0.917 | 0.869 |
| Mom 8 | 0.160 | 0.264 | 0.759 | 7.165 | 0.236 | -0.043 | -0.206 | 0.916 | 0.760 | 3.289 | 0.876 |
| Mom 9 | -0.004 | -0.006 | 0.877 | 7.617 | 0.259 | -0.365 | -1.664 | 0.925 | 0.784 | 2.870 | 0.858 |
| Mom10 | 0.897 | 0.997 | 0.974 | 6.193 | 0.188 | 0.375 | 1.238 | 0.916 | 2.072 | 5.309 | 0.830 |
| B1 | 0.138 | 2.871 | 0.016 | 1.911 | 0.022 | 0.144 | 2.878 | 0.033 | 0.152 | 3.360 | 0.033 |
| B2 | 0.110 | 0.366 | 0.207 | 3.951 | 0.086 | 0.232 | 0.736 | 0.078 | 0.525 | 1.814 | 0.052 |
| B3 | 0.183 | 1.581 | 0.060 | 2.978 | 0.051 | 0.207 | 1.696 | 0.049 | 0.270 | 2.439 | 0.041 |
| B4 | 0.206 | 1.178 | 0.098 | 3.204 | 0.058 | 0.255 | 1.384 | 0.049 | 0.365 | 2.182 | 0.038 |
| B5 | 0.198 | 0.927 | 0.130 | 3.477 | 0.068 | 0.278 | 1.228 | 0.052 | 0.431 | 2.096 | 0.038 |
| B6 | 0.145 | 0.582 | 0.158 | 3.633 | 0.074 | 0.250 | 0.949 | 0.056 | 0.460 | 1.914 | 0.036 |
| Mkt | 0.149 | 0.209 | 0.539 | 4.336 | 0.102 | | | | | | |
| SMB | 0.494 | 0.990 | 0.122 | 1.399 | 0.012 | | | | | | |
| HML | 0.950 | 1.651 | 0.029 | 0.289 | 0.001 | | | | | | |
| MOM | 0.247 | 0.401 | 0.779 | 7.238 | 0.240 | | | | 3.212 | 6.107 | 0.382 |
| LMP | | | | | | -0.068 | -0.270 | 0.706 | 1.905 | 4.817 | 0.117 |

## Table 11: Time-Series Alphas: Comparing Models

We give the time-series alphas generated by each model (LMP, Fama-French, and Fama-French plus momentum), MAPE represents the mean absolute pricing error given in percent per annum (ie, MAPE=$\frac{1}{N}\sum_{i=1}^{N}|\alpha_i|$). MSPE represents the mean squared pricing error. SBM represents the 25 size and book-to-market portfolios, IND the 30 industry, MOM the 10 momentum, and Bond the 6 bond portfolios. The first column (MEAN) gives the absolute average return to be explained. We also report the GRS F-statistic that the alphas are jointly zero and its associated p-value. The sample period is Jan. 1968 - Dec. 2009.

MAPE

| | MEAN | LMP | FF+MOM | FF |
|---|---|---|---|---|
| Total | 6.39 | 1.85 | 1.71 | 2.32 |
| | | | | |
| SBM | 7.86 | 2.26 | 1.04 | 1.57 |
| IND | 6.43 | 1.93 | 2.56 | 2.44 |
| MOM | 5.80 | 1.47 | 1.46 | 4.36 |
| Bond | 3.04 | 0.92 | 0.94 | 2.42 |

MSPE

| | LMP | FF+MOM | FF |
|---|---|---|---|
| Total | 0.357 | 0.393 | 0.722 |
| | | | |
| SBM | 0.381 | 0.202 | 0.309 |
| IND | 0.445 | 0.675 | 0.629 |
| MOM | 0.229 | 0.230 | 2.376 |
| Bond | 0.028 | 0.054 | 0.150 |

Model Fit Statistics

| | LMP | FF+MOM | FF |
|---|---|---|---|
| GRS | 2.25 | 2.10 | 2.73 |
| P-value | 0 | 0 | 0 |

## Table 12: Pricing the benchmark factors with LMP

We run time-series regressions of four benchmark factors, the market, smb, hml, and momentum factors, on the LMP. We report the quarterly results for our main sample 1968-2009, as well as monthly results that begin in 1936, which is the sample consistent with our beta sorting exercise. We provide the average mean return to be explained, along with the time-series regression statistics. Mean returns and alphas are reported in annual percentage terms for consistency.

