Financial Intermediaries and the Cross Section of Asset Returns*

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Abstract

Financial intermediaries trade frequently in many markets using sophisticated models. Their marginal value of wealth should therefore provide a more informative stochastic discount factor (SDF) than that of a representative consumer. Guided by theory, we use shocks to the leverage of securities broker-dealers to construct an intermediary SDF. Intuitively, deteriorating funding conditions are associated with deleveraging and high marginal value of wealth. Our *single*-factor model prices size, book-to-market, momentum, and bond portfolios with an R^2 of 77% and an average annual pricing error of 1%—performing as well as standard multi-factor benchmarks designed to price these assets.

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

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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 expectations. 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.[1] 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.

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

[1] See Jagannathan and Wang (2007) for evidence that households may optimize infrequently and Malloy, Moskowitz, and Vissing-Jorgensen (2009) for evidence that limited participation in the stock market can help explain the cross-section of stock returns and equity premium puzzle.

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 broad class of assets.[2] In other words, the marginal value of wealth of intermediaries can be expected to provide a more informative SDF.

Backed by 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 the broker-dealer leverage factor can *alone* explain the average excess returns on a wide variety of test assets, including equity portfolios sorted by size, book-to-market, and momentum, 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-square statistics, low cross-sectional pricing errors, and prices of risk that are significant and remarkably consistent across portfolios.[3] 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 five-factor model that includes the momentum factor and a bond pricing factor. Figure 1 provides an example of the leverage factor's pricing performance in a cross-section that spans 35 common equity portfolios sorted on size, book-to-market, and momentum, and 6 Treasury bond portfolios sorted by maturity. The single-factor model we present explains 77% of the variation in average returns in these cross-sections, with an average absolute pricing error around 1% per annum.

[2] An insight due to He and Krishnamurthy (2009).

[3] The returns on momentum portfolios have thus far been particularly difficult to connect to risk. 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.

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, the fact that we have a one-factor model avoids the typical criticisms that plague asset pricing tests (see Lewellen, Nagel, and Shanken, 2010). We provide simulation evidence supporting this: the probability that a random "noise" factor could spuriously replicate our cross-sectional results, in terms of high R-square and low cross-sectional intercept, is zero. We also 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 portfolios based on our leverage factor betas and find substantial dispersion in average returns that line up well with the post-formation leverage betas.

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. As funding constraints tighten, balance sheet capacity falls and intermediaries are forced to deleverage by selling assets at fire sale prices. These are times when their marginal value of wealth is high. Second, our results can be interpreted in light of intermediary asset pricing models where broker-dealer leverage measures financial sector health as a whole. Taken together, these theories 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 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.

We provide empirical support for the view that leverage represents funding constraints by showing that our leverage factor correlates with funding constraint proxies such as volatility, the Baa-Aaa spread, asset growth, and a betting-against-beta factor that goes long leveraged low beta securities and short high beta securities. Frazzini and Pedersen (2011) show that investors who face funding constraints will prefer to hold naturally high beta securities rather than levering up low beta ones, resulting in a positive average return spread between a levered low beta asset and a naturally high beta assets. This betting-against-beta factor should co-move with funding constraints. Consistent with this view, we find our leverage factor correlates well with the betting-against-beta portfolio and explains the cross-section of returns sorted on betas as well.

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, which provides an explicit link between intermediary balance sheets and asset prices. To quote John H. Cochrane's 2011 Presidential Address on discussing intermediary-based theories of asset pricing: "A crucial question is, as always, what data will this class of theories use to measure discount rates? Arguing over puzzling patterns of prices is weak. The rational-behavioral debate has been doing that for 40 years, rather unproductively. Ideally, one should tie price or discount-rate variation to central items in the models, such as the balance sheets of leveraged intermediaries."

The remainder of the paper is organized as follows. Section 2 provides a discussion of the related theory and literature, reviewing a number of theoretical rationalizations for the link between financial intermediary leverage and aggregate asset prices. Section 3 describes the data and empirical strategy, 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 and forms portfolios sorted on leverage betas, providing a variety of robustness checks. Section 6 discusses directions and challenges for existing theories. Section 7 concludes.

2 Financial Intermediary Asset Pricing

We motivate our financial intermediary pricing kernel in two ways. While neither of them yields direct empirical implications in terms of observable balance sheet components, they are 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 funding 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 the Lagrange multiplier on the funding constraint, 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). Brunnermeier and Pedersen show how funding liquidity enters the pricing kernel when investors are risk neutral and face funding constraints. Specifically, let ϕ_1 be the Lagrange multiplier on the time-one margin constraint and let W_1 denote time-one wealth. Risk-neutral investors subject to these constraints maximize $E_0\left[\phi_1 W_1\right]$. Immediately, we see the SDF is given by $\frac{\phi_1}{E_0[\phi_1]}$ as this problem is clearly equivalent to an investor maximizing the present value of her portfolio using ϕ_1 as the time-one state price. Thus even with risk-neutrality, the constraint gives rise to non-trivial state-pricing since it places higher value on states in which funding constraints are tighter.

Taking the first order conditions of the risk-neutral intermediary, the ex-ante time-zero price of security j is given by $p_{0,j} = E_0[p_{1,j}] + \frac{Cov_0[p_{1,j},\phi_1]}{E_0[\phi_1]}$ where ϕ_1 is the Lagrange multiplier on the time-one margin constraint, which is monotonically decreasing in time-one leverage (see Brunnermeier and Pedersen's equation 31). Rearranging and stating this in returns, we have the following equation for excess returns

$$E_0\left[R^e_{1,j}\right] = -\frac{Cov_0\left[\phi_1, R^e_{1,j}\right]}{E_0\left[\phi_1\right]} \tag{1}$$

When funding constraints tighten intermediaries are forced to deleverage by selling off assets they can no longer finance. Since leverage provides a proxy for funding conditions in their model, they provide justification for our one-factor leverage model. Along similar lines, Danielsson, Shin, and Zigrand (2010) consider risk-neutral financial intermediaries that are subject to a value at risk (VaR) constraint.[4] 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.

In the language of Brunnermeier and Pedersen, we propose $\phi_1 \approx a - b\ln\left(Leverage_1\right)$, such that lower leverage $Leverage_1$ corresponds to tighter funding constraints. We therefore

[4]Other examples include Chabakauri (2010), Prieto (2010) and Rytchkov (2009), which are dynamic versions of models with funding constraints. These 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.

have the approximation,

$$E_0\left[R^e_{1,j}\right] = \lambda Cov_0\left[\ln\left(Leverage_1\right), R^e_{1,j}\right] \tag{2}$$

where $\lambda > 0$. Thus assets that covary with leverage are risky and hence earn a larger risk premium.

Second, it is possible that broker-dealer leverage proxies for the wealth of the entire intermediary sector, as broker-dealers facilitate many of the trades of active investors. He and Krishnamurthy (2010) assert 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. In this framework, only financial intermediaries are capable of investing 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. However, note that the wealth of the intermediary sector is difficult to measure as it includes, for example, hedge funds whose wealth is not easily observable. Acting as market makers, broker-dealers facilitate the trades of active investors such as hedge funds and asset managers. As substantial 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.[5] Indeed, Cheng, 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

[5]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.

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.

While two theoretical linkages between financial intermediaries and asset pricing 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 as economic conditions change. Broker-dealers' balance sheet management practices result in highly pro-cyclical leverage. 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:

$$Leverage_t^{\text{BD}} = \frac{\text{Total Financial Assets}_t^{\text{BD}}}{\text{Total Financial Assets}_t^{\text{BD}} - \text{Total Liabilities}_t^{\text{BD}}}. \tag{3}$$

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 2010.

3.1 Aggregate Balance Sheet of Broker-Dealers

The balance sheet composition of security brokers and dealers combined with the evidence of Adrian and Shin (2010) of intermediary balance sheet adjustements suggest that shocks to leverage growth of financial intermediaries may provide a more informative pricing kernel than the growth rate of average consumption or the balance sheet of the average market participant that are usually used as pricing kernel proxies. The asset side of broker dealers' balance sheets consists largely of risky assets, while a substantial portion of the liability side consists of short-term, collateralized 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. 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 innovations to broker-dealer leverage.

The total financial assets of $2075 billion in 2010 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 reports finer categories of credit market instruments (commercial paper, Treasury securities, agencies, municipal securities and loans, corporate and foreign bonds, syndicated loans). The category called "miscellaneous assets" arises as the flow of funds statistics only keep track of a limited number of asset classes, while security broker-dealers are involved in many financial transactions that are not captured by these broad asset classes. Because the security broker dealer statistics are derived from the SEC's FOCUS reports, it is possible to reconstruct the missing items of the miscellaneous assets from those reports. In particular, Table 2 shows the following asset categories that are the miscellaneous assets: receivables;[6] reverse repos; options and arbitrage; spot commodities; investments not readily marketable; securities borrowed under subordination agreements; se-

[6] Receivables from broker-dealers and clearing organizations, and reverse repos from broker-dealers are subtracted from the total assets in the FOCUS reports because the Flow of Funds reports the balance sheet for the aggregate broker-dealer sector.

cured demand notes; membership in exchanges; investment in and receivables from affiliates, subsidiaries, and associated partnerships. A further category that appears in the FOCUS reports, but not in the Flow of Funds, are non-financial assets (property, furniture, etc.). The liabilities that the Flow of Fund reports are (1) net repo; (2) corporate and foreign bonds; (3) trade payables; (4) security credit; (5) taxes payable, and (6) miscellaneous liabilities. The miscellaneous liabilities can be extracted from the FOCUS reports: payables;[7] securities sold not yet purchased; liabilities subordinated to claims of general creditors. The repos that appear on the liability side of the flow of funds are the difference between repos and reverse repos from the FOCUS reports. The Flow of Funds thus only report the net repo funding of the broker dealers, and not the total size of the repo market.[8]

3.2 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. However, we show that our results do not depend on this exact date and are robust to using a 5-year window around this period.

We construct the leverage factor as seasonally adjusted log changes in the level of broker-dealer leverage.

$$LevFac_t = \left[\triangle \ln \left(Leverage_t^{\mathrm{BD}}\right)\right]^{SA} \tag{4}$$

We seasonally adjust the log changes by using quarterly seasonal dummies. We do this in real time, meaning that we compute an expanding window regression at each date using

[7] Payables to broker-dealers and clearing corporations are subtracted from the FOCUS report liabilities before entering the Flow of Funds.

[8] One peculiarity of the Flow of Funds is that Foreign Direct Investment in US broker-dealers is subtracted from the total liabilities.

the data up to that date. This ensures we have real time leverage shocks.[9] We note that the results are robust to using alternate measures as well, such as more complicated seasonal filtering techniques, but we prefer the current construction for its simplicity. There is strong evidence of seasonal components in the data – in a regression using the full sample, all seasonal dummies are highly statistically significant. Note that, due to the high persistence of the leverage series, using log changes in leverage as shocks is virtually identical to using log innovations from an AR(1) model. Therefore, we prefer to use log changes rather than adding the complication of an AR(1) specification.

