Broker-Dealer Leverage and the Cross-Section of Expected Returns*

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Abstract

We document that average stock returns can be largely explained by their covariance with shocks to the aggregate leverage of security broker-dealers. Our single-factor leverage model compares favourably with standard multi-factor models in the cross-section of size and book-to-market portfolios and outperforms such models when considering momentum, industry, and Treasury bond portfolios. We interpret the risk captured by shocks to broker-dealer leverage as a reflection of unexpected changes in broader economic conditions.

Keywords: cross sectional asset pricing, financial intermediation
JEl codes: G1, G12, G21

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1 Introduction

Security brokers and dealers are active investors that aggressively adjust their risk exposures in response to changes in economic conditions. To the extent that the portfolio choice of broker-dealers is optimized relative to the economic environment, broker-dealer aggregate balance sheets can be expected to contain information about the marginal utility of wealth in different states of the economy. By implication, it may be possible to use broker-dealer balance sheet aggregates to proxy for the stochastic discount factor that explains the cross-section of average returns on risky financial assets.

In this paper, we present empirical evidence to support this hypothesis. Our cross-sectional tests show that broker-dealer financial leverage constitutes a state variable that passes important asset pricing tests. Specifically, we show that risk exposure to broker-dealer leverage shocks can alone explain the average excess returns on a wide variety of test assets, including portfolios sorted on 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. 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 our leverage factor's pricing performance in a cross-section that spans 65 common test portfolios.

Importantly, we do not argue that shocks to broker-dealer leverage *drive* aggregate asset prices. Rather, adjustments in broker-dealer leverage endogenously reflect changes in underlying economic state variables that may not otherwise be easily captured by an econometrician.

We provide a long list of robustness checks that confirm the strong pricing ability of our leverage factor. First and foremost, 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 our leverage factor. A second important and hard to pass test is the exceptional pricing performance across a wide variety of portfolios, including a wide range of stock portfolios and Treasury bond portfolios sorted by maturity. We conduct a third robustness check by constructing a leverage factor mimicking portfolio (LMP). The LMP allows us to construct a pricing factor with higher frequency and longer time series. 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 provide mean-variance analysis and find the LMP to have the highest Sharpe ratio of any portfolio return, and nearly as high as the maximum possible Sharpe ratio of any combination of the Fama-French three factors and momentum factor (i.e., it is nearly on the sample efficient frontier). 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 that post-formation LMP betas line up well with average returns.

Our strong empirical results are consistent with a growing literature on the link between financial institutions and asset prices. First, shocks to leverage may capture the time-varying balance sheet capacity of financial intermediaries. In such settings, leverage of financial intermediaries is limited by risk management constraints such as those related to Value at Risk. Time-variation in leverage is then driven by changes

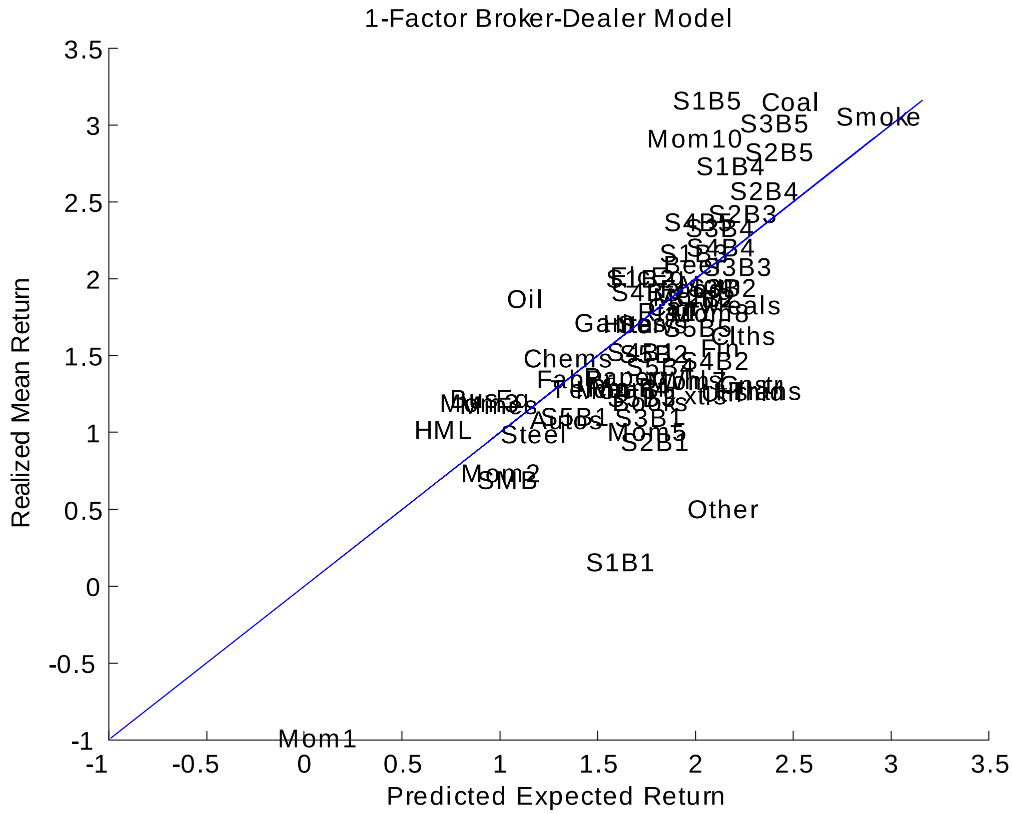

Figure 1: Realized vs. Predicted Mean Returns. We plot the realized mean excess returns of 65 portfolios (25 Size and Book-to-Market Sorted Portfolios, 30 Industry Portfolios, and 10 Momentum Sorted Portfolios) and 4 factors (market, SMB, HML, MOM) against the mean excess returns predicted by a 1-factor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

in the funding environment, which may reflect broader economic conditions. It is also possible that the underlying economic conditions that drive changes in funding liquidity also interact with variables driving market liquidity. Second, our results can be interpreted in light of intermediary asset pricing models. In such models, intermediaries are the marginal investor, and the aggregate pricing kernel is proportional to the growth of financial sector wealth. The leverage of broker-dealers rises with the wealth of the overall financial sector as the demand for broker-dealer services increases. Thus, the leverage of broker-dealers is proportional to the health of the overall financial system. Third, our findings are consistent with intertemporal, heterogenous agent models where constraints on arbitrageur leverage are driven by economy-wide investment opportunities. Because the portfolio choice of arbitrageurs tracks the investment opportunity set, leverage arises naturally as a state variable capturing shifts in the marginal utility of wealth.

The common thread between 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 utility of wealth of investors. By implication, investors are expected to require higher compensation for holding assets whose returns exhibit greater comovement with shocks to broker-dealer leverage. 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 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 number of robustness checks. Section 6 concludes.

2 Financial Intermediaries and Asset Prices

2.1 Broker-Dealers and Procyclical Leverage

Financial intermediaries serve an important economic role in the allocation of savings from ultimate savers to ultimate borrowers. As agents of savers, financial intermediaries are subject to constraints that can be interpreted as the outcome of agency problems. The managers of the financial intermediaries can be expected to take dynamically optimal, rational decisions to maximize the institution's value subject to such constraints, which in practice take the form of restrictions on risk management and compensation. The profit-maximizing balance sheet management of financial intermediaries is in stark contrast to the portfolio choice of households, which may be subject to many potential issues, such as slow adjustment (Jagannathan and Wang, 2006; Calvet, Campbell and Sodini, 2009), habits (Campbell and Cochrane, 1999), limited participation (Vissing-Jorgensen, 2002), and model uncertainty (Hansen and Sargent, 2007). Financial intermediaries, on the other hand, optimize their portfolio holdings frequently based on sophisticated models and extensive historical data on the distribution of returns, and report timely and accurate data to their regulators. The aggregate portfolio choice of financial intermediaries can thus be expected to provide a better empirical window to the time-varying investment opportunity set than aggregate measures based on household behavior.