Model: $R_t^e = \alpha + \beta \; LMP_t + \varepsilon_t$

| Quarterly Data: 1968-2009 | | | | | | |
|---|---|---|---|---|---|---|
| | Mean Ret | Alpha | T-Alpha | Beta | T-Beta | R2 |
| Mkt | 5.44 | 0.59 | (0.21) | 0.54 | (4.34) | 0.10 |
| SMB | 3.07 | 1.98 | (0.99) | 0.12 | (1.40) | 0.01 |
| HML | 4.06 | 3.80 | (1.65) | 0.03 | (0.29) | 0.00 |
| Mom | 7.99 | 0.99 | (0.40) | 0.78 | (7.24) | 0.24 |
| **Monthly Data: 1936-2009** | | | | | | |
| | Mean Ret | Alpha | T-Alpha | Beta | T-Beta | R2 |
| Mkt | 6.93 | -0.86 | (-0.51) | 0.83 | (17.43) | 0.26 |
| SMB | 2.44 | 0.96 | (0.78) | 0.16 | (4.51) | 0.02 |
| HML | 5.04 | 2.45 | (2.05) | 0.28 | (8.14) | 0.07 |
| Mom | 8.03 | 1.69 | (1.10) | 0.67 | (15.44) | 0.21 |

## Table 13: Mean-Standard Deviation Analysis

We give the monthly mean, variance, and Sharpe ratios of the Fama-French three factors, momentum factor, leverage mimicking portfolio (LMP), and the maximum possible Sharpe ratio from any combination of the Fama-French three factors and momentum factor. Data are monthly from Jan. 1936 - Dec. 2009.

| | Mean | Std | Sharpe Ratio |
|---|---|---|---|
| Market | 0.5712 | 4.2973 | 0.1329 |
| SMB | 0.1523 | 2.8623 | 0.0532 |
| HML | 0.4001 | 2.7496 | 0.1455 |
| Mom | 1.3168 | 6.4799 | 0.2032 |
| LMP | 1.1201 | 3.3715 | 0.3036 |
| Max Sharpe | | | 0.3541 |

## Table 14: Simulation and Robustness

We randomly draw samples from the empirical distribution leverage factor with replacement and report p-values of the observed cross-sectional test statistics using 100,000 samples. The p-value for alpha represents the probability of observing an absolute average pricing error as low as we report, while the p-value for R-Squared represents the probability of seeing a cross-sectional R-Square as high as we report. We use the large cross-section of 65 returns based on industry, momentum, and size and book-to-market. We also simulate the weights of the leverage mimicking portfolio (LMP) from a uniform distribution, as well as simulating the factor used for the LMP itself by sampling from the leverage series, with replacement, and projecting onto the benchmark factors.

| | | P-value | Number of Occurences | Replications |
|---|---|---|---|---|
| Simulation of Original factor | | | | |
| | Alpha | 0.00010 | 10 | 100,000 |
| | R-Squared | 0.00016 | 16 | 100,000 |
| | Alpha, R-Squared Jointly | 0.00001 | 1 | 100,000 |
| Simulation of LMP factor | | | | |
| | Alpha | 0.00002 | 2 | 100,000 |
| | R-Squared | 0 | 0 | 100,000 |
| | Alpha, R-Squared Jointly | 0 | 0 | 100,000 |
| Simulation of LMP weights | | | | |
| | Alpha | 0.00065 | 65 | 100,000 |
| | R-Squared | 0.00040 | 40 | 100,000 |
| | Alpha, R-Squared Jointly | 0.00005 | 5 | 100,000 |

Table 15: LMP Beta-Sorts

We sort the entire cross-section of CRSP stocks based on their exposure to the LMP using 20 year rolling-window regressions, requiring at least 10 years worth of initial observations. We rebalance in July of each year. We report both the equal and value-weighted returns, in terms of percent per month, on the 10 portfolios, along with their average market capitalization, and their post-ranking LMP beta computed using the value-weighted return, computed over the entire sample. The estimation period is Jan. 1926 - Dec. 2009 and the holding period is Jan. 1936 - Dec. 2009,