A plot of broker-dealer leverage and leverage shocks 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, supporting the idea that sharp decreases in leverage represent "bad times" where funding is tight and the marginal value of intermediary wealth is high. We see sharp drops in leverage during the 70's oil crisis, the '87 stock market crash, the collapse of LTCM, and, most notably, in the recent financial crisis. We also emphasize the *pro*-cyclical evolution of broker-dealer leverage, which is precisely opposite to the mechanical effects one expects. To highlight this, we plot leverage growth vs asset growth for broker-dealers and contrast it with that of households in Figure 3. If there is no active balance sheet adjustment, we expect the two to be negatively correlated – as asset values improve, leverage mechanically falls as equity grows, and vice versa. This is exactly what we see for households. In contrast, broker-dealers display the exact *opposite* pattern. Asset growth and leverage growth are positively correlated. Increases in asset values are thus associated with increases in leverage. This supports our claim that broker-dealers manage balance sheets aggressively and actively. Table 1 documents the correlation of our leverage factor with other intermediary indicators. We confirm the strong correlation between the

[9] We initialize the series in 1968Q1 using data from the previous 10 quarters to compute our shocks. However, this is robust to starting at later dates to allow for a longer initialization (e.g., starting in 1971Q1 and using 22 quarters to initialize the series).

leverage factor and asset growth (0.73). Leverage shocks are negatively related to volatility (-0.37) and the default spread (-0.16), and positively related to the value weighted return on the financial sector (0.18). Therefore decreases in leverage are associated with a reduction in broker-dealer assets, spikes in volatility and credit spreads, and decreases in financial sector equity—all of which are consistent with a high marginal value of wealth for intermediaries. These findings are also consistent with the "margin spiral" of Brunnermeier and Pedersen (2009), where both increases in volatility and declines in asset values cause funding conditions to deteriorate, forcing intermediaries to deleverage.

3.3 Empirical Strategy

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

$$SDF_t = 1 - bLevFac_t.$$

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

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

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

$$E[R^e_{i,t}] = bCov\left(R^e_{i,t}, LevFac_t\right) \tag{5}$$

$$= \lambda_{Lev}\beta_{i,Lev}, \tag{6}$$

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

For each asset $i = 1, ..., N$, we estimate the risk exposures from the time-series regression:

$$R^e_{i,t} = c_i + \beta'_{i,f}\mathbf{f}_t + \epsilon_{i,t}, \quad i = 1, ..., N, \ t = 1, ..., T \tag{7}$$

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 a cross-sectional regression of time-series average excess returns, $E\left[R^e_t\right]$, on risk factor exposures:

$$E\left[R^e_{i,t}\right] = \mu_{\mathbf{R},\mathbf{i}} = a + \beta'_{i,f}\lambda_f + \xi_i, \quad i = 1, ..., N \tag{8}$$

This approach yields estimates of the cross-sectional prices of risk λ and the average cross-sectional pricing error or zero-beta rate, a. A good pricing model features an economically small and statistically insignificant intercept (a), statistically significant and stable prices of risk (λ) across different cross-sections of test assets, and individual pricing errors (ξ_i) that are close to zero. We measure the size of the pricing errors in several ways: by the cross-sectional adjusted R-square statistic which focuses on whether the sum of squared errors is relatively small $(1 - \sigma^2_\xi/\sigma^2_{\mu_\mathbf{R}})$, by the mean absolute pricing error or MAPE $(\frac{1}{N}\sum|\xi|)$ which focuses less on outliers than the R-square,[10] and by a χ^2 statistic that tests whether the pricing errors are jointly zero – measured by a weighted sum of squared pricing errors $(\xi' cov(\xi)^{-1}\xi \sim \chi^2_{N-K}$, where K is the number of factors and $cov(\xi)$ includes the estimation error in βs)[11]. The latter is the only formal statistical measure of whether the pricing errors are "too big," while the MAPE and R-square are easier diagnostics to interpret from an economic standpoint. In order to correct the standard errors for the pre-estimation of betas, we report t-statistics of Shanken (1992) in addition to the t-statistics of Fama and MacBeth (1973). We also provide confidence intervals for the R-square statistic using bootstrap as the

[10] We also report the Total MAPE as $(|a| + \frac{1}{N}\sum|\xi|)$ which includes the cross-sectional intercept as a pricing error.

[11] Specifically, $cov(\xi) = \frac{1}{T}\left(I_N - \beta\left(\beta'\beta\right)^{-1}\beta'\right)\Sigma_\epsilon\left(I_N - \beta\left(\beta'\beta\right)^{-1}\beta'\right)\left(1 + \lambda'\Sigma_f^{-1}\lambda\right)$, where Σ_f is the variance-covariance matrix of the factors and Σ_ϵ is the variance-covariance matrix of the time-series errors, $\epsilon_{i,t}$.

sample R-square can be misleading or uninformative due to large sampling errors. We follow Lewellen, Nagel and Shanken (2010) in computing confidence intervals and relegate the exact details to their paper. The issue with the sample R-square is the following: even if the "true" R-square is close to zero, the sample R-square can easily be fairly large. Similarly, even if the true R-square is close to one, the sample R-square will likely be well below one. Therefore, a particular sample R-square can in principle correspond to a large range of true R-square values. We construct the sampling error for any true R-square by simulating a model with the true value of the R-square. We then compute the sampling error via bootstrap to see what range of sample R-square could in principle correspond to the given true value. We step over all true values from zero to one. We are then able to determine, for any given sample R-square, the range of true R-square statistics that is likely to produce the sample value. This range forms our confidence interval.

Following the above evaluation criteria, and by applying our single-factor model to a wide range of test assets, we address the criticisms of traditional asset pricing tests raised by Lewellen, Nagel and Shanken (2010). First, since we use a one-factor model, we avoid most of the statistical issues present in asset pricing tests that can mechanically produce high explanatory power. Our simulations show the probability of a random "noise" factor replicating our results is zero. Importantly, we also 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, pricing this cross-section with multiple factors is a relatively low hurdle. We will see that our one factor model prices the cross section of size and book to market sorted portfolios as well as the Fama French three factor model. In addition, we avoid the pitfall of relying only on this cross section by including the more challenging momentum portfolios as test assets. We also show strong pricing performance across U.S. Treasury bond portfolios of various maturities. This further strengthens our results since the model should apply to *all* assets, yet most existing tests only focus on stocks. Finally, the economic motivation of our factor provides further support since it implies the price of risk should be significant and positive.

We test specifications of the linear factor model (8) in the cross-section of asset returns. As test assets, we consider the size and book-to-market portfolios and the momentum portfolios, each of which are well known to exhibit large cross-sectional dispersion in average returns. We also consider the cross-section of bond returns, using returns on Treasury portfolios sorted by maturity as test assets. We compare our single leverage factor ($\mathbf{f} = LevFac$) 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 and return data from Kenneth French's data library 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. We express all returns and our leverage factor in percent per year (quarterly percentages multiplied by 4). Our main sample period is Q1/1968-Q4/2009, though we also display the results for the subsample that excludes the recent financial crisis. 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.

4 Main Empirical Results

4.1 Cross-Sectional Analysis

Table 3 presents our main results. We test the leverage factor model in the cross-section of 41 test assets *simultaneously*. The test assets are: 25 size and book-to-market portfolios, 10 momentum sorted portfolios, and 6 Treasury bond portfolios sorted by maturity. Panel A presents the cross-sectional prices of risk, while Panel B presents several test diagnostics for each model. As comparisons, we consider the CAPM, Fama-French model, and multi-factor models that include the momentum factor as well as the level factor (PC1) – defined as shocks to the first principal component of the yield curve – which prices the cross-section of bond returns (Cochrane and Piazzesi, 2009). These factors constitute the relevant benchmark factors to price the cross-sections considered.

Starting in the first two columns, neither the CAPM nor the Fama-French model is able to account for the spread in average returns across portfolios. Each has a cross-sectional intercept that is economically large at over 3% per annum and statistically significant. The factor prices of risk are not statistically significant, and the pricing errors are large – as seen by both the low adjusted R-square (10% and 16%, respectively) and the χ^2 test which measures the sum of squared pricing errors. In Panel B, we also break up the mean absolute pricing error (MAPE) by asset class. We see the Fama-French model does relatively well on the size and book-to-market portfolios, with a MAPE of about 2% per annum out of a total average return of about 8% per annum, but does poorly on the momentum and bond portfolios. The results are substantially better when we add the momentum factor and the level factor. The adjusted R-square increases to 81%, while the zero-beta rate falls to 66 basis points. The MAPE for each cross-section is fairly low, as is the total MAPE at 1.6% when we include the intercept, which is also a pricing error.[12]

The final column shows the results for the leverage factor as a sole pricing factor. The cross-sectional intercept is extremely low at 12 basis points and the price of risk is positive and significant. The adjusted R-square is 77%, while the total MAPE is only 1.3%. In addition, we see that the MAPE for each cross-section is fairly low: 1.2% for the size and book-to-market portfolios, 1.8% for the momentum portfolios, and 0.4% for the bond portfolios. The confidence interval for the R-square is [82%, 100%], well above the sample value. At first, it seems surprising that the lower bound for the confidence interval is *higher* than the sample

[12]We define the total MAPE as the average absolute pricing error across all 41 portfolios, plus the cross sectional intercept.

adjusted R-square. However, recall that the confidence interval tells us what the most likely values of the *true* R-square are, *given* the sample adjusted R-square we observe. Even if the true R-square were 100%, we would never observe this due to sampling error. A similar logic holds for very high values of the R-square, and especially with few factors and many test assets where sampling error is larger (see Lewellen, Nagel, and Shanken, 2010; Figure 2). Thus a sample adjusted R-square of 77% with many assets and a single-factor most likely corresponds to a *true* R-square of between 82% and 100%, but that is biased downward due to sampling error. Finally, the χ^2 value, while rejected at the 1% level, is still substantially lower (68) than any of the other models (110), despite the far fewer degrees of freedom (the statistic associated with the leverage model is χ^2_{N-2} while that associated with the 5-factor model is χ^2_{N-6}). In summary, the leverage factor—on its own—does exceptionally well across these portfolios; the performance relative to the 5-factor benchmark is quite significant considering the far fewer degrees of freedom.

We plot the predicted vs realized average returns in Figure 1. Aside from the highest momentum portfolio (Mom10), the test assets line up very close to the 45-degree line. We contrast this with the Fama-French model and the 5-factor model in Figures 4 and 5. We further examine which portfolios are mispriced in Table 4, which compares the individual pricing errors of the leverage and 5-factor models. We notice two patterns: the leverage factor is not able to price the highest momentum portfolio (pricing error of 7%) and neither model does well in pricing the "small growth" portfolio (pricing errors of 5% and 3% for the 5-factor and leverage factor models, respectively). Panel B confirms this result by re-running the cross-sectional tests with each of these portfolios dropped in turn. We see that the explanatory power of the 5-factor model increases from 81% to 88% when the small growth portfolio is dropped; and the explanatory power of the leverage factor model increases from 77% to 87% when the highest momentum portfolio is dropped. Importantly, the leverage factor model is no longer rejected if *either* of these portfolios is dropped (the 5-factor model remains rejected).