Adrian and Shin (2010) provide empirical evidence to such profit-maximizing balance sheet management practices across security broker-dealers. Specifically, the authors demonstrate that security broker-dealers adjust their financial leverage aggressively in response to changing economic conditions.[1] The dynamics of U.S. security

[1] Leverage is measured by the the ratio of financial assets to equity.

broker-dealer aggregate balance sheet components are easily quantified using the Federal Reserve's Flow of Funds Accounts. These data reveal that 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 *procyclical*.

Table 1: Broker-dealer leverage is pro-cyclical. The correlation of broker-dealer leverage growth with a selection of state variables, 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

The procyclicality of broker-dealer leverage can be understood in terms of its co-movement with other state variables, which we compute in the Table 1. We display the correlations of broker-dealer leverage growth with the value-weighted return on the U.S. equity market, profit growth of the U.S. financial sector (obtained from the Bureau of Economic Analysis), the value-weighted stock return on the U.S. financial sector, and the asset growth of broker-dealers. Positive correlation in each case shows that leverage growth is pro-cyclical and related to wealth, compensation, and investment opportunities. The strong correlation of leverage growth with broker-dealer asset growth moreover suggests that the *ability* of broker-dealers to borrow is close to the amount *actually* borrowed, making leverage a proxy for funding liquidity.

2.2 Theories on Financial Intermediaries and Aggregate Asset Prices

A number of studies have derived theoretical models that relate financial intermediaries to aggregate asset prices. While none of them yield direct empirical implications in terms of observable balance sheet components of intermediaries, 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.

First, our results are closely linked to the broad literature on limits of arbitrage (Shleifer and Vishny, 1997): broker-dealers are forced to unwind positions precisely when asset prices are decreasing and expected returns are rising. Gromb and Vayanos (2002) extend the results of Shleifer and Vishny by allowing arbitrageurs to take on leverage. The endogenous amplification mechanism via the margin spiral of Brunnermeier and Pedersen (2009) is also consistent with our results. In their paper, margin constraints are time-varying and can serve to amplify market fluctuations through changes in risk-bearing capacity. Danielsson, Shin and Zigrand (2009) endogenize risk and risk-bearing capacity simultaneously by solving for the equilibrium stochastic volatility function in a setting with value-at-risk constraints on financial intermediaries. Other studies that investigate the impact of balance sheet constraints on aggregate asset prices include Aiyagari and Gertler (1999), Basak and Croitoru (2000), and Caballero and Krishnamurthy (2004). Geanakoplos (2009) takes a different approach and shows how leverage can drive the business cycle and how asset prices can depend on the ability of optimists to use leverage.

Second, our results can be interpreted in light of the emerging literature on intermediary asset pricing models. For example, He and Krishnamurthy (2010) derive an intermediary CAPM in which intermediaries are marginal investors and the return on intermediary wealth can be used as a pricing kernel. Since the leverage of broker-dealers rises with the wealth and compensation in the broader financial sector as the demand for broker-dealer services increases (see Table 1), our empirical results also support this view. Times of high broker-dealer leverage are associated with good health of the overall financial system and thus low marginal utility of wealth.

Finally, our findings are consistent with intertemporal models where constraints on arbitrageur leverage are driven by economy-wide investment opportunities. In such theories, which build on heterogeneous agent extensions of the Intertemporal Capital Asset Pricing Model (ICAPM) of Merton (1969, 1971, 1973), the portfolio choice of arbitrageurs tracks the investment opportunity set and leverage arises as a state variable, capturing shifts in the marginal utility of wealth. Examples include Chabakauri (2009) and Rytchkov (2009).

2.3 Factor Models and Cross-Sectional Asset Pricing

The theories reviewed above provide a variety of intuitive justifications for why times of growing broker-dealer leverage are likely to be associated with low marginal utility of wealth. We investigate this prediction via a linear factor model. As such, our study is related to a vast empirical asset pricing literature that seeks to address the failures of the CAPM via different factor approaches.

One way to motivate factor models is via the ICAPM where long-term investors care about shocks to investment opportunities in addition to wealth shocks. Campbell (1993) solves a discrete-time empirical version of the ICAPM with a stochastic market premium, writing the solution in the form of a multi-factor model. Campbell (1996) tests this model on industry portfolios, but finds little improvement over the CAPM. Other empirical studies of the ICAPM include Li (1997), Hodrick, Ng, and Sengmueller (1999), Lynch (1999), Brennan, Wang, and Xia (2004), Guo (2002), Chen (2003), Ng (2004), Ang, Hodrick, Xing, Zhang (2006, 2009), Adrian and Rosenberg (2008), and Bali and Engle (2009).

Another way to motivate a factor approach is the Arbitrage Pricing Theory (APT) of Ross (1976), which allows any pervasive source of common variation to be a priced risk factor. Fama and French (1993) follow the APT insight and describe the average returns on portfolios sorted by size and value using a three-factor specification, which complements the market model with a size factor and a value factor. However, since the APT is silent about the determinants of factor prices of risk, a model such as that of Fama and French cannot explain why the risk premia associated with certain factors are positive or negative. The same caveat applies to other APT-motivated factors specifically tailored to explain asset pricing anomalies. The momentum anomaly of Jegadeesh and Titman (1993, 2001) and the momentum factor of Carhart (1997) is another example.[2]

The failures of standard asset pricing models can also be interpreted in behavioral terms by arguing that the size, value, and momentum effects are due to mispricing. Lakonishok, Shleifer, and Vishny (1994), for example, suggest that investors irrationally extrapolate past earnings growth and thereby overvalue companies that have performed well in the past. DeBondt and Thaler (1985, 1987), Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), and Hong, Lim and Stein (2000) suggest that both momentum and long-term reversal are the results of mispricing.

The evidence presented in this paper is consistent with risk based explanations of asset pricing anomalies, as we show that covariance with broker-dealer leverage shocks explains the cross section of expected returns. In other words, assets are fairly priced relative to their exposures to broker-dealer leverage risk. However, we cannot rule out the possibility that some of the shocks to broker-dealer leverage are due to regulatory changes or behavioral biases, in addition to reflecting rational responses to changing

[2]See also Rouwenhorst (1998, 1999), and Chui, Titman, and Wei (2000).

economic conditions.

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:

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

We construct this variable using aggregate quarterly data on the book values of total financial assets and total financial liabilities of the security broker-dealer sector 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 2009Q4. This table was released on March 11, 2010 by the Federal Reserve.

Total financial assets of $2080 billion are broken down to 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 (see the items listed under the credit market instruments in Table 2). According to the "Guide to the Flow of Funds" publication that accompanies the data, miscellaneous assets consist of three subcategories : (1) direct investment of broker-dealers abroad, (2) the net of receivables versus payables vis-a-vis other broker-dealers or clearing corporations, and (3) tangible assets. Note that the net of receivables consist primarily of cash collateral associated with securities lending transactions. The miscellaneous assets represent over half of total assets, while credit market instruments represent a bit over one fourth of total assets. While the credit market instruments and

Table 2: Assets and Liabilities of Security Broker 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, Page: 83, 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

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 the cash collateral positions.