| Pre-Beta Decile | N Obs | Variable | Mean | t-Value | Mkt Cap | Post LMP Beta |
|---|---|---|---|---|---|---|
| 1 | 876 | ewret | 1.21 | 7.47 | 276.56 | 0.265 |
| | | vwret | 1.09 | 6.77 | | |
| 2 | 876 | ewret | 1.23 | 8.82 | 268.16 | 0.572 |
| | | vwret | 1.25 | 7.90 | | |
| 3 | 876 | ewret | 1.232 | 8.82 | 212.71 | 0.683 |
| | | vwret | 1.28 | 7.82 | | |
| 4 | 876 | ewret | 1.30 | 7.42 | 265.24 | 0.850 |
| | | vwret | 1.37 | 7.66 | | |
| 5 | 876 | ewret | 1.33 | 6.95 | 315.36 | 0.981 |
| | | vwret | 1.39 | 7.36 | | |
| 6 | 876 | ewret | 1.33 | 6.20 | 340.15 | 1.077 |
| | | vwret | 1.41 | 6.95 | | |
| 7 | 876 | ewret | 1.38 | 6.04 | 265.11 | 1.133 |
| | | vwret | 1.45 | 6.48 | | |
| 8 | 876 | ewret | 1.47 | 6.08 | 286.62 | 1.220 |
| | | vwret | 1.59 | 6.40 | | |
| 9 | 876 | ewret | 1.53 | 5.96 | 249.27 | 1.377 |
| | | vwret | 1.62 | 6.53 | | |
| 10 | 876 | ewret | 1.71 | 6.28 | 191.023 | 1.563 |
| | | vwret | 1.81 | 6.85 | | |

Table A1: Pricing the Cross-Section of 25 Size and Book-to-Market Portfolios (1968-2005)

We use Fama-MacBeth two-pass regressions to price the cross-section of 25 size and book-to-market sorted portfolios. The table reports estimated coefficients in quarterly percentage points with Fama-MacBeth and Jagannathan-Wang t-statistics in parentheses. The sample period is Q1/1969 - Q4/2005.

| | Benchmarks | | | | |
|---|---|---|---|---|---|
| | | 3-Factor | 1-Factor | Leverage and | |
| | CAPM | Benchmark | Leverage Model | 3-Factor Benchmark | Combined |
| | (i) | (ii) | (iv) | (v) | (vii) |
| Constant | 1.804 | -0.105 | 0.190 | -0.040 | -0.040 |
| | (4.082) | (-0.960) | (1.138) | (-0.343) | (-0.580) |
| | (4.069) | (-0.957) | (1.134) | (-0.342) | (-0.578) |
| Leverage | | | 0.282 | 0.133 | 0.163 |
| | | | (2.772) | (1.663) | (2.072) |
| | | | (2.763) | (1.657) | (2.066) |
| Market | 0.037 | 0.183 | | 0.160 | 0.158 |
| | (0.391) | (2.242) | | (1.949) | (1.949) |
| | (0.390) | (2.235) | | (1.943) | (1.943) |
| SMB | | 0.114 | | 0.106 | 0.103 |
| | | (1.390) | | (1.304) | (1.266) |
| | | (1.385) | | (1.300) | (1.262) |
| HML | | 0.272 | | 0.242 | 0.245 |
| | | (3.139) | | (2.785) | (2.849) |
| | | (3.129) | | (2.776) | (2.840) |
| Stambaugh | | | | | 0.798 |
| | | | | | (3.713) |
| | | | | | (3.701) |
| R-Squared | 2% | 72% | 44% | 72% | 81% |
| Adj. R-Squared | -2% | 68% | 41% | 68% | 77% |

## Table A2: Pricing the Cross-Section of 65 Equity Portfolios (1968-2005)

We use Fama-MacBeth two-pass regressions to price the cross-section of 25 size and book-to-market sorted portfolios, 10 momentum sorted portfolios, and 30 industry portfolios. The table reports estimated coefficients in quarterly percentage points with Fama-MacBeth and Jagannathan-Wang t-statistics in parentheses. The sample period is Q1/1969 - Q4/2005.

| | Benchmarks | | | Leverage | | |
|---|---|---|---|---|---|---|
| | CAPM | Fama-French 3-Factor Benchmark | 4-Factor Benchmark | 1-Factor Leverage Model | Leverage and 3-Factor Benchmark | Combined |
| | (i) | (ii) | (iii) | (iv) | (v) | (viii) |
| Constant | 1.976 | 1.793 | 0.590 | 0.534 | 0.573 | 0.425 |
| | (5.092) | (6.735) | (3.174) | (1.130) | (3.134) | (3.441) |
| | (5.076) | (6.713) | (3.164) | (1.127) | (3.124) | (3.430) |
| Leverage | | | | 0.205 | 0.167 | 0.164 |
| | | | | (2.747) | (2.197) | (2.161) |
| | | | | (2.738) | (2.190) | (2.154) |
| Market | -0.010 | -0.005 | 0.127 | | 0.111 | 0.128 |
| | (-0.106) | (-0.060) | (1.532) | | (1.338) | (1.569) |
| | (-0.106) | (-0.060) | (1.527) | | (1.334) | (1.564) |
| SMB | | 0.024 | 0.050 | | 0.059 | 0.056 |
| | | (0.286) | (0.597) | | (0.711) | (0.680) |
| | | (0.285) | (0.595) | | (0.709) | (0.678) |
| HML | | 0.082 | 0.138 | | 0.108 | 0.114 |
| | | (0.946) | (1.589) | | (1.245) | (1.316) |
| | | (0.943) | (1.584) | | (1.241) | (1.312) |
| Momentum | | | 0.265 | | 0.260 | 0.262 |
| | | | (3.290) | | (3.214) | (3.255) |
| | | | (3.279) | | (3.203) | (3.244) |
| Pastor-Stambaugh | | | | | | 0.015 |
| | | | | | | (0.063) |
| | | | | | | (0.063) |
| R-Squared | 0% | 4% | 51% | 32% | 61% | 62% |
| Adj. R-Squared | -1% | 1% | 48% | 31% | 57% | 58% |
| R-Squared Confidence Interval | [0%, 1%] | [0%, 8%] | [32%, 74%] | [17%, 73%] | [49%, 85%] | [48%, 83%] |