It is worth addressing the price of leverage risk, which we estimate to be 62% per annum. While we do not pin down the exact magnitude by theory (only that it should be positive), the number seems economically large. However, note that an inflated price of risk is typical for most non-traded factors because they contain noise that is un-correlated with returns, which in turn tends to deflate the beta estimates. To see this, let:

$$LevFac_t = LMP_t + \omega_t$$

where $Cov(\omega_t, R_t) = 0$ for any return R_t and LMP_t is a leverage mimicking portfolio – the projection of leverage onto the return space. We will return to the LMP in great detail in the next section. Since ω_t is noise that is orthogonal to the return space, it will inflate our point estimate of the price of risk. However, since ω_t does not affect *covariances*, it will not affect our cross-sectional results in terms of R-squares, etc. Specifically, the presence of ω_t will attenuate the time-series β of *every* asset by a factor of $var(LevFac)/var(LMP)$. It is clear, then, that the cross-sectional price of risk will have to be higher by exactly this amount to compensate. We find this ratio to be about 6, making the price of traded leverage risk about 10% per annum – a number much more in line with standard traded factors. Again, it is crucial to understand that the presence of noise like ω_t will not impact the cross-sectional results in any way since those rely solely on covariances, but will affect the time-series regressions and cross-sectional price of risk estimates. Specifically, the time-series β's, t-stats, and R-squares will all be deflated (something we return to later) and the cross-sectional price of risk will be inflated.

Having seen the cross-sectional results for all assets simultaneously, we now turn to analyze the cross-sections individually to see more precisely how our leverage factor fares on each set of test assets. Table 5 gives the results for the 25 size and book-to-market portfolios as well as the 25 size and momentum portfolios. We use the 25 size and momentum portfolios since the 10 momentum portfolios would leave too many degrees of freedom for multi-factor models; e.g., a 4-factor model with an intercept would have 5 degrees of freedom with 10 portfolios. The results echo and strengthen what we have already seen. For the 25 size and book-to-market portfolios, the leverage factor outperforms the Fama-French factors in terms of the cross-sectional intercept (1% vs 16% per annum), adjusted R-square (74% vs. 68%) and p-value for the χ^2 statistic (5.2% vs. 0%). The confidence interval for the R-square is [70%, 100%] and the MAPE is only 2% per annum. The largest absolute pricing error for both models is the well known "small growth" portfolio, at 3.7% for the leverage factor and 4.3% for the Fama-French factors. While the model is still rejected at the 10% level, it performs substantially better than the Fama-French factors which are tailored to explain these portfolios. The price of risk is 56% for the leverage factor, which is close in magnitude to the 62% we estimated in the larger cross-section.

Turning next to the 25 size and momentum portfolios, we compare the leverage factor to the Fama-French and momentum factors. While the adjusted R-square for the 4 factor benchmark is substantially higher (84% vs. 51%), the intercept for the 4 factor benchmark is substantially higher as well (12% vs. 0.3%). The confidence intervals for the R-square are [72%, 90%] and [40%, 100%], respectively, showing the wide dispersion in R-square values for the leverage factor. Still, the lower bound of 40% is quite high when comparing to the CAPM. The χ^2 statistic is fairly low, and the p-value is 41%, meaning the model is not rejected. Given the large challenge these portfolios have posed in the literature, we take our results as a relative success in explaining a large amount of variation in the average returns of these portfolios.

Finally, we look at the cross-section of Treasury bond portfolios, sorted by maturities in Table 6. We take average maturities of 0-1, 1-2, 2-3, 3-4, 4-5, and 5-10 years, as reported in the CRSP database. We compare the leverage factor with the level factor – or shocks to the first principal component of the yield curve (PC1), as well as to the standard equity factors discussed before. With fewer assets, we do not estimate an intercept for the non-traded factors, and for traded-factors we report the time-series alphas (equivalently, we impose the prices of risk to be equal to the factor means). We report individual pricing errors for each portfolio in Panel A. Panel C gives the MAPE for each model. The average absolute portfolio return is 1.65%, yet the multi-factor equity models all have MAPEs greater than 0.9%—meaning they do not explain even half of the average returns. In constrast, the level factor (PC1), has a MAPE of only 23 bps, with an adjusted R-square of 78%.[13] The leverage factor has a MAPE of merely 17 bps and an adjusted R-square of 85%. The p-value of the χ^2 statistic is 10.5%, meaning the leverage factor model is not rejected, whereas the level factor model is. Moreover, the price of risk, at 53%, is broadly consistent with earlier esimates. When we do not re-estimate the price of risk (that is we impose the price of risk to equal 62% as in the full cross-section) the MAPE only increases to 32 bps per annum.[14] Thus the leverage factor does an excellent job explaining the cross-section of bond portfolios, out-performing the standard benchmarks.

4.2 Time-Series Analysis

Table 7 reports the results for the time-series regressions of returns on the leverage factor. For each cross-section, we report the average returns, betas, t-stats, and R-squares for the time-series regression of each portfolio. Starting with the size and book to market portfolios, we see that the average returns increase from low to high book-to-market portfolios, and generally decrease from small to large (a notable exception is the "small growth" portfolio, which only offers 1% per annum). The leverage betas typically echo this pattern, increasing from left to right as book-to-market increases, and decreasing from top to bottom as market capitalization increases. The t-stats for the betas show the same patterns – for higher book-

[13]In this case, without an intercept, we define the R^2 as $1-\frac{(\Sigma\xi_i^2)}{\left(\Sigma(\mu_{R,i}-\overline{\mu_{R,i}})^2\right)}$, for the model $\mu_{R,i}=\lambda_f\beta_{i,f}+\xi_i$, where $\mu_{R,i}$ is the average excess return return on asset i, and $\overline{\mu_{R,i}}=\frac{1}{N}\sum\mu_{R,i}$ is the average mean return across assets.

[14]This is important to check since with few assets and a relatively small spread in average returns, it may be possible to fit this cross-section with an "unreasonable" price of risk.

to-market portfolios whose average returns are large, the leverage betas are significantly different from zero, while for portfolios whose average returns are smaller, and closer in magnitude to zero, the leverage betas are not statistically different from zero. There is only one portfolio with an average return above 6% per annum whose leverage beta is not significant at 10% levels, and there are no portfolios with an average return above 10% per annum whose leverage beta is not significant at 1% levels. The next panel shows the time-series R-squares which increase from left to right and from top to bottom. The values are typically low, as is common for non-traded factors.

We see similar patterns for the momentum and bond portfolios. Betas and t-stats typically increase along with average returns. A notable exception is the highest momentum decile (the "past winners" portfolio). The leverage factor beta is too small, and the t-stat is only 1.08. This is consistent with Figure 1, which graphically shows this is the most mis-priced portfolio for the leverage factor. The bond portfolios typically have larger t-stats and R-squares.

The apparently low R-squares are again consistent with noise or other uncorrelated measurement error in the leverage factor, as noted above. We do not propose to explain all the movements in leverage over our sample period, which may occur for a number of other reasons unrelated to the intermediary SDF. The presence of such noise will lower the t-stats and the R-square in time-series regressions. However, it will not change our pricing results since it does not affect return covariances.[15] The literature often worries about the significance of the time-series betas since one would like to see statistically significant exposures to the portfolios in question. The argument is that if the betas are not well estimated they may be spuriously explaining the cross-section of returns. Our results speak clearly against such spurious relationships: First, we correct for the estimation in betas in our cross-sectional

[15] One can easily show this by adding noise to the market portfolio, and running repeated cross-sectional pricing tests. While the time-series results can look as noisy as one wants, the cross-section results remain unchanged on average as the noise has no covariance with returns.

tests and still find statistically significant prices of risk. Second, and most importantly, if one indeed believes that the betas are spuriously explaining the average returns, one needs to evaluate its likelihood—that is, the probability of betas lining up in just the right way to explain the large spread in average returns across 41 assets. The next subsection will provide simulation evidence to show that the odds of this happening are essentially zero.

4.3 Additional Robustness Tests

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 8 show that the probability of randomly achieving an R-square as high as we do, a MAPE as low as we do, and an intercept as low as we do with the observed leverage factor, are 0.01%, 0.00%, and 0.19%, respectively. Taking these together, there is essentially no chance that the low pricing errors we see are due to chance.[16]

Table 8 also shows the robustness of the results to different starting dates. We show that the results are essentially unchanged whether we start in the years 1966-1972.[17] Similarly, the results in the last column show that the leverage factor does well in the pre-crisis sample (1968-2005). The R^2 drops from 77% to 67% and the intercept stays low at 37 bps per

[16] We also construct the "noise" factor using random draws from a normal dstribution. The results are very similar – with the p-values being essentially zero.

[17] In unreported results, we show this is also not affected by starting at different quarters within any of these years. In other words, the results are essentially the same for a 20-quarter window around our start date.

annum. We argue that the better performance using the full sample is supportive of our interpretation of the leverage factor—we would expect an intermediary-based factor to reveal stronger risk exposures when we include the financial crisis.

5 The Leverage Factor Mimicking Portfolio

In order to conduct additional tests, we project the leverage factor onto the space of traded returns to form a "leverage factor mimicking portfolio" (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 concerns 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 findings hold at a monthly frequency going back to the 1930s. 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 help 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 of the traded factors considered and it is close to the maximum possible Sharpe ratio using any combination of the three Fama-French factors and momentum factor. Finally, we use the entire cross-section of CRSP stock returns to construct portfolios based on real time leverage factor betas and find substantial dispersion in average returns that line up well with the post-formation leverage betas.

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:

$$LevShock_t = a + b'[BL, BM, BH, SL, SM, SH, Mom]_t + \epsilon_t, \quad (9)$$

where $[BL, BM, BH, SL, SM, SH, Mom]$ are the excess return of the six Fama-French benchmark portfolios on size (Small and Big) and book-to market (Low, Medium and High) 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 ϵ_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.[18] Most of our results are strengthened if we also include a long maturity bond portfolio. However, our bond data is only available starting in 1952 and one of our main goals is to use use a longer history to provide out of sample evidence for our results. We thus do not include a bond portfolio in the results. We normalize the weights, b', to sum to one, which is without loss of generality and is more convenient in terms of units. The factor mimicking portfolio return is given by:

$$LMP_t = \widetilde{b}'[BL, BM, BH, SL, SM, SH, Mom]_t,$$

where we estimate $\widetilde{b} = \frac{b}{\Sigma b} = [-0.25, -0.11, 0.62, -0.64, 1.37, -0.48, 0.47]$ via ordinary least squares over the sample 1968-2009. While the LMP loads positively on momentum, the loadings on the other factors are less clear. On net, we do see a higher loading on value as opposed to growth. However, there is no substantial difference between small and large loadings. We find that the correlation between our original leverage factor and the LMP is 0.37.

[18] 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 acknowledge that some information may be lost in this procedure.

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 use 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.

For brevity, we report the mean absolute pricing error (MAPE) by each asset class rather than at the individual portfolio level. These results are given in Panel A of Table 9. For comparison, we also report the annualized average absolute return to be explained in the first column. Note that in this case the pricing error is simply the time-series alpha. We also report the GRS F-statistic that tests whether the alphas are jointly zero. We find that the LMP has an average annual alpha of 1.19%, compared with 2.24% and 1.13% using the Fama-French and Fama-French plus momentum factors, respectively. The LMP MAPE is small relative to the 6.33% return to be explained, and nearly as small as the 4-factor benchmark. In terms of portfolios, we see the LMP does well on the size and book-to-market portfolios and especially the bond portfolios (MAPE of 1.15% and 0.59% out of 7.68% and 3.04%, respectively). On the momentum portfolios, the LMP MAPE of 1.66% is low relative to the Fama-French MAPE of 4.36%, and is fairly close the the 4-factor MAPE of 1.46%. The GRS statistic is 2.57 for the LMP, 2.28 for the 4-factor model, and 4.48 for the Fama-French model, though each model is decisively rejected.