On the liability side of Table 2, we can see that the largest liabilities 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: (1) foreign direct investment into broker-dealers, (2) investment into the broker-dealer by the parent company, and (3) unidentified liabilities ("other"). At the end of 2009, these unidentified liabilities were largely negative, reflecting pecularities in the accounting of the flow of funds (relating to derivatives positions and other items that broker-dealers report but that do not have a corresponding Flow of Funds category).

It should be noted that the broker-dealer leverage computed from the Flow of Funds is a net number, as several items on the balance sheet are netted (particularly repos and receivables). We thus do not emphasize the level of broker-dealer leverage but instead focus solely on the shocks to broker dealer leverage. One should also note that the Flow of Funds report the sheet data at the subsidiary level. Security brokers and dealers are usually subsidiaries of larger bank or financial holding companies. 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 flow of funds compiles these subsidiary level balance sheet information from various regulatory filings. In particular, the balance sheet information for the security broker-dealers is primarily aggregated from SEC Focus and Fog reports. 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.

Taken together, the balance sheet suggests that the asset side consists largely of risky assets, while the liability side consists largely of short-term risk-free borrowing (net repos 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.

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. In particular, 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.[3] A plot of broker-dealer leverage is displayed Figure 2.

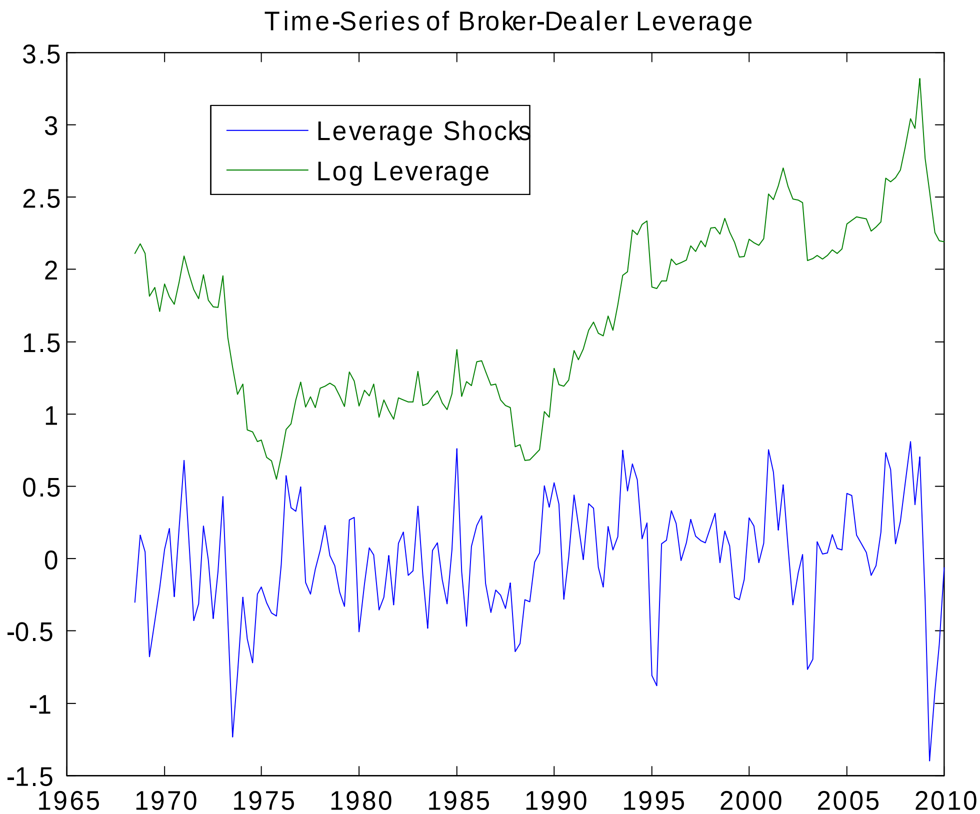

Figure 2: The plot shows the log leverage and the innovations in log leverage of the broker-dealers from 1968Q1-2009Q4.

In order to capture risk that stems from unexpected changes in broker-dealer leverage, we construct shocks to log broker-dealer leverage as innovations from a first-order

[3]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.

autoregression conditioned on information available at each point in time. We incorporate the one-quarter Flow of Funds announcement lag in the construction of the leverage shocks.[4] Note that using growth in leverage (over two-quarters) is virtually identical to the log innovations, since the leverage series is very persistent. Hence, our results are not sensitive to the choice of growth versus innovations.[5] A plot of broker-dealer leverage shocks is displayed Figure 2.

We estimate the exposures of excess returns r^i_{t+1} on broker-dealer leverage shocks from the time-series regression:

$$r^i_{t+1} = a_i + \beta_i LevShock_{t+1} + \gamma_i' Controls_{t+1} + \epsilon^i_{t+1}, \tag{2}$$

where $Controls_{t+1}$ represent additional risk factors obtained from Kenneth French's data library and Robert Stambaugh's website. The data on equity returns and U.S. Treasury returns are obtained from Kenneth French's data library and the Federal Reserve Board's Data Releases, respectively. In order to estimate the cross-sectional price of risk associated with leverage shocks, we run the Fama and MacBeth (1973) cross-sectional regression for the time series average excess of returns, Er^i_{t+1}, on risk factor exposures:

$$Er^i_{t+1} = \alpha + \beta_i \lambda_{Lev} + \gamma_i' \lambda_C + \xi^i, \tag{3}$$

where λ_{Lev} and λ_C are the prices of risk associated with leverage shocks and controls and α is the average cross-sectional pricing error.

We will consider the estimation with only leverage shocks, with only controls (multi-factor models), and jointly. The first two specifications allow comparison of the leverage

[4] For instance, the conditional expectation of broker-dealer leverage at the end of March 2000 uses data from the most recent Flow of Funds release, which corresponds to December 1999.

[5] Our results are also not sensitive to using a two quarter moving average of leverage growth to avoid measurement error. That is levfac$_t = \frac{lev_t + lev_{t-1}}{lev_{t-1} + lev_{t-2}}$

factor model to existing multi-factor models, while the joint estimation will tell us how much the multi-factor models add to the leverage factor alone.

4 Empirical Results

We test specifications of the linear factor model (3) in the cross-section of stock returns. The model predicts that the average cross-sectional pricing error (α) is zero such 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 (1993) factors market, SMB and HML also as test assets. This forces traded factors to "price themselves" and also allows us to evaluate how our model 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 success of the model 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 criticism by also including the more challenging momentum portfolios and industry portfolios as test assets. We also show strong pricing performance on bond portfolios of various U.S. Treasury maturities. This further strengthens our results since the model should apply to all assets, yet most existing tests only focus on stocks.

The sample considered in the main text is Q1/1968-Q4/2009. We display the results for the subsample that excludes the 2007-09 financial crisis in the Appendix.[6] 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 may have been an important event in revealing the inherent riskiness of some assets. However, we note that the performance comparisons between our leverage model and existing models remain qualitatively unaffected across different subsamples. Using the pre-crisis sample, we also show that the Pastor and Stambaugh (2003) market liquidity factor does not affect our comparisons.[7]

[6] See Tables A1-A4. The appendix also shows the performance of our model in the cross-section sorted on size and long-term reversal (Table A5).

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

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 test 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 3: The single market factor has no explanatory power for the average returns, yielding 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 broker-dealer 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 quite high.

We next compare the performance of our broker-dealer factor to the Fama-French three-factor benchmark. 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 *single*-factor broker-dealer model. Moreover, the confidence interval 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 significant prices of risk. To complete the picture, column (iv) combines our broker-dealer factor with the three Fama-French factors in a four-factor specification. Stunningly, our broker-dealer factor *drives out* the value factor: the price of risk associated with HML nearly halves and the factor is no longer significant at *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 capital ratio shocks overlap to an important extent with the information content of the Fama-French factors. The four panels of Figure 5 provide a graphical illustration of the performance of our broker-dealer models relative to the single and multi-factor benchmarks.

