Back to Basics : The Impact of Financial Leverage on Asset Pricing

(*Job Market Paper*)

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Abstract

This paper examines the impact of financial leverage on time-varying betas and on the conditional CAPM using a framework in which a firm's equity beta is decomposed into the product of financial leverage and its asset beta. The unique aspect of this analysis is that a firm's asset beta is estimated using asset returns constructed from market data not only on equity, but also on corporate bonds and loans. Several results emerge. The first finding is that leverage alone can explain a substantial portion of the well-documented unconditional alphas of book-to-market–sorted portfolios. Second, this improvement is shown to be due to the tight link between book-to-market and leverage, explaining my empirical finding that firms' asset returns do not increase across book-to-market–sorted portfolios. Third, I document that high book-to-market firms have counter-cyclical asset betas, further improving the fit of the model. In summary, high book-to-market firms have both high leverage and high asset betas in economic downturns and, therefore, have high expected equity returns.

1 Introduction

It is a widespread view amongst financial economists that the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) has been soundly rejected by the data. That is, the cross-sectional variation in expected returns is not solely explained by beta. Both a firm's size and book-to-market, as well as other variables, are important factors in describing average returns.[1] Many such analyses are performed in an unconditional setting that assumes that the betas (and other factor regression coefficients) are constant. This is unfortunate as the CAPM, similar to all asset pricing models, is a theory about conditional expected returns.

It is well known that the conditional CAPM does not imply the unconditional version if betas move through time (e.g., Dybvig and Ross (1985) and Bollerslev et al. (1988)). In fact, recent tests of the conditional CAPM explicitly address this issue and find more support for the conditional specification (Jagannathan and Wang (1996), Ferson and Harvey (1999), Lettau and Ludvigson (2001), Lustig and Van Nieuwerburgh (2005) and Santos and Veronesi (2006)). A recent paper by Lewellen and Nagel (2006), however, questions these findings by arguing that the variation in betas and the equity premium would have to be incredibly large to explain the differences between conditional and unconditional tests. Instead, they argue that the recent studies' test results suffer from low power due to not exploiting the full set of model restrictions, and that researchers are being misled by high R^2's which are an artifact of the factor covariance structure (e.g., Lewellen et al. (2008)).

This paper adds to this debate by performing a simple analysis that refutes some of these assertions. The starting point of my framework is the assumption that the beta of a firm's assets (not equity) does not time vary and that expected returns follow the CAPM, so that both the conditional and unconditional versions of the CAPM hold in the firm's asset return space. Almost all previous studies, however, focus on the firm's equity, and not asset, returns.[2] What is the impact on CAPM testing when equity returns are used in place of firms' asset returns under my constant beta framework?

As a preview, consider the graphs in Figure 1. The graph on the left shows the market leverage ratio of 10 book-to-market–sorted portfolios; the graph on the right shows their asset and equity excess returns. Surprisingly, there is a monotonic relationship between book-to-market and leverage, and there seems to be no value premium at the firms' asset level.[3] These facts signal

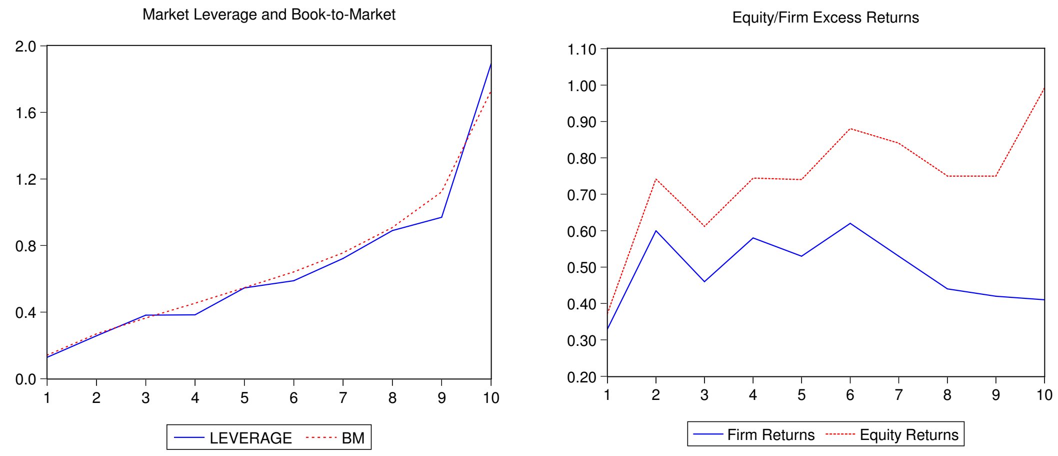
[1] See, for example, Banz (1980), Fama and French (1992), among others.

[2] Exceptions are Asness (1993), Charoenrook (2004) and Hecht (2004).

[3] The finding that firms' asset returns are flat across the book-to-market–decile portfolios is also reported by Hecht (2004).