Panel B presents cross-sectional results using the LMP and gives important out of sample evidence. Using the constant weights we estimate, we compute cross-sectional tests with the LMP using monthly data going back to 1936.[19] The cross-sectional R-square for the LMP

[19] While the underlying data are available starting in 1926, we find that none of the benchmark factor models work well including this period. Since the LMP is projected onto these underlying benchmark factors, it can not perform any better than the factors themselves. Therefore including the Great Depression does not lend itself to a meaningful comparison, since all models do relatively poorly. Thus, we skip the first 10 years of data and start in 1936. The R-squared from the 4-factor benchmark model nearly doubles from

is 63% vs. 81% for the 4-factor model and 53% for the Fama-French model. The cross-sectional intercepts are 3%, 15%, and 28% per annum, respectively. Thus, the LMP performs well in comparison to the benchmarks in terms of relatively a relatively high R-square and much lower intercept. The performance is particularly impressive since the weights used are constant and the LMP cannot by definition outperform the 4-factor benchmark on an R-square basis. Our empirical results thus continue to hold over the longer time-span and at the higher monthly frequency, providing out of sample robustness for our results. Overall, the LMP alone performs comparably to the Fama-French and momentum factors.

Lastly, we compute time-series alphas on the Fama-French and momentum factors themselves, asking whether the LMP can price these portfolios. We use both the main sample period (1968-2009) and the earlier sample (1936-2009) and report these results in Table 10. In the main sample, the time-series alphas are all relatively low, with the exception of momentum, which has an alpha of 4% per annum (about half of the 8% average momentum return), but which is not statistically significant. In the earlier sample, the momentum alpha is larger at 5% per annum (out of a total momentum portfolio return of 8%) and is statistically significant, while the alphas on the Fama-French portfolios are all under 1% and are not statistically significant.

One may be concerned that, as 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* does nearly as well in terms of pricing as the three Fama-French factors and the momentum factor combined. Second, using the simulation technique discussed earlier, we generate a "random" LMP by drawing from the empirical distribution of our leverage factor (with replacement) and projecting the resulting random factor onto the benchmark portfolios. We do this 100,000 times and report the probability that the resulting portfolio is able to

46% to 81% going from the 1926 to 1936 starting dates. We also do not use bonds as test assets since the bond data is not available in this time period.

replicate the LMP's pricing ability (see Table 8). The likelihood of seeing an R-square as high as we see is 0.2%, a MAPE as low as we see is 0%, and a Sharpe ratio as high as we see is 1.6%. Thus, it is extremely unlikely that the LMP is spuriously picking up the pricing information of the benchmarks.

5.3 Mean-Variance Properties of the LMP

We now turn to the mean-variance properties of our mimicking portfolio. Figure 6 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 6 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 0.29, 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 11). In fact, the LMPs Sharpe ratio is comparable to the Sharpe ratio of P. The annualized (monthly multiplied by $\sqrt{12}$) LMP Sharpe ratio is about 1, compared to the maximum possible Sharpe ratio of 1.2. Since the true mean-standard deviation space will in general be much tighter than its sample counterpart, the close proximity of the LMP to the sample mean-standard deviation frontier is an impressive additional piece of evidence that our leverage factor provides a good approximation to the stochastic discount factor.

5.4 Leverage Beta Sorting

Finally, 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 form portfolios based on ex-ante leverage betas and show the resulting portfolios have a large spread in average returns. Specifically, at each quarter (the formation date), we sort the universe of AMEX, NASDAQ, and NYSE stocks from CRSP based on their estimated leverage betas over the past 10 years (40 quarters), which we call pre-ranking betas. We compute leverage betas by regressing quarterly firm level excess returns (over the 3-month risk-free rate) on the leverage factor. Since the leverage factor is constructed in real time, this procedure would have been available to an investor in real time as well. We drop the smallest 10% of firms at formation date to avoid having thinly traded, illiquid firms bias our results. Other filters, such as dropping stocks with share price under $5, produce qualitatively similar results. We require at least 5 years (20 quarters) of non-missing returns for each stock, making our holding period 1973-2009. We group stocks based on pre-ranking betas and form value-weighted portfolios, though our results are qualitatively unchanged using equal-weighted portfolios. We do this each quarter and report the average returns and post formation leverage betas of each group, as well as the average return and beta of a high-minus-low portfolio spread.

Our results, presented in Table 12 Panel A, can most easily be seen by forming 3 portfolios based on pre-ranking betas (using, e.g., 5 portfolios produces stronger, but qualitatively similar results as shown in Panel B). Using 3 groups also makes the results directly comparable to the procedure used to construct the Fama-French factors. The leverage betas, average returns, and Sharpe ratios increase mechanically over the low, medium, and high pre-ranked leverage beta portfolios. The resulting high minus low portfolio has an annualized spread of 2.8%, which is roughly comparable to that of the SMB and HML factors (3.6% and 4.4% in this sample, respectively). Moreover, the leverage high minus low portfolio has a positive and significant leverage beta, with a t-stat of 2.01. The CAPM alpha is 2.6% per annum, which is nearly as large as the average return of 2.8%. However, the CAPM alpha is not statistically significant, suggesting that while there is a spread in returns that is not explained by the CAPM, the portfolio construction is still fairly noisy.

The high minus low leverage portfolio does not, however, replace the leverage factor in our empirical tests because sorting on non-traded, quarterly factor covariances is a noisy procedure. It is well known that sorting on characteristics is less noisy than sorting on covariances, making factors formed on covariance sorts less equipped to capture the underlying discount factor variation. In other words, even if past covariances are perfectly measured, they may not measure *future* conditional covariances well, and in particular characteristics often give a better proxy. This problem is, however, much worse in our case, since our factor is non-traded and our data is only of quarterly frequency, meaning estimated covariances with returns are even noisier. The evidence is consistent with such noise: While the correlation between our non-traded leverage factor and the LMP formed earlier is 0.37, the correlation with the high minus low leverage beta portfolio is only 0.18. We therefore take the evidence that the high minus low leverage beta portfolio produces a positive average return as additional supporting evidence for our model.[20]

In sum, the evidence from the cross-section of individual stock returns lends additional support to our finding that a higher covariance with broker-dealer leverage is associated with higher expected return. Using the entire universe of traded stocks avoids the criticism that leverage betas only explain the average returns across the portfolios we have analyzed, providing an important additional diagnostic despite the many challenges associated with the procedure.

[20] In unreported results, we also find that sorting stocks based on LMP betas provides even more support. Using the LMP allows us to use monthly data and a longer time-series (1936-2009) to compute more accurate betas. The spread in returns in this case is economically larger. However, since the LMP is constructed using the full sample, the strategy is not implementable in real time for an investor, in contrast to the strategy employed above.

6 Discussion of Results

6.1 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 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. 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 (2003) liquidity factor—a measure of innovations to market liquidity—challenging the theoretical predictions that funding liquidity and market liquidity are intertwined.[21] 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.

Broker-dealer leverage may also 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

[21] Results available upon request.

services from broker-dealers increases leading them to leverage 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 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.

6.2 Further Economic Interpretation of Funding Constraints

We have argued based on theory that leverage may measure funding constraints faced by the financial sector. Here we provide additional supporting evidence that our leverage factor measures funding constraints. As Frazzini and Pedersen (2011) show, investors who face funding constraints will tend to prefer high-beta assets that do not require leverage, thus bidding up their price and creating a spread between high- and low-beta assets. To see this, consider the portfolio choice of an investor who can hold either a high-beta stock or a low-beta bond combined with an instantaneous risk-free asset—for simplicity, assume the investor can hold only *one* of the risky assets and has no other wealth. Modern portfolio theory guides the investor to hold the asset with the highest Sharpe ratio, combining it with risk-free borrowing or lending, depending on risk aversion. However, if the investor is sufficiently risk tolerant and cannot take leverage or is funding constrained, she will prefer to hold the stock because it provides a higher expected return without the use of leverage. Therefore, a spread arises between the leveraged bond and the stock, which co-moves with the tightness of funding conditions—as funding constraints tighten investors bid up the prices of riskier assets relative to safer assets. Using this logic, Frazzini and Pedersen argue that stocks sorted on market betas should display a spread in returns that co-moves with funding conditions. If our leverage factor measures funding constraints, this spread should also be related to our leverage factor.

To construct beta sorted portfolios, we follow the procedure in Fama and French (1992).

Specifically, in June of each year, we sort the universe of AMEX, NASDAQ, and NYSE stocks from CRSP based on past market betas and form 10 portfolios. We use 10-year betas (120 months) and require 60 months of observations for a firm to be included. This is in contrast to Fama and French (1992) who use 5-year betas (60 months) and require 24 months of data. We find that using the longer history for the estimation of betas produces a wider spread in returns and a substantially greater Sharpe ratio for the low minus high portfolio.[22] As before, we drop the lowest decile of firms based on market capitalization on formation date to avoid illiquid, thinly traded firms whose returns may be unreliable, although this is not crucial for our results. We then compute excess returns on the sorted portfolios over the following year. We rescale each of these portfolios to have a market beta of 1. That is, we leverage up the low-beta securities and combine the high-beta securities with the risk-free asset in such a way that the ex-post market betas of all 10 portfolios are 1. Note that since these are excess returns, multiplying each portfolio by a constant still gives us excess returns and hence these are valid test assets. We find results consistent with the previous literature: the annual spread between a leveraged low-beta security and a high-beta security (low-minus-high) is about 7% per annum (see Table 13, Panel A). We also see average returns and Sharpe ratios that are decreasing from low to high.

Consistent with our interpretation of the leverage factor, the correlation between the leverage factor and the low-minus-high beta portfolio is positive, 0.22. That is, as funding tightens and leverage decreases, low-beta stocks that require high leverage underperform high-beta stocks. The correlation is sizable given that the correlation between the leverage factor and the leverage mimicking portfolio is 0.37. This finding complements the results in Table 1 where we show that the leverage factor is correlated with variables commonly associated with funding constraints (volatility, Baa-Aaa spread, and asset growth). Note that the leveraged, low-beta portfolios all have large and statistically significant betas and

[22] Our results are weaker but qualitatively similar when we use sorts based on 5-year betas.

relatively high time-series R-square values, all of which decrease as we move toward the high beta portfolios.

We next test our leverage factor in the cross-section of the beta sorted portfolios. The results are presented in Panels B and C of Table 13. Consistent with our previous results, the leverage model produces a high cross-sectional R-square of 73% and the cross-sectional price of risk associated with the leverage factor is positive and significant. However, at 33% the price of risk is relatively low compared to our earlier estimates. When we estimate the model without an intercept, the price of risk increases to 50%, more in line with our earlier estimates, but the R-square falls to 51%. In either case, the model is not rejected. We also compare the pricing error of the leverage model with that of the Fama-French three-factor model and Fama-French-Carhart four-factor model. The one-factor leverage model with no intercept has an average absolute pricing error of 1.33% (out of 6.41% to be explained), which compares with 1.36% and 0.61% for the three and four-factor models, respectively.