4.2 Size and Momentum Portfolios

Table 4 and Figure 6 report the pricing results for the 25 size and momentum sorted portfolios. The format follows that of Table 1 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 for this cross-section. This is contrasted with column (iii), which shows that the broker-dealer capital ratio 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 shocks to the capital ratio is negative and statistically significant. Columns (iv)-(v) demonstrate that the price of risk associated with the scaled broker-dealer wealth ratio is statistically insignificant and neither it nor the market adds further explanatory power to the model. The alphas remain statistically insignificant. The three-factor benchmark in column (ii) explains 77% of the cross-sectional returns but produces a statistically significant alpha of 0.36%. Thus, our single-factor broker-dealer model again rivals the multi-factor benchmark on its very own turf.

Combining our broker-dealer factor with the three-factor benchmark in column (vi) 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.

4.3 Industry Portfolios

Table 5 and Figure 7 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 as much as 1.44% of quarterly average returns unexplained. The results for our leverage factor in columns (iii) tell a different story. In contrast to the CAPM, our single-factor broker-dealer 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 is 11% and 78%, respectively.

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-square) with a larger and statistically significant alpha of -1.39%. The 95% confidence interval for the R-squared is 0% and 32%, respectively, showing that the explanatory power on this cross-section is indeed quite limited. Also, the prices of risk associated with the market, SMB and HML factors are statistically insignificant.

Thus, our single broker-dealer factor greatly outperforms the three-factor benchmark in this cross-section. The specification in column (vi) combines our broker-dealer factor with this benchmark to show that the price of risk associated with shocks to the capital ratio 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 model.

4.4 Simultaneous Testing of Portfolios

We have seen that our single broker-dealer 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.[8] These results are reported in Table 6 with graphical illustrations in Figure 8. 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 on the R-square confidence interval of only 5%. The four-factor benchmark in column (iii)—which appends the Fama-French model with the momentum factor—explains 42% of the cross-sectional variation in average returns but produces an alpha

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

of 0.80% per quarter that is highly statistically significant. We contrast this result with column (iv), which demonstrates that our single broker-dealer factor *alone* outperforms the four-factor benchmark with an adjusted R-squared of 46%. Importantly, the alpha for the single broker-dealer factor is 0.67% and statistically insignificant while the price of risk associated with shocks to broker-dealer capital ratio 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 1, 3, and 4 plot the realized average returns against predicted average returns with labels on the individual portfolios. Figure 1 shows that the strong performance of the single broker-dealer 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. 4) . 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 broker-dealer factor is able to correctly price the value factor (HML) and size factor (SMB)—a dimension where the Fama-French model itself fails miserably (see Fig. 3).

4.5 Bond Portfolios

We now examine our pricing results on the cross-section of bonds, using various maturities of returns on Treasury bills. We consider 1-5, 7, and 10 year maturities. Our single leverage factor explains 92% of the cross-sectional variation in Treasury returns: longer maturity excess Treasury returns have systematically larger leverage betas. Figure 9 shows how leverage betas match average excess returns quite nicely. Since there are only 7 portfolios, we do not test the Fama-French three factor or augmented 4-factor model here. They will naturally fit the 7 portfolios in a cross-sectional test, given that there are virtually no degrees of freedom. Instead, we compare the pricing power of the two models later, using time-series alphas from the Fama-French three factor models versus the leverage mimicking portfolio (LMP). For now, we simply note how well the leverage betas line up with average returns on bond portfolios.

4.6 Discussion of Main Pricing Results

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 leverage factor are not only statistically significant across different sets of test assets, but are also relatively stable in magnitude across all four cross-sections, which was confirmed above in the combined cross-section of 65 test assets. In the single-factor broker-dealer 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). Including many portfolios at once (size/book-to-market, momentum, and industries) gives a price of risk of 0.23%. These findings lend additional support to the broad-based performance of our broker-dealer leverage model.

To provide further support for the model, and to overcome potential criticisms that our leverage factor is not explicitly connected to theory, we show that our results are not due to chance. Specifically, we simulate a noisy factor by randomly drawing from the leverage factor with replacement. We construct this noise factor to have the same length as our original leverage factor and use it in our cross-sectional pricing tests. We do this 100,000 times and ask, how likely is it that a "random" factor would perform as well as our leverage factor in a cross-sectional test? We find 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. The results are given in Table 7. This makes it highly unlikely that our results are due to chance.[9]

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 how the factor prices of risk implied by our broker-dealer model relate to the factor prices of risk implied by such benchmarks. Table 8 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).[10] Specifically,

[9] 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.

[10] 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.

we use the Fama-MacBeth procedure on the size and book-to-market portfolios to construct a time-series of prices of risk and capture the comovement of prices of risk 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 broker-dealer leverage risk. While our tests certainly do not show that broker-dealers are driving the value premium, the findings are however consistent with the notion that a common source of risk may be driving both the value premium and the fluctuations in broker-dealer leverage. For the size factor SMB, its price of risk 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 make inference about the relationship of 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 positive exposure to consumption risk receives the same sign of a risk premium as exposure to leverage risk. Note that the signs of the correlations of consumption growth, of *cay*, and of scaled consumption growth with the price of risk of broker-dealer leverage are the same as the correlations with the prices of risk with the market return.

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 of the price of risk of the market return.

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

5 The Leverage Factor Mimicking Portfolio

In order to conduct additional tests, we project our non-traded leverage factor onto the space of traded returns to form the leverage "factor mimicking portfolio" (LMP), a traded portfolio that "mimicks" our 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 demonstrate that our results hold at 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 Fama-French three factors. Third, we can take a mean-variance approach to our results (see Hansen and Jagannathan 1991). We find that the LMP has the largest Sharpe ratio of any traded factor return and is comparable to the maximum possible Sharpe ratio using any combination of the Fama-French three factors and momentum factor. Finally, using the higher frequency and longer time-series, we sort the entire cross-section of traded stocks by their factor mimicking betas and document a large spread in returns that monotonically increases in betas.

5.1 Construction of the LMP

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

$$LevShock_t = \alpha + [weights]'[BV, BN, BG, SV, SN, SG, Mom]_t + \epsilon_t, \tag{4}$$

where $[BV, BN, BG, SV, SN, SG, Mom]$ are the excess return of the six Fama-French benchmark portfolios on size (Small and Big) and book-to market (Value, Neutral and Growth) over 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. The idea is that the error should be orthogonal to the space of returns, so using the LMP is without loss of generality. That is, covariance with leverage should be identical to covariance with LMP for any return. To see this, note that by construction

$$cov(LevShock_t, R_t) = cov(LMP_t, R_t) + cov(\epsilon_t, R_t) = cov(LMP_t, R_t) \tag{5}$$

for all $R_t \in span\{[BV, BN, BG, SV, SN, SG, Mom]_t\}$. Since the benchmark factors span a large amount of return space, the covariance of a return with the LMP should be quite close to its covariance with leverage. However, we should acknowledge that we may lose some information in this procedure, particularly for portfolios such as industry, where the benchmark factors have little power compared to our leverage factor.

We choose to normalize the weights to sum to one and take the mimicking portfolio return as the resulting excess return. The normalization does not change our results, but avoids choosing extreme long-short portfolios.

$$LMP_t = [normweights]'[BV, BN, BG, SV, SN, SG, Mom]_t \tag{6}$$

We find the following weights: [-0.39, 0.48, 0.13, -0.42, 1.19, -0.49, 0.50]. While the leverage factor loads strongly on momentum, the other trends are less clear. The LMP generally shorts value stocks, but does not go long growth stocks. Still on net, we do see a higher emphasis on value as opposed to growth. Also, on net, there is no large difference between small and large loadings. This intuitively suggest that the resulting factor is quite different from the Fama-French three-factors.