Figure 1: Market Leverage and Equity and Firm Returns

For book-to-market decile portfolios, average market leverage and average book-to-market are plotted on the left and the average of equity and firm excess returns are plotted on the right. Market leverage, book-to-market and equity excess returns are weighted with the market value of equity and firm excess returns are weighted with the market value of assets.



that the value premium could be driven by high leverage among high–book-to-market firms.

If firms do not instantaneously adjust their debt levels to movements in their underlying equity prices, then expected equity returns will vary through time. This time-variation will be driven by changing betas due to time-variation in firm leverage and the risk premium. In my framework, the time-varying beta is a function of the risk premium, because a high market risk premium reduces the firm's current value and, in turn, increases the leverage ratio. In bad times, the leverage ratios of highly levered firms become even higher and their stocks become riskier and have high expected returns. Given that value firms are typically highly levered firms, it is consistent with the empirical evidence that their betas are higher in bad times (Lettau and Ludvigson (2001) and Petkova and Zhang (2005)). Furthermore, due to this interaction between the risk premium and leverage, the unconditional CAPM will fail for the reasons outlined in Lewellen and Nagel (2006), albeit at a much more severe level than implied in their setting.

Depending on firms' current and past investment decisions and market conditions, their asset betas can also change through time.[4] Then, time-variation in leverage and firms' asset betas together will change the risk of equity and could have a large amplifying effect in economic downturns. In normal times, low asset beta firms will take on a large amount of debt, because the

[4]Berk et al. (1999), Carlson et al. (2004), Zhang (2005) and Gomes and Schmid (2007) are theoretical studies that link the history of firms' investment decision and their risk characteristics.

cost of risk-adjusted financial distress is low.[5] When a big negative shock hits the economy, leverage will shoot up and those highly levered firms whose asset betas also increase will have high equity betas. If a firm characteristic such as book-to-market happens to capture these countercyclical time variations in leverage and asset betas, it will show up as an explanatory variable for cross-sectional returns although the underlying mechanism is through leverage and asset betas.

Given the importance of leverage in financial markets, and its role here in explaining the cross-sectional pattern in equity returns, it may be surprising that the literature has focused more on equity than firm returns. The reason is undoubtedly that firm leverage has been unobservable. While Compustat allows a periodic snapshot of book leverage and some datasets allow a look at market leverage across a limited number of bonds in a subsample of firms, it has been difficult to map out a firm's capital structure. This paper manages to move one step further by employing the Reuter's Fixed Income (commonly known as the EJV) Database on public and private bonds and the Loan Pricing Corporation database on loans. These databases are quite extensive and are used in the marketplace to objectively mark securities of financial institutions' fixed income portfolios.

The contribution of my paper is threefold. First, the paper formally investigates the conditional CAPM in a model with constant firm betas and financial leverage. The results are generally more supportive of the CAPM than previously documented. For example, I show empirically that leverage alone can explain 40% of the unconditional alphas between the high and the low book-to-market portfolios, and the conditional alphas are not statistically significant. In order to reconcile these results with Lewellen and Nagel (2006), I investigate the reasons for the magnitude of these effects. In particular, in a world where the CAPM holds for firm returns, the pricing errors can be decomposed into two parts, the covariance between the conditional beta and the market return, and the difference between the unconditional beta and the mean of the conditional beta. For firms with high leverage ratios, I estimate the two terms to be much greater than that implied by Lewellen and Nagel (2006).

Second, I analyze more closely why financial leverage reduces the value premium. In particular, I document a strong relationship between book-to-market and financial leverage, which goes a long way toward explaining the cross-sectional pattern in asset and equity returns. For example, while equity returns tend to show the usual value premium, with high book-to-market firms earning

[5] Almeida and Philippon (2007) show that the risk-adjusted cost of financial distress is much larger than the expected costs and therefore firms should care about systematic risks when they issue debt. Shleifer and Vishny (1992), Altman et al. (2005) and Acharya et al. (2007) also suggest that the loss given default is larger in economic recessions or industry-wide distress and the risk of financial distress is systematic.

higher expected returns, this becomes much weaker once I focus on firm returns alone. This fact also suggests that the value premium is, in fact, a leverage effect: the investors in the equity of value firms earn high returns because they are levering up the underlying firms by taking short positions in the debt claims issued by the firms.

Third, working off this finding, this paper investigates the economics of high-book-to-market firms in my framework. In particular, given the tight link between book-to-market and financial leverage, I delve into the issue on why book-to-market has explanatory power for the cross-section of returns, while it is leverage that changes the risks. First, I document a strong negative relationship between the underlying risks of firms and financial leverage, which explains why high-book-to-market firms have high leverage on average. I then show that, although high-book-to-market firms have low asset betas, they become very risky when big negative shocks hit the economy. I document that high-book-to-market firms' asset betas increase in bad times and decrease in good times. Combined with counter-cyclical leverage, high-book-to-market firms' equity betas have a strong counter-cyclical pattern. I also relate this finding to those of Vassalou and Xing (2004) and show that most of the high book-to-market firms are in financial distress in recessions.

This paper is organized as follows. Section 2 presents a preliminary discussion in two parts. The first part outlines the unconditional and conditional versions