Note that we chose to exclude the beta sorted portfolios from our main test portfolios because they are largely subsumed by standard risk factors for US equities (the 4-factor alphas are essentially zero and the 4-factor time-series R-squares are high). In other words, they add no additional degrees of freedom to our main test assets. This is in line with Kogan and Papanikolaou (2012) who show that the variation in beta sorted portfolios is related to the variation in book-to-market sorted portfolios and a common principal component explains both. However, the beta sorted portfolios do serve to enhance the economic interpretation of our leverage factor as one related to funding constraints.

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 broker-dealers can be expected to reflect the marginal value of wealth of intermediaries because it may proxy for funding constraints or intermediary wealth. 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 outperforms the Fama-French model in the cross-section of size and book-to-market sorted portfolios, outperforms the level factor in the cross-section of bond portfolios, and compares well to 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 the above portfolios remarkably well. The success of the leverage factor across all these cross-sections is measured in terms of high adjusted R-square statistics, low values for the χ^2 statistic based on the sum of squared pricing errors, small and statistically insignificant cross-sectional pricing errors, and cross-sectional prices of risk that are statistically significant and consistent across portfolios. When taking all these criteria into account, our single factor performs as well as standard 4 and 5-factor models tailored to price the cross-sections considered, and provides an economic explanation for their average returns. 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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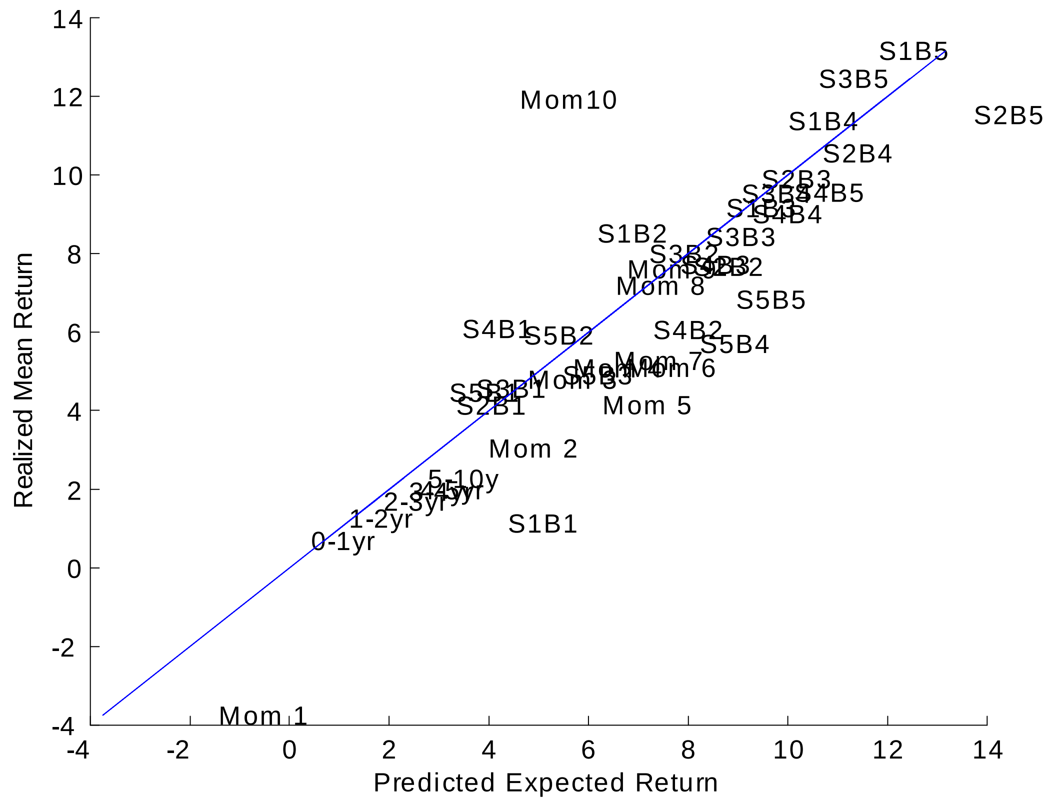

Figure 1: Realized vs. Predicted Mean Returns: Leverage Factor. We plot the realized mean excess returns of 35 equity portfolios (25 Size and Book-to-Market Sorted Portfolios and 10 Momentum Sorted Portfolios) and 6 Treasury bond portfolios (sorted by maturity) against the mean excess returns predicted by our single-factor financial intermediary leverage model, estimated without an intercept ($E[R^e] = \beta_{lev}\lambda_{lev}$). The sample period is Q1/1968-Q4/2009. Data are quarterly, but returns are expressed in percent per year.

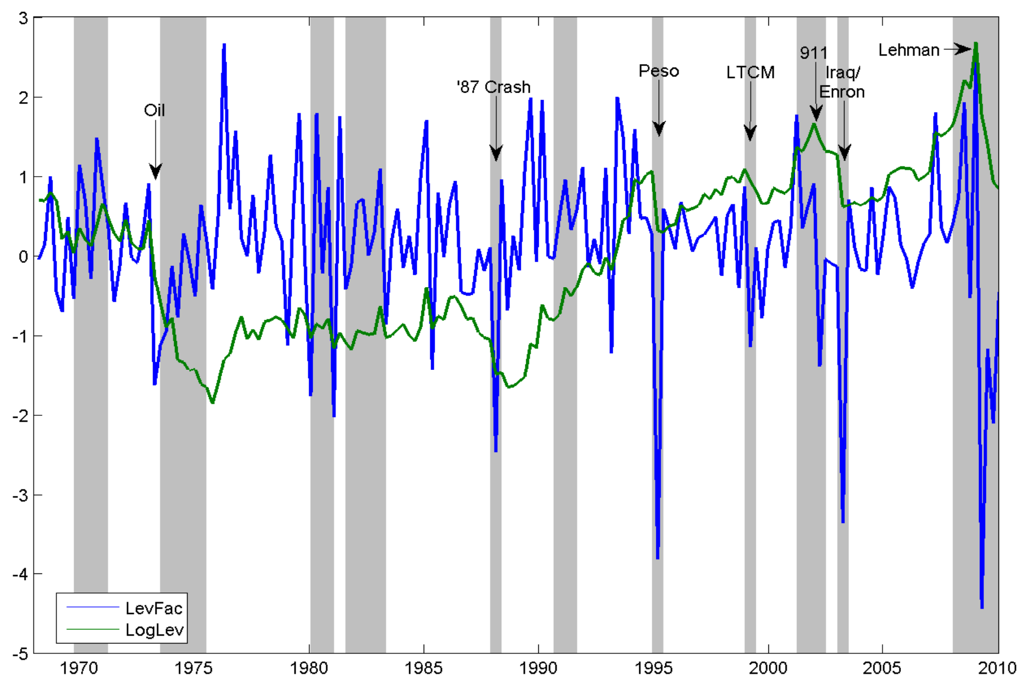

Figure 2: We plot the log leverage and the leverage factor (changes in log leverage) of security broker-dealers, Q1/1968-Q4/2009. We normalize each series to have zero mean and unit variance for convenience. The labels indicate macro / financial sector events associated with large changes in leverage 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, "Sep 11" represents the attacks on the world trade center in September 2001, "Enron" is the Enron scandal and subsequent SEC regulation, "Iraq War" is the decision by congress to invade Iraq, and "Lehman" is the collapse of Lehman Brothers and the ensuing market turmoil in fall 2008. Non-labeled gray areas indicate recessions, based on NBER dates.

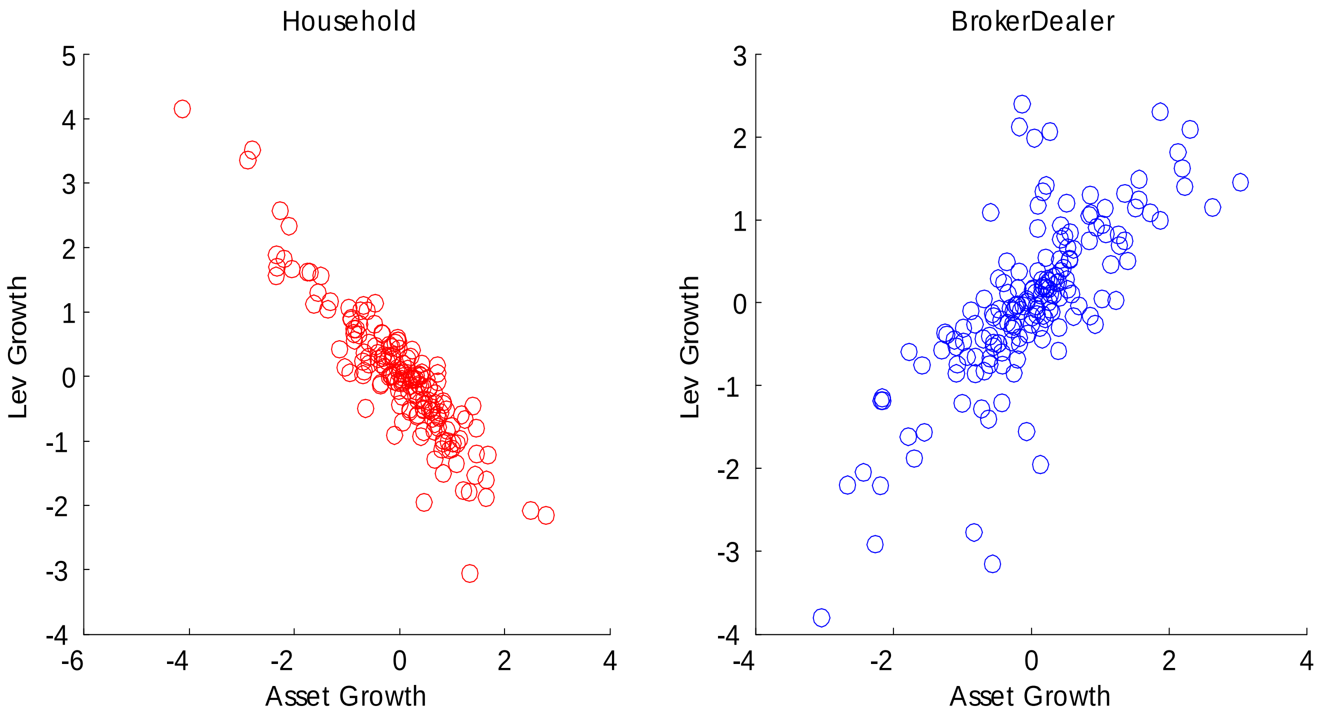

Figure 3: We plot leverage growth vs asset growth for households and broker-dealers. In both cases, leverage is defined as (Total Assets)/(Total Assets - Total Liabilities). A downward sloping line (households) indicates passive balance sheet management, as increasing asset values mechanically decreases leverage and vice versa. An upward sloping line (broker-dealers) indicates active balance sheet management, whereby increases in asset values are associated with increases in leverage. Data are quarterly, 1968-2009 from the Flow of Funds.