5.2 Pricing Results Using the LMP

We re-estimate the results for the various cross-sections of stock and bond returns using the LMP. We first use quarterly data from 1968-2009, the same data as in our main sample. Instead of a cross-sectional regression, we record the time-series alphas on each test asset. This avoids freely choosing the cross-sectional price of risk, since it imposes that the price of risk must equal the sample mean. We report these results in Table 6. We also report two other meaningful diagnostics, the mean absolute pricing error (MAPE), and the mean squared pricing error (MSPE) in Table 10. We further break these down into the individual cross-sections to compare the performance for a specific cross-section. 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 at 0.16 is significantly lower than the corresponding MAPEs for the Fama-French benchmark (0.37) or four-factor benchmark (0.23), highlighting the ability of our factor to price the cross-section of bond returns. The total MAPE for the LMP is

0.45 vs. 0.44 for the four-factor benchmark, while the MSPE is 0.36 for the LMP vs. 0.39 for the four-factor benchmark.

One may be concerned that, since the returns we project onto have 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 single mimicking factor portfolio has stronger pricing power than the combined Fama-French three factors and 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 only achieved 5 times (individually, the low alpha is reached 65 times, the high R-Square 40 times), making it highly unlikely that our results are due to chance. We find similar results by projecting a simulated vector of random draws from the leverage factor, with replacement, onto the returns and obtaining resulting weights (i.e., we simulate the LMP using random draws from the leverage factor and are unable to replicate its performance). 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 8.

We also use monthly frequency and, for stocks, go back to 1936 and repeat this exercise. (Note: While the stock return data start in 1926, we require 10 years of data to start our rolling estimation of betas discussed later. Thus, we will keep the "longer sample" consistent with starting at this date). We do this only for stocks, since the bond return data is not available before 1952, and confirm the leverage factor's strong pricing ability using both time-series alphas and cross-sectional tests.[11] Our strong empirical results thus continue to hold over the longer time-span and at the higher

[11] For the tests using monthly data and longer time-series, we do not report the time-series alphas of every test asset for every cross-section we consider, for convenience. 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 shorter time-period.

monthly frequency.

Finally, we use our single factor to price the Fama-French three factors and momentum factors *themselves*, and report the results in Table 11. 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 around 3% per annum on the HML factor. These results strengthen 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 again attributes to the strength of our results.

5.3 Mean-Variance Properties of LMP

We now turn to the mean-variance properties of our mimicking portfolio. Figure 10 plots the efficient frontier implied by the 25 book-to-market, 10 momentum, and 30 industry portfolios. 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 on the return space, which follows from the Hansen and Jagannathan (1991) bounds. The tangency portfolio just touching the mean-standard deviation hyperbola would give the highest Sharpe ratio on the sample efficient frontier .

Figure 10 also plots the largest possible Sharpe ratio of any linear combination of the Fama-French three factors and momentum factor, labeled P. At 0.30, the leverage mimicking portfolio has a much larger Sharpe ratio than the market (0.13), smb (0.05), hml (0.15), or even momentum (0.20) factors. In fact, the LMPs Sharpe ratio of 0.30 is comparable to P, the largest possible Sharpe-ratio of *any* linear combination of the pricing factors, at 0.35, which is essentially the sample stochastic discount factor. Table 12 summarizes the results. The close proximity of the LMP to the sample mean-standard deviation frontier indeed supports our results that our leverage factor is relatively close to the stochastic discount factor, especially since the true mean-standard deviation space will in general be tighter than its sample counterpart.

5.4 LMP Decile Ranking Portfolios

As a final check, we use the traded LMP portfolio to construct portfolios over 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. 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-estimation betas, which we estimate over the entire sample (1936-2009) in Table 13. 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%, 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 for the cross-section of portfolios we have analyzed.

6 Conclusion

Broker-dealers are active, forward-looking investors that aggressively adjust their portfolios and risk exposures in response to economic conditions. In this study, we ask whether broker-dealer leverage captures the marginal utility of wealth of the marginal investor that proxies for the pricing of risk. We thus indirectly investigate the extent to which shocks to aggregate broker-dealer leverage are a reduced form representation of shocks to the pricing kernel.

Our empirical results are remarkably strong. Specifically, we show that broker-dealer leverage as the *single* risk factor does well in pricing the challenging cross-section of industry portfolios, clearly dominating benchmark models. The single leverage factor also compares favorably to the Fama-French model in the cross section of size and book-to-market sorted portfolios and it rivals the benchmark tailored to explain the cross section of size and momentum sorted portfolios. Furthermore, the leverage factor prices the combined cross-section of all of the above equity portfolios, a challenge where all of the 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 result.

We interpret our results as evidence that the portfolio choice of rational forward-looking investors provides a window to broader economic conditions and underlying state variables that may not be easily captured by an econometrician. While a number of theories exist that are consistent with our empirical findings, the results beg a unified theoretical framework that would quantitatively explain the nuances. We expect this to be a fruitful area for future research.

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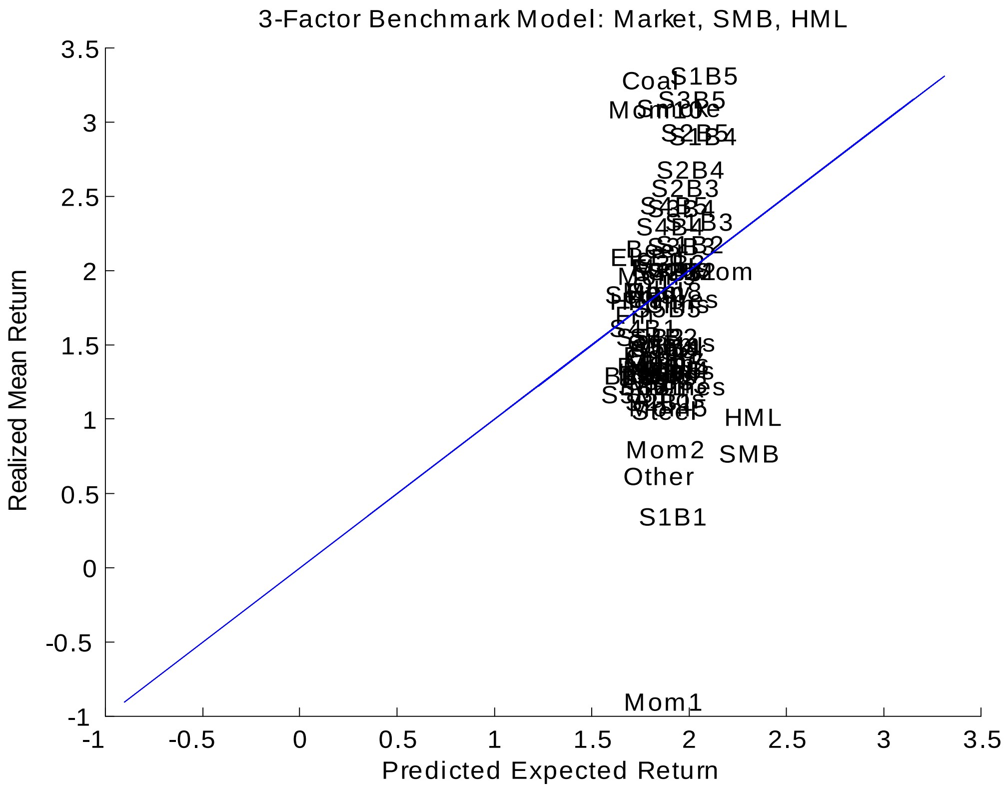