Table A3: Pricing the Cross-Section of 65 Equity Portfolios and 6 Bond Portfolios

We use Fama-MacBeth two-pass regressions to price the cross-section of 25 size and book-to-market sorted portfolios, 10 momentum sorted portfolios, 30 industry portfolios, and 6 treasury portfolios sorted on maturity. We also include the Fama-French factors (Mkt, SMB, HML), momentum factor, and leverage mimicking portfolio (LMP) as test assets. The table reports estimated coefficients in quarterly percentage points with Fama-MacBeth and Jagannathan-Wang t-statistics in parentheses. We also report bootstrap confidence intervals for the R-Squared statistic using 100,000 draws of size 168 (the total number of quarters in the sample) with replacement. The sample period is Q1/1968 - Q4/2009.

| | Benchmarks | | | LMP |
|---|---|---|---|---|
| | | Fama-French | | |
| | | 3-Factor | 4-Factor | 1-Factor |
| | CAPM | Benchmark | Benchmark | Leverage Model |
| | (i) | (ii) | (iii) | (iv) |
| Constant | 1.210 | 1.153 | 0.451 | 0.363 |
| | (5.183) | (6.168) | (3.472) | (0.786) |
| | (5.178) | (6.153) | (3.196) | (0.729) |
| Leverage | | | | 2.167 |
| | | | | (3.927) |
| | | | | (3.797) |
| Market | 0.399 | 0.399 | 1.065 | |
| | (0.529) | (0.558) | (1.512) | |
| | (0.529) | (0.558) | (1.506) | |
| SMB | | 0.138 | 0.213 | |
| | | (0.291) | (0.449) | |
| | | (0.291) | (0.446) | |
| HML | | 0.281 | 0.639 | |
| | | (0.499) | (1.135) | |
| | | (0.499) | (1.123) | |
| Momentum | | | 1.840 | |
| | | | (2.801) | |
| | | | (2.793) | |
| R-Squared | 4% | 6% | 52% | 53% |
| Adj. R-Squared | 3% | 2% | 50% | 52% |
| R-Squared Confidence Interval | [0%, 4%] | [0%, 19%] | [28%, 78%] | [46%, 83%] |

## Table A3: Pricing the Cross-Section of 65 Equity Portfolios and 6 Bond Portfolios

We use Fama-MacBeth two-pass regressions to price the cross-section of 25 size and book-to-market sorted portfolios, 10 momentum sorted portfolios, 30 industry portfolios, and 6 Treasury bond portfolios sorted by maturity. The table reports estimated coefficients in quarterly percentage points with Fama-MacBeth and Jagannathan-Wang t-statistics in parentheses. We also report bootstrap confidence intervals for the R-Squared statistic using 100,000 draws of size 168 (the total number of quarters in the sample) with replacement. The sample period is Q1/1968 - Q4/2009.

| | Benchmarks | Leverage |
|---|---|---|
| | 5-Factor Benchmark | 1-Factor Leverage Model |
| | (iii) | (iv) |
| Constant | 0.2706 | 0.5477 |
| | (1.7993) | (0.9426) |
| | (1.6250) | (0.7171) |
| Leverage | | 0.1642 |
| | | (4.6596) |
| | | (3.6855) |
| Market | 1.2062 | |
| | (1.6916) | |
| | (1.6788) | |
| SMB | 0.2576 | |
| | (0.5437) | |
| | (0.5400) | |
| HML | 0.6508 | |
| | (1.1549) | |
| | (1.1387) | |
| Momentum | 1.8460 | |
| | (2.8105) | |
| | (2.8013) | |
| Level Shock | 0.0516 | |
| | (1.3420) | |
| | (1.2312) | |
| R-Squared | 54% | 50% |
| Adj. R-Squared | 51% | 49% |
| R-Squared Confidence Interval | [28%, 77%] | [48%,78%] |