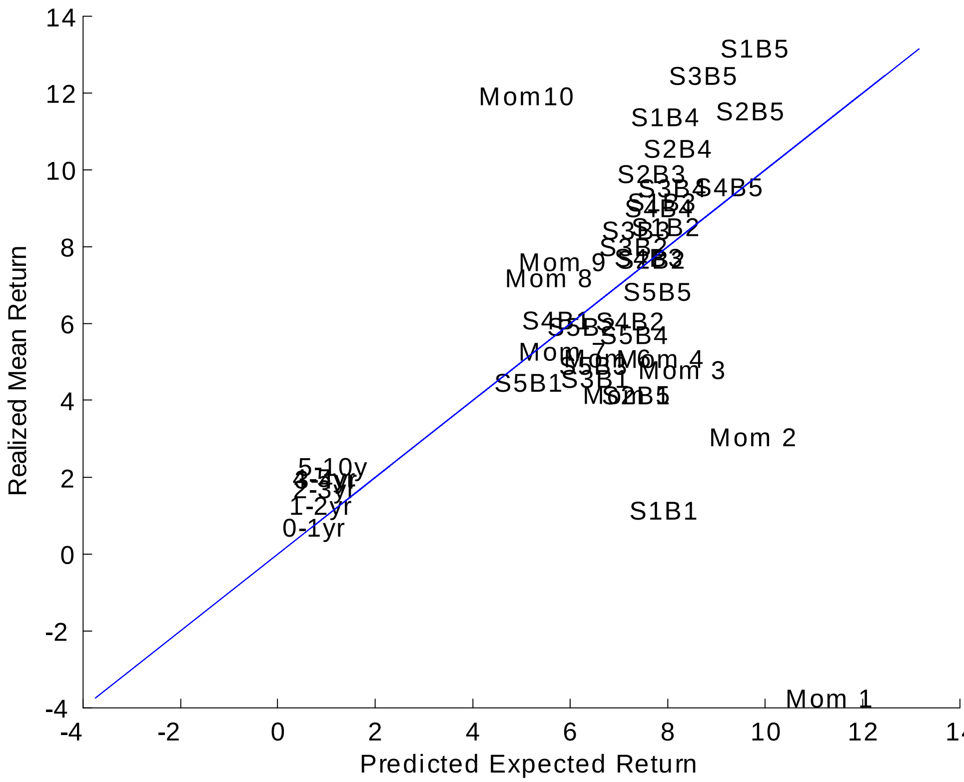

Figure 4: Realized vs. Predicted Mean Returns: Fama-French Factors. We plot the realized mean excess returns of 35 equity portfolios (25 Size and Book-to-Market Sorted Portfolios and 10 Momentum Sorted Portfolios) and 6 Treasury bond portfolios (sorted by maturity) against the mean excess returns predicted by the Fama-French 3-factor benchmark (Mkt, SMB, HML). The sample period is Q1/1968-Q4/2009. Data are quarterly, but returns are expressed in percent per year.

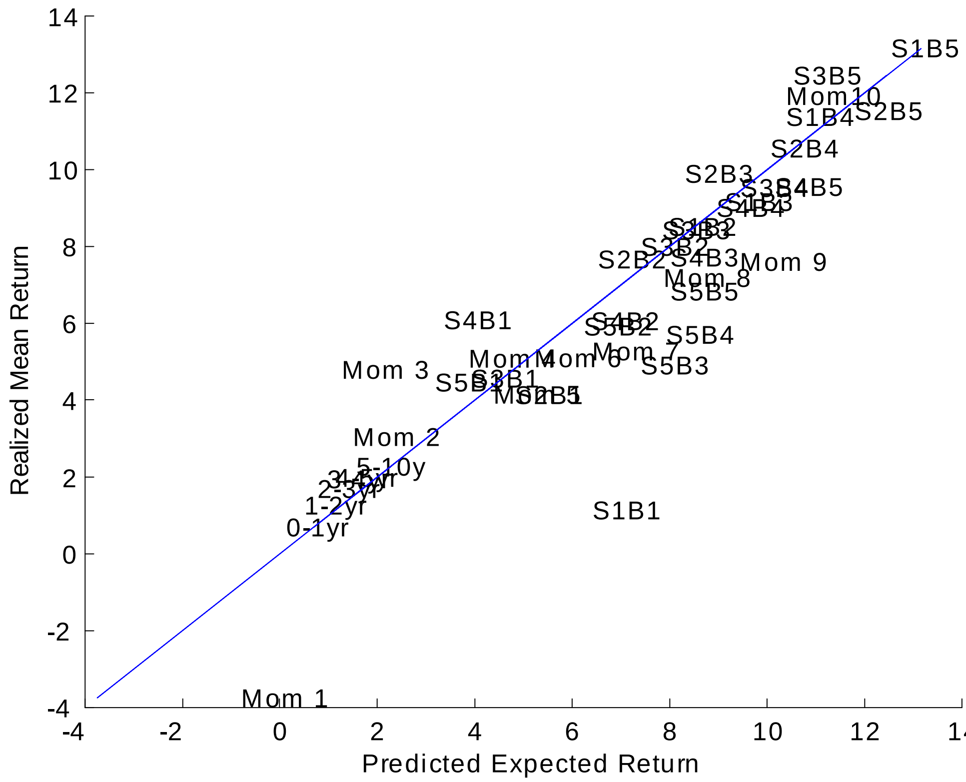

Figure 5: Realized vs. Predicted Mean Returns: 5-Factor Benchmark. We plot the realized mean excess returns of 35 equity portfolios (25 Size and Book-to-Market Sorted Portfolios and 10 Momentum Sorted Portfolios) and 6 Treasury bond portfolios (sorted by maturity) against the mean excess returns predicted by a 5-factor benchmark model (Mkt, SMB, HML, MOM, PC1). PC1 represents shocks to the first principal component of the yield curve, which prices the cross-section of bond portfolios. The sample period is Q1/1968-Q4/2009. Data are quarterly, but returns are expressed in percent per year.

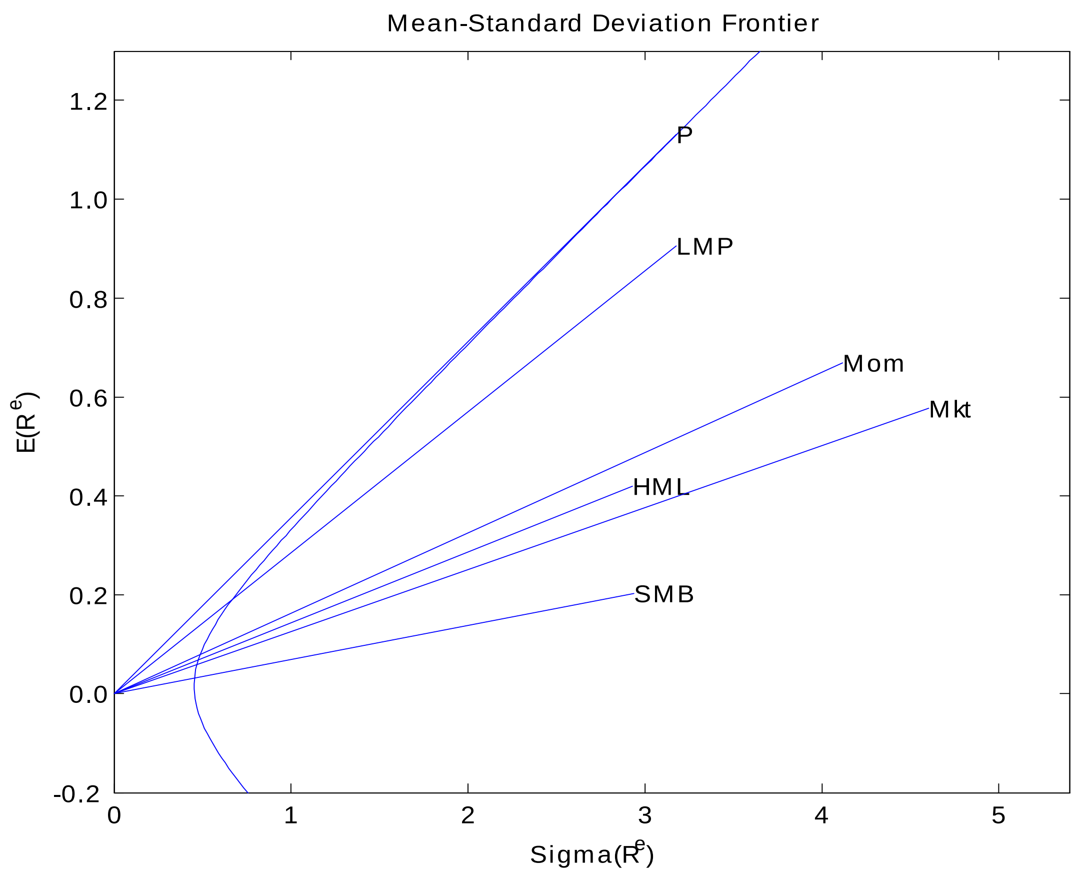

Figure 6: The hyperbola plots the sample mean-standard deviation frontier ("the efficient frontier") for the six Fama-French benchmark portfolios, the Fama-French factors (Mkt, SMB, HML), and the momentum factor. LMP is the leverage mimicking portfolio (see text for description), Mkt, SMB, HML are the 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.

Table 1: Broker-dealer leverage is pro-cyclical. We display the correlation of U.S. broker-dealer leverage growth with a selection of variables, including the log asset growth of U.S. broker-dealers, market volatility (constructed quarterly using weekly data of the value-weighted market return), the Baa-Aaa spread, and the value-weighted stock return of the U.S. financial sector. The sample is Q1/1968-Q4/2009.

Correlation of Broker-Dealer Leverage Factor with:				
	Log Broker-Dealer Asset Growth	Market Volatility	Baa-Aaa Spread	Financials Stock Return
ρ	0.73	-0.37	-0.16	0.18
p-value	0.00	0.00	0.03	0.02

Table 2: Assets and Liabilities of Security Brokers and Dealers as of the end of Q4/2010. The remaining assets and liabilities from the FOCUS reports implicitly appear as miscellanuous assets and liabilities in the Flow of Funds. The amounts are in billions of dollars, not seasonally adjusted. (Source: U.S. Flow of Funds Table L.129., released March 10, 2011)

Assets from Flow of Funds (billions)		Liabilities from Flow of Funds (billions)	
Cash (including seggregated cash)	$96.9	Net repo	$404.7
Credit market instruments	$557.6	Corporate and foreign bonds	$129.7
Commercial paper	$36.2	Trade payables	$18.1
Treasury securities (net of shorts)	$94.5	Security credit	$936.6
Agencies	$149.8	Taxes payable	$3.6
Municipal securities	$40.0	Miscellaneous liabilities*	$480.7
Corporate and foreign bonds	$185.6	Payables to brokers and dealers	
Other (syndicated loans etc)	$51.4	Securities sold not yet purchased	
Corporate Equities	$117.2	Payables	
Security credit	$278.2	Subordinated liabilities	
Miscellaneuous assets*	$1,025.3		
Receivables			
Reverse repos			
Options and Arbitrage			
Commodities			
Investments not readily marketable			
Securities borrowed			
Secured demand notes			
Membership in exchanges			
Affiliates, subsidiaries, and associated partnerships			
Property, furniture, equipment, etc.			
TOTAL	$2,075.1	TOTAL	$1,973.4

*Sub-categories implicit in FOCUS Reports

Table 3: Main Table: Pricing the Size, Book to Market, Momentum, and Bond Portfolios

Pricing results for the 25 size and book-to-market and 10 momentum portfolios, and 6 Treasury bond portfolios sorted by maturity. Each model is estimated as $E[R^e] = \lambda_0 + \beta_{fac}\lambda_{fac}$. FF denotes the Fama-French 3 factors, Mom the momentum factor, PC1 the first principal component of the yield curve, LevFac our leverage factor. Panel A reports the prices of risk with Fama-MacBeth and Shanken t-statistics, respectively. Panel B reports test diagnostics, including mean absolute pricing errors (MAPE) by portfolio group, adjusted R-Squares with corresponding confidence intervals (C.I.), and a χ^2 statistic that tests whether the pricing errors are jointly zero. $E[R^e]$ gives the average excess return to be explained. Data are quarterly, 1968Q1-2009Q4. Returns and risk premia are reported in percent per year (quarterly percentages multiplied by 4).