Figure 3: Realized vs. Predicted Mean Returns. We plot the realized mean excess returns of 65 portfolios (25 Size and Book-to-Market Sorted Portfolios, 30 Industry Portfolios, and 10 Momentum Sorted Portfolios) and 4 factors (market, SMB, HML, MOM) against the mean excess returns predicted by the Fama-French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

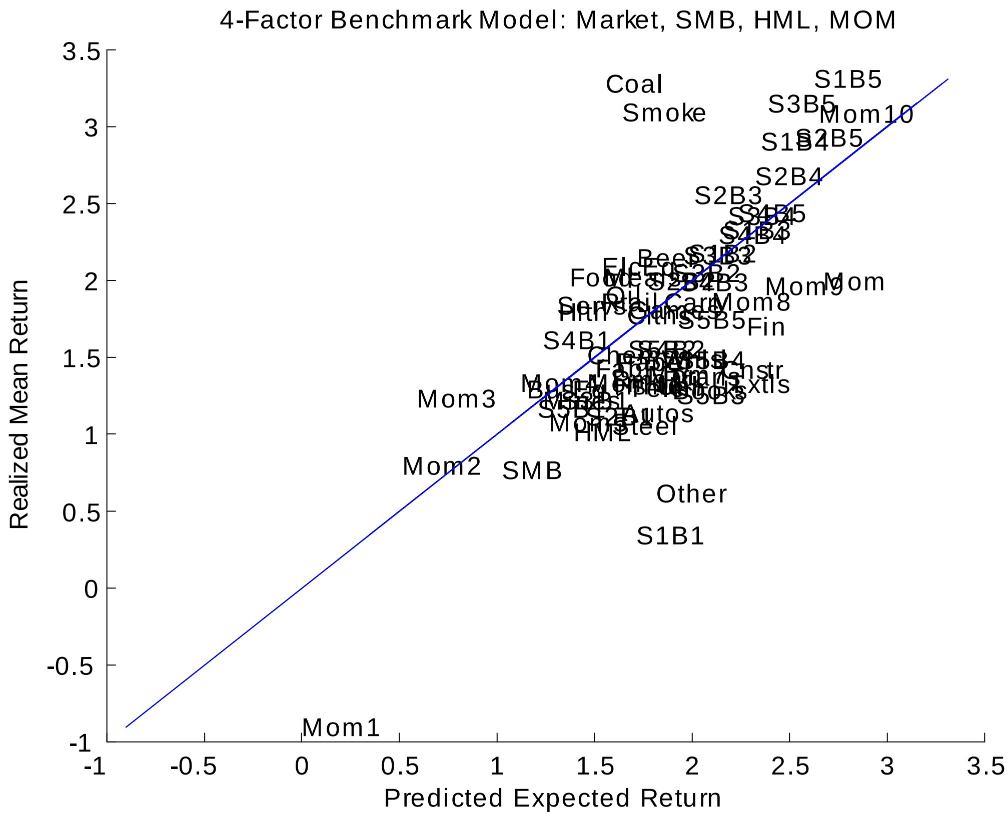

Figure 4: Realized vs. Predicted Mean Returns. We plot the realized mean excess returns of 65 portfolios (25 Size and Book-to-Market Sorted Portfolios, 30 Industry Portfolios, and 10 Momentum Sorted Portfolios) and 4 factors (market, SMB, HML, MOM) against the mean excess returns predicted by a 4-factor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

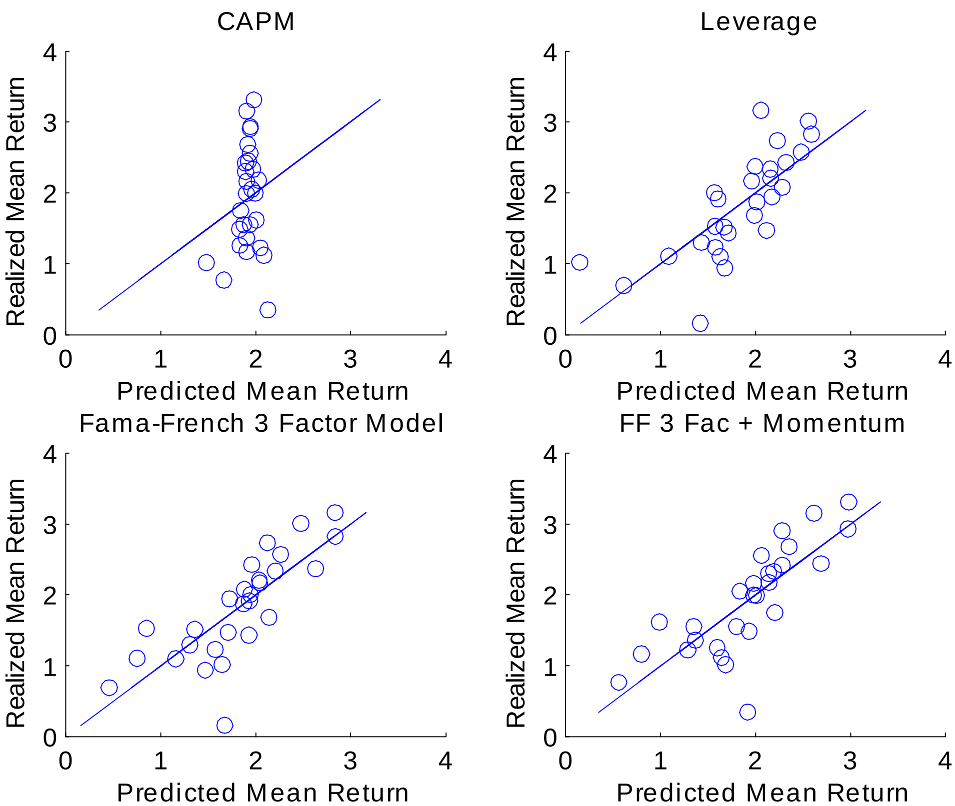

Figure 5: Realized vs. Predicted Mean Returns for 25 Size and Book-to-Market Sorted Portfolios. The sample period is Q1/1968-Q4/2009.

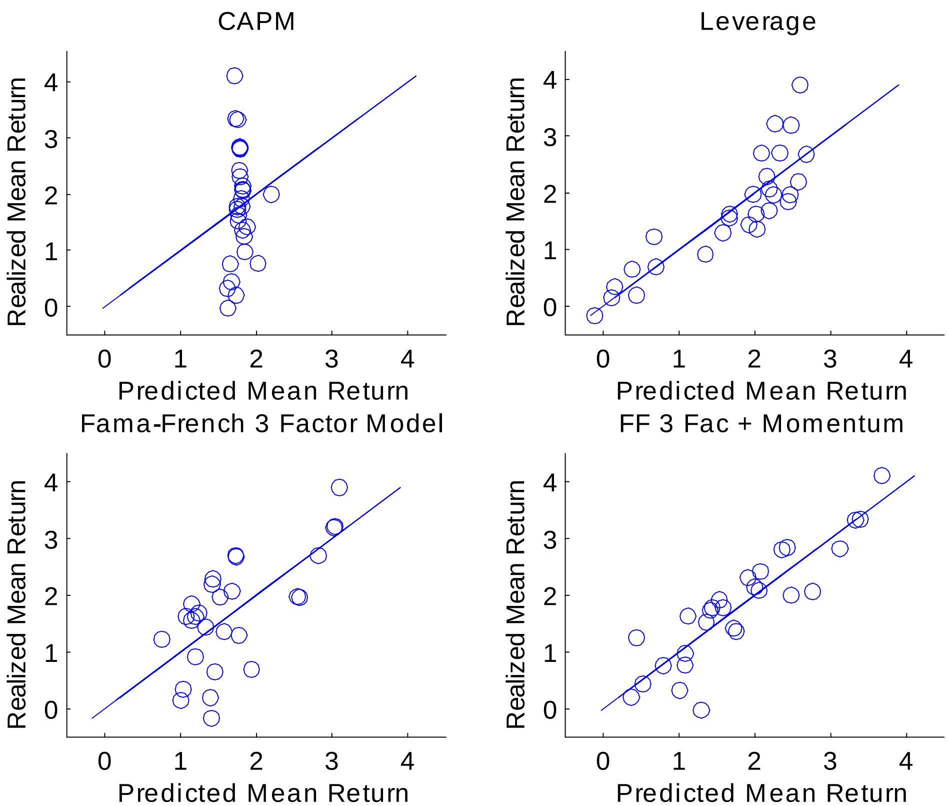

Figure 6: Realized vs. Predicted Mean Returns for 25 Size and Momentum Sorted Portfolios. The sample period is Q1/1968-Q4/2009.

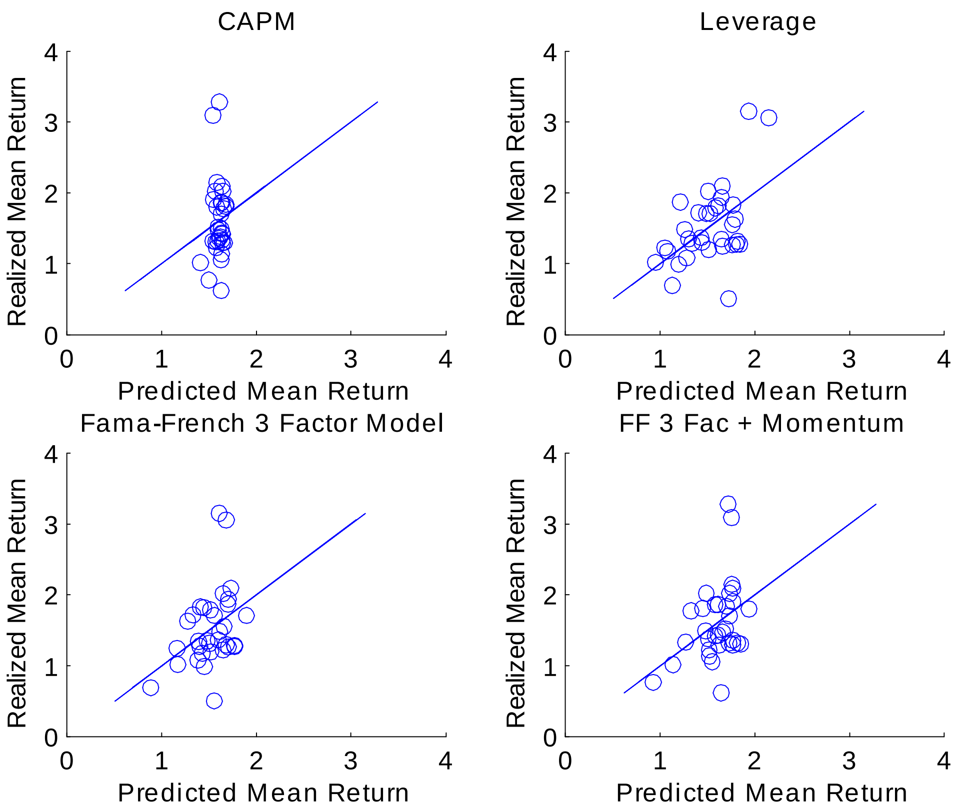

Figure 7: Realized vs. Predicted Mean Returns for 30 Industry Portfolios. The sample period is Q1/1968-Q4/2009.

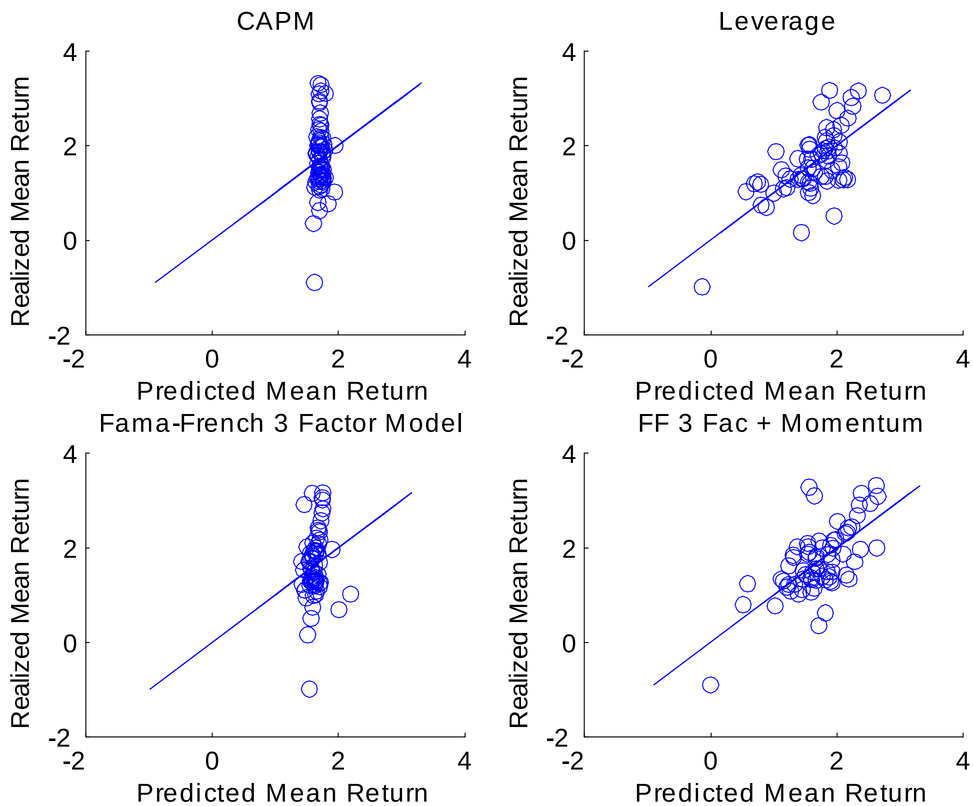

Figure 8: Realized vs. Predicted Mean Returns for 25 Size and Book-to-Market Sorted Portfolios, 30 Industry Portfolios, and 10 Momentum Sorted Portfolios. The sample period is Q1/1968-Q4/2009.