Panel A: Prices of Risk						
		CAPM	FF	FF,Mom	FF,Mom,PC1	LevFac
Intercept		3.39	3.16	1.06	0.66	0.12
t-FM		3.55	4.09	1.51	1.14	0.06
t-Shanken		3.54	4.03	1.34	1.01	0.04
LevFac						62.21
t-FM						4.62
t-Shanken						3.12
Mkt		3.06	2.30	4.54	4.89	
t-FM		0.99	0.80	1.59	1.71	
t-Shanken		0.99	0.80	1.58	1.70	
SMB			1.76	1.57	1.63	
t-FM			0.93	0.83	0.87	
t-Shanken			0.93	0.82	0.86	
HML			3.33	4.37	4.34	
t-FM			1.45	1.90	1.89	
t-Shanken			1.45	1.86	1.85	
MOM				7.82	7.75	
t-FM				2.94	2.91	
t-Shanken				2.92	2.89	
PC1					14.99	
t-FM					1.03	
t-Shanken					0.93	
Panel B: Test Diagnostics						
MAPE	$E[R^e]$	CAPM	FF	FF,Mom	FF,Mom,PC1	LevFac
Size B/M	7.86	2.62	1.81	1.05	1.01	1.16
MOM	5.80	3.05	3.75	1.47	1.48	1.79
Bond	1.65	1.83	1.59	0.17	0.17	0.37
Intercept		3.39	3.16	1.06	0.66	0.12
Total	6.45	6.00	5.41	2.08	1.66	1.31
AdjR2		0.10	0.16	0.81	0.81	0.77
C.I.AdjR2		[0.02, 0.30]	[0.02, 0.36]	[0.74, 0.88]	[0.72, 0.88]	[0.82, 1]
$T^2(\chi^2_{N-K})$		174.48	167.46	111.45	110.19	67.87
P-Value		0.0%	0.0%	0.0%	0.0%	0.3%

Table 4: Pricing Errors: Pricing the Size, Book to Market, Momentum, and Bond Portfolios

We report pricing errors ($E[R^e] - \lambda_0 - \beta_{fac}\lambda_{fac}$) in percent per year for our leverage factor model and 5-factor benchmark (Mkt, SMB, HML, Mom, PC1) corresponding directly to the previous table. Panel B reports our cross-sectional results when we drop the two most mispriced portfolios: the small-growth (S1B1), and the past winners portfolio (Mom10).

Panel A: Individual Pricing Errors

Size and Book-to-Market Portfolios

	Low	Book-to-Market			High
	$E[R^e]$: Average Returns				
Small	1.15	8.52	9.17	11.38	13.16
	4.14	7.67	9.91	10.55	11.54
Size	4.56	8.00	8.43	9.54	12.46
	6.09	6.07	7.72	9.01	9.57
Big	4.47	5.93	4.93	5.72	6.83
	Leverage Pricing Errors				
Small	-3.27	2.31	0.43	1.40	1.39
	0.73	-0.42	0.46	-0.10	-2.10
Size	0.76	0.79	0.09	0.49	1.88
	2.57	-1.24	-0.11	-0.27	-0.53
Big	1.20	1.18	-0.59	-2.51	-2.11
	5-Factor Pricing Errors				
Small	-5.26	0.47	-0.05	0.89	0.78
	-0.64	0.97	1.46	0.50	0.00
Size	0.52	0.48	0.43	0.02	1.88
	2.76	-0.43	-0.28	0.03	-0.45
Big	1.30	-0.18	-2.32	-2.14	-1.06

Momentum Portfolios

	$E[R^e]$	LevFac	5-Fac
Mom 1	-3.75	-2.46	-2.96
Mom 2	3.06	-1.00	1.71
Mom 3	4.80	-0.03	3.52
Mom 4	5.10	-0.63	1.02
Mom 5	4.15	-2.15	-0.27
Mom 6	5.11	-1.67	-0.10
Mom 7	5.29	-1.23	-1.23
Mom 8	7.19	0.63	-0.57
Mom 9	7.61	0.81	-1.61
Mom 10	11.93	7.25	1.81

Bond Portfolios

	$E[R^e]$	LevFac	5-Fac
0-1yr	0.70	0.15	-0.17
1-2yr	1.28	-0.56	-0.43
2-3yr	1.70	-0.02	-0.08
3-4yr	1.95	-0.27	-0.03
4-5yr	2.00	-0.52	-0.05
5-10y	2.29	-0.70	-0.24

Panel B: Pricing Resuts Dropping Largest Pricing Error Portfolios

	All Portfolios		Drop Small Growth		Drop Mom 10		Drop Both	
	5-Fac	LevFac	5-Fac	LevFac	5-Fac	LevFac	5-Fac	LevFac
MAPE	1.00	1.20	0.78	1.13	0.94	1.01	0.74	0.93
AdjR2	0.81	0.77	0.88	0.79	0.82	0.87	0.89	0.87
$T^2(\chi^2)$	110.19	67.87	72.42	42.95	85.15	45.78	55.27	27.40
P-Value	0.0%	0.0%	0.0%	26.8%	0.0%	18.1%	0.9%	87.5%

Table 5: Equity Portfolios

Pricing results for the 25 size and book-to-market (left panel) and 25 size and momentum portfolios (right panel). Each model is estimated as $E[R^e] = \lambda_0 + \beta_{fac}\lambda_{fac}$. FF denotes the 3 Fama-French factors, Mom the momentum factor, LevFac our leverage factor. Panel A reports the estimated risk premia, along with Fama-MacBeth and Shanken t-statistics, respectively. Panel B reports test diagnostics, including mean absolute pricing errors (MAPE), the largest absolute pricing error (MAX), adjusted R-Squares with corresponding confidence intervals (C.I.), and a χ^2 statistic testing whether the pricing errors are jointly zero. $E[R^e]$ gives the average excess return to be explained. Data are quarterly, 1968Q1-2009Q4. Returns and risk premia are reported in percent per year (quarterly percentages multiplied by 4).

Panel A: Prices of Risk								
	25 Size and Book-to-Market Portfolios				25 Size and Momentum Portfolios			
		CAPM	FF	LevFac		CAPM	FF,Mom	LevFac
Intercept		12.11	15.58	1.00		3.51	11.72	0.31
t-FM		2.99	3.84	0.25		3.41	1.72	0.07
t-Shanken		2.97	3.57	0.18		3.37	1.60	0.04
LevFac				55.78				69.66
t-FM				3.30				3.66
t-Shanken				2.34				2.28
Mkt		-3.81	-10.19			-5.88	-4.76	
t-FM		-0.80	-2.09			-1.17	-0.64	
t-Shanken		-0.79	-1.98			-1.16	-0.60	
SMB			1.85				2.39	
t-FM			0.98				1.12	
t-Shanken			0.97				1.10	
HML			5.76				-4.01	
t-FM			2.42				-1.00	
t-Shanken			2.38				-0.95	
MOM							8.40	
t-FM							3.19	
t-Shanken							3.18	
Panel B: Test Diagnostics								
	25 Size and Book-to-Market Portfolios				25 Size and Momentum Portfolios			
MAPE:	$E[R^e]$	CAPM	FF	LevFac	$E[R^e]$	CAPM	FF,Mom	LevFac
Intercept		12.11	15.58	1.00		3.51	11.72	0.31
Total	7.86	14.41	16.69	2.09	7.17	6.48	12.83	2.47
MAX	13.16	5.71	4.33	3.72	16.15	9.99	4.54	7.01
AdjR2		0.03	0.68	0.74		0.05	0.84	0.51
C.I.AdjR2		[0, 0.28]	[0.48, 0.82]	[0.70, 1]		[0, 0.30]	[0.72, 0.90]	[0.40, 1]
$T^2(\chi^2_{N-K})$		71.99	55.38	34.98		75.83	50.70	23.88
P-Value		0.0%	0.0%	5.2%		0.0%	0.0%	41.1%

Table 6: Treasury Bonds

Pricing results for the 6 Treasury Bond portfolios sorted by maturity. Each model is estimated as $E[R^e] = \beta_{fac}\lambda_{fac}$, without an intercept. FF denotes the Fama-French 3 factors, Mom the momentum factor, PC1 the first principal component of the yield curve, LevFac our leverage factor. For the traded factors, we report time-series α's as pricing errors, since there are only 6 test assets. The last column, LevFac NRE (not re-estimated), gives pricing errors for the leverage factor using the price of risk from the larger cross section of stocks and bonds. Panel B reports the estimated risk premia, along with Fama-MacBeth and Shanken t-statistics, respectively. Panel C reports test diagnostics, including mean absolute pricing errors (MAPE), the largest pricing error (MAX), adjusted R-Squares with corresponding confidence intervals (C.I.), and a χ^2 statistic testing whether the pricing errors are jointly zero. $E[R^e]$ gives the average excess return to be explained. Data are quarterly, 1968Q1-2009Q4. Returns and prices of risk are reported in percent per year (quarterly percentages multiplied by 4).

				Panel A: Pricing Errors			
	$E[R^e]$	CAPM	FF	FF,Mom	PC1	LevFac	Lev NRE
0-1yr	0.70	0.65	0.61	0.58	0.36	0.33	0.27
1-2yr	1.28	1.16	1.08	0.84	0.31	0.28	0.10
2-3yr	1.70	1.54	1.47	1.04	0.22	0.12	-0.15
3-4yr	1.95	1.77	1.73	1.13	0.11	-0.05	-0.40
4-5yr	2.00	1.84	1.85	1.03	-0.13	-0.19	-0.58
5-10y	2.29	2.01	2.11	0.96	-0.27	-0.03	-0.44
				Panel B: Prices of Risk			
					PC1	LevFac	Lev NRE
LevFac						52.90	62.21
t-FM						2.28	NA
t-Shanken						1.65	NA
PC1					31.52		
t-FM					2.27		
t-Shanken					2.14		
				Panel C: Test Diagnostics			
MAPE:	$E[R^e]$	CAPM	FF	FF,Mom	PC1	LevFac	Lev NRE
Total	1.65	1.50	1.47	0.93	0.23	0.17	0.32
MAX	2.29	2.01	2.11	1.13	0.36	0.33	0.58
AdjR2					0.78	0.85	
C.I.AdjR2					[0.28, 0.90]	[0.48, 1]	
$T^2(\chi^2_{N-K})$					17.96	9.10	
P-Value					0.3%	10.5%	

Table 7: Time Series Regressions

Time series regressions of excess returns on the leverage factor $R^e_{i,t} = c_i + \beta_{i,Lev} LevFac_t + \epsilon_{i,t}$. Data are quarterly, 1968Q1-2009Q4. Returns are reported in percent per year (quarterly percentages multiplied by 4). Leverage betas are multiplied by 100 for convenience.