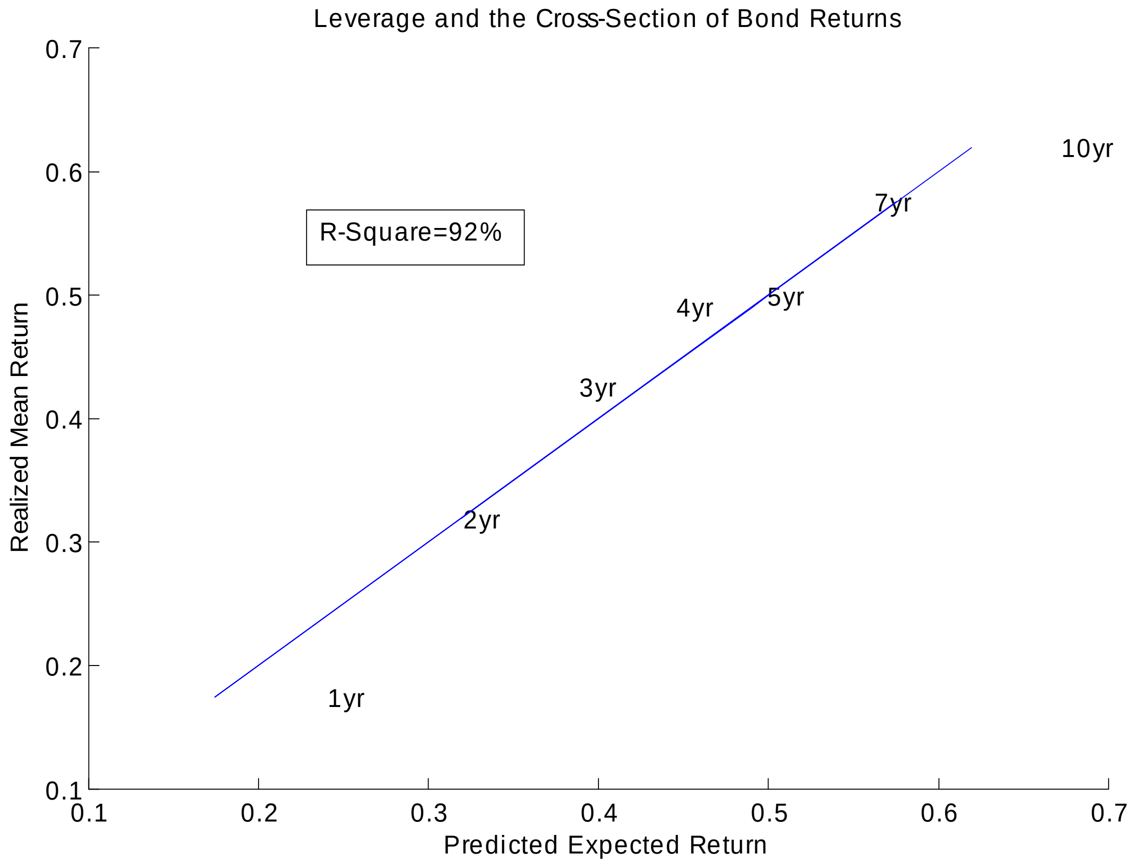

Figure 9: Realized vs. Predicted Mean Returns. We plot the realized mean excess returns of 7 US treasury bond portfolios sorted on maturity against the mean excess returns predicted by the single leverage factor. The sample period is Q1/1968-Q4/2009.

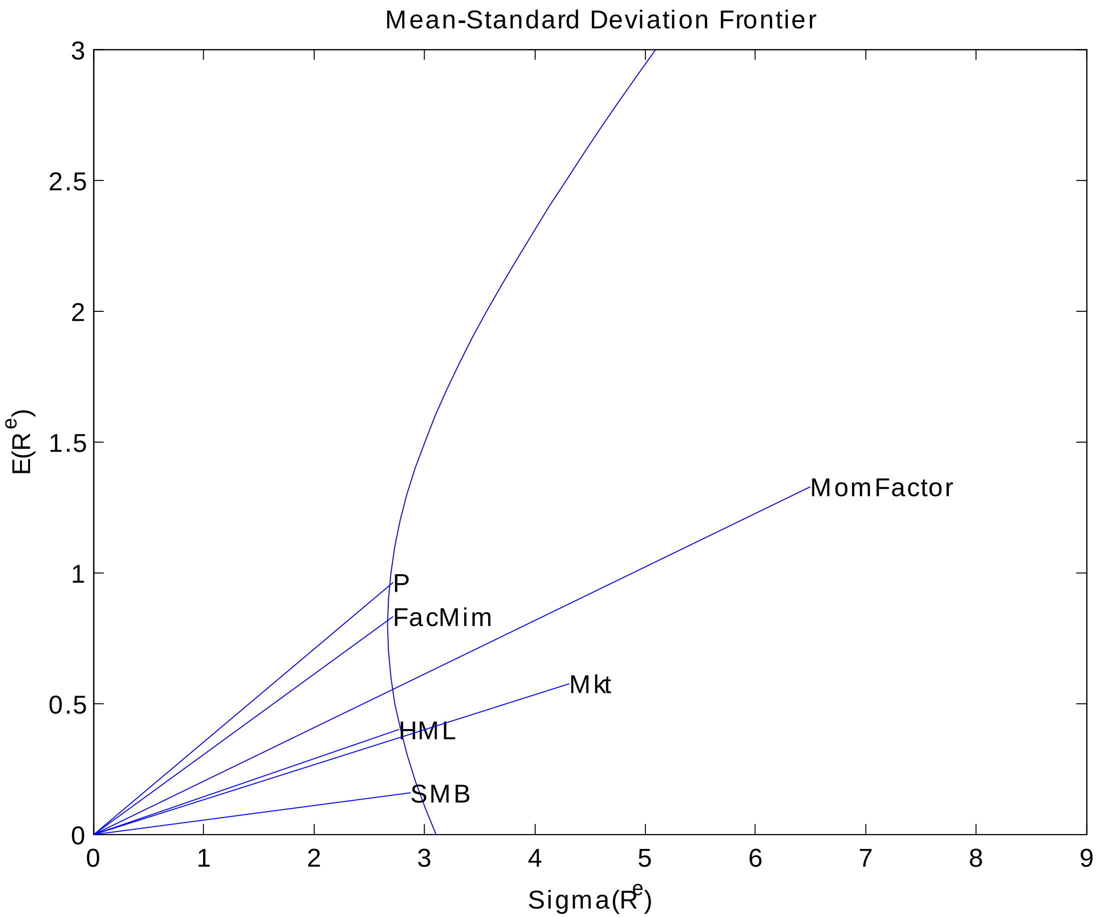

Figure 10: The hyperbola plots the sample mean-standard deviation space for the size and book-to-market, momentum, and industry portfolios. FacMim is the leverage mimicking portfolio, Mkt, SMB, HML are the Fama-French factors, MomFactor is the momentum factor, and P is the portfolio of Mkt, SMB, HML, and MomFacor that produces the largest possible Sharpe ratio. Data are monthly from 1936-2009.

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 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	
		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 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	
		3-Factor	1-Factor	Leverage and
	CAPM	Benchmark	Leverage Model	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 9: Time-Series Alphas

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

	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 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 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	
		3-Factor	1-Factor	Leverage and
	CAPM	Benchmark	Leverage Model	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 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	
		Fama-French			
		3-Factor	4-Factor	1-Factor	Leverage and
	CAPM	Benchmark	Benchmark	Leverage Model	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: Simulation and Robustness

We randomly draw samples from the leverage series 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-Square 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-Square	0.00016	16	100,000
	Alpha, R-Square Jointly	0.00001	1	100,000
Simulation of LMP factor				
	Alpha	0.00002	2	100,000
	R-Square	0	0	100,000
	Alpha, R-Square Jointly	0	0	100,000
Simulation of LMP weights				
	Alpha	0.00002	65	100,000
	R-Square	0.00040	40	100,000
	Alpha, R-Square Jointly	0.00005	5	100,000

Table 8: 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)
Δc	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: 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. 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 time period is 1968-2009.

MAPE

	LMP	FF+MOM	FF
Total	0.454	0.435	0.582
SBM	0.510	0.268	0.395
IND	0.497	0.637	0.608
MOM	0.357	0.372	1.104
Bond	0.163	0.228	0.367

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

Table 11: 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 12: 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 1936-2009,

	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 13: 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 1926-2009 and the holding period is 1936-2009,

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 (1968-2006)

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 - Q4/2006.

	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 - Q4/2006.

	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%]