Size and Book-to-Market Portfolios					
	Low	Book-to-Market			High
	$E[R^e]$: Average (Annualized) Returns				
Small	1.15	8.52	9.17	11.38	13.16
	4.14	7.67	9.91	10.55	11.54
Size	4.56	8.00	8.43	9.54	12.46
	6.09	6.07	7.72	9.01	9.57
Big	4.47	5.93	4.93	5.72	6.83
	β_{Lev}: Leverage Betas (x 10^{-2})				
Small	6.92	9.79	13.86	15.85	18.72
	5.29	12.82	15.01	16.93	21.73
Size	5.92	11.41	13.22	14.35	16.81
	5.48	11.55	12.41	14.72	16.04
Big	5.06	7.45	8.68	13.03	14.19
	T-Stats				
Small	0.72	1.21	1.93	2.33	2.44
	0.62	1.79	2.40	2.78	3.18
Size	0.76	1.81	2.32	2.53	2.67
	0.78	1.93	2.23	2.70	2.55
Big	0.93	1.51	1.90	2.81	2.79
	R^2: R-Square				
Small	0.31%	0.87%	2.18%	3.14%	3.43%
	0.23%	1.89%	3.32%	4.43%	5.73%
Size	0.34%	1.91%	3.12%	3.70%	4.10%
	0.36%	2.17%	2.89%	4.17%	3.74%
Big	0.52%	1.34%	2.12%	4.52%	4.46%

Momentum Portfolios				
	$E[R^e]$	β_{Lev}	T-Stat	R^2
Mom 1	-3.75	-2.26	-0.24	0.03%
Mom 2	3.06	6.32	0.85	0.43%
Mom 3	4.80	7.56	1.23	0.89%
Mom 4	5.10	9.01	1.64	1.58%
Mom 5	4.15	9.94	1.98	2.30%
Mom 6	5.11	10.71	2.07	2.49%
Mom 7	5.29	10.30	2.26	2.98%
Mom 8	7.19	10.37	2.23	2.89%
Mom 9	7.61	10.73	2.09	2.55%
Mom10	11.93	7.33	1.08	0.69%

Bond Portfolios				
	$E[R^e]$	β_{Lev}	T-Stat	R^2
0-1yr	0.70	0.69	1.89	2.63%
1-2yr	1.28	1.89	1.46	2.56%
2-3yr	1.70	2.98	2.04	3.30%
3-4yr	1.95	3.79	2.06	3.58%
4-5yr	2.00	4.14	2.00	3.82%
5-10y	2.29	4.39	1.68	3.36%

Table 8: Robustness

Panel A shows robustness of our main measure to several starting dates. End dates are 2009Q4 except the last column which excludes the financial crisis, ending in 2005Q4. Panel B asks how likely a "noise" factor could produce our results. We run 100,000 simulations where we draw randomly from the empirical distribution of our leverage factor. We re-do all our tests, including constructing the LMP (Leverage Mimicking Portfolio). For each statistic, we report the probability that the random factor does as well as our leverage factor (i.e., the probability the random factor has an R^2 as large as our leverage factor or an intercept as small as our leverage factor, or both jointly in "Joint" column).

Panel A: Robustness to Various Start Dates

Years	1966-	1967-	1968-	1969-	1970-	1971-	1972-	1968-2005
Intercept	0.46	0.37	0.12	0.19	0.67	1.53	1.29	-0.37
Adj R2	0.72	0.74	0.77	0.77	0.79	0.76	0.79	0.67
$T^2(\chi^2)$	60.49	64.20	67.87	72.00	74.72	69.07	61.83	67.61
P-Value	2%	1%	0%	0%	0%	0%	1%	0%

Panel B: Robustness – What are the odds a random factor could produce our results?

		R^2	MAPE	Intercept	Joint R^2-Int
Noise Factor	P-value	0.01%	0.00%	0.19%	0.00%
		R^2	MAPE	Sharpe	Joint R^2-Sharpe
Noise LMP	P-value	0.18%	0.00%	1.63%	0.05%

Table 9: The Leverage Mimicking Portfolio (LMP): 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= $\frac{1}{N}\sum_{i=1}^{N}|\alpha_i|$). SBM represents the 25 size and book-to-market portfolios, 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. The last panel compares cross-sectional results using each of the factor models. We confirm our pricing results using monthly data going back to 1936. For the 1936-2009 sample, we only use the size and book-to-market and momentum portfolios, since the bond data are not available.

Panel A: Time-Series Alphas

MAPE	Mean	LMP	FF,MOM	FF
SBM	7.86	1.15	1.04	1.57
MOM	5.80	1.66	1.46	4.36
Bond	3.04	0.59	0.93	1.47
Total	6.33	1.19	1.13	2.24

Model Fit		LMP	FF,MOM	FF
GRS		2.57	2.28	4.48
P-value		0	0	0

Panel B: Cross-Sectional Results Across Time-Periods

Time-Period		LMP	FF,MOM	FF
1968-2009,	Intercept	-0.32	1.06	3.12
Quarterly	AdjR2	0.78	0.81	0.16
1936-2009,	Intercept	-3.00	14.74	27.97
Monthly	AdjR2	0.63	0.81	0.52

Table 10: Pricing the benchmark factors with the Leverage Mimicking Portfolio (LMP)

We run time-series regressions of the four benchmark factors, Market, SMB, HML, and Momentum, on the LMP. We report the quarterly results for our main sample 1968-2009, as well as monthly results that begin in 1936. 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						
	$E[R^e]$	Alpha	T-Alpha	Beta	T-Beta	R2
Mkt	5.44	0.08	(0.03)	0.52	(2.90)	0.10
SMB	3.07	1.72	(0.75)	0.13	(1.19)	0.02
HML	4.06	-0.22	(-0.74)	0.44	(2.92)	0.12
Mom	7.99	4.24	(1.08)	0.36	(1.85)	0.06
Monthly Data: 1936-2009						
	$E[R^e]$	Alpha	T-Alpha	Beta	T-Beta	R2
Mkt	6.93	-0.22	(-0.90)	0.81	(20.17)	0.30
SMB	2.44	0.89	(0.72)	0.16	(5.25)	0.03
HML	5.04	0.66	(0.02)	0.47	(17.87)	0.30
Mom	8.03	5.08	(2.86)	0.29	(6.82)	0.05

Table 11: Mean-Standard Deviation Analysis

We give the monthly mean, standard deviation, 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. We provide the annual Sharpe ratio by multiplying by $\sqrt{12}$. Data are monthly from Jan. 1936 - Dec. 2009.

	$E[R^e]$	$\sigma[R^e]$	Sharpe Ratio	Annualized Sharpe
Market	0.57	4.30	0.13	0.46
SMB	0.15	2.86	0.05	0.18
HML	0.40	2.75	0.15	0.50
Mom	1.32	6.48	0.20	0.70
LMP	1.92	3.23	0.29	0.99
Max Sharpe			0.35	1.20

Table 12: Leverage Beta Sorts

We sort the entire universe of CRSP stocks into portfolios based on pre-ranking leverage betas, found by regressing quarterly firm-level excess returns (over the 3-month risk-free rate) on our leverage factor. We use 10 years (40 quarters) for pre-sorting regressions. We exclude the smallest 10% of firms based on market capitalization on formation date and exclude firms that do not have at least 20 quarters of past return data on formation date. We report the mean, standard deviation, Sharpe ratio, post-formation leverage beta and t-stat as well as the CAPM α and associated t-stat. We report numbers in percent per year. Leverage betas are multiplied by 100 for convenience. Our holding period is 1973-2009.

Panel A: 3 Sorted Leverage Portfolios

	Low	Med	High	High-Minus-Low
$E[R]$	5.17	5.94	7.99	2.82
$\sigma[R]$	19.63	16.99	21.01	13.44
$E[R]/\sigma[R]$	0.26	0.35	0.38	0.21
Leverage β	3.81	7.76	11.39	7.58
t-β	0.61	1.54	1.86	2.01
CAPM α	-0.53	1.08	2.12	2.64
t-α	-0.56	1.38	1.48	1.17

Panel B: 5 Sorted Leverage Portfolios

	1 (Low)	2	3	4	5 (High)	5-1
$E[R]$	4.91	5.62	5.81	7.12	8.78	3.87
$\sigma[R]$	22.76	17.80	17.14	18.73	24.06	18.56
$E[R]/\sigma[R]$	0.22	0.32	0.34	0.38	0.36	0.21
Leverage β	0.86	6.02	7.52	10.91	10.61	9.74
t-β	0.12	1.07	1.50	2.01	1.52	1.83
CAPM α	-1.31	0.35	0.76	1.82	2.17	3.48
t-α	-0.79	0.42	0.93	1.51	1.20	1.13

Table 13: "Betting Against Beta" Portfolios

We sort CRSP stocks on 10 year pre-ranking market betas. We lever up low-beta stocks so that each portfolio has a market beta of 1. The resulting portfolios co-move with funding conditions since leverage constrained investors will bid up high beta securities (Frazzini and Pedersen (2011)). See text for complete description. FF represents the Fama-French factors, FF,Mom adds the momentum factor. The holding period is 1968-2009. All data are quarterly but returns and Sharpe ratios are presented as annualized numbers (multiplied by 4 and 2, respectively).

Panel A: Time-Series Regressions: $R^e_{i,t} = c_i + \beta_{Lev,i} LevFac_t + \epsilon_{i,t}$					
	$E[R^e]$	Sharpe	β_{Lev}(x 10^{-2})	T-stat	R^2
BAB1	10.98	0.46	19.45	2.93	4.90%
BAB2	8.94	0.40	21.71	3.50	6.88%
BAB3	7.29	0.36	16.41	2.91	4.84%
BAB4	6.87	0.35	11.33	2.01	2.38%
BAB5	6.68	0.34	11.67	2.11	2.60%
BAB6	4.67	0.25	12.91	2.41	3.38%
BAB7	5.68	0.30	10.19	1.89	2.10%
BAB8	4.68	0.25	8.90	1.67	1.66%
BAB9	4.29	0.22	3.97	0.72	0.31%
BAB10	3.99	0.20	3.51	0.62	0.23%
$1-10$	6.99	0.36	15.94	2.90	4.82%

Panel B: Cross-Sectional Prices of Risk					
				LevFac	LevFac, NoInt
Intercept				2.48	
t-FM				0.77	
t-Shanken				0.66	
LevFac				32.75	49.62
t-FM				2.06	2.48
t-Shanken				1.78	1.84

Panel C: Cross-Sectional Test Diagnostics					
MAPE:	$E[R^e]$	FF	FF,Mom	LevFac	LevFac, No Int
Intercept				2.48	
Total	6.41	1.36	0.61	3.29	1.33
MAX	10.98	4.06	1.81	2.14	2.32
AdjR2				0.73	0.51
C.I.AdjR2				[0.42, 1]	[0.20, 1]
$T^2(\chi^2)$				7.38	6.62
P-Value				49.61%	67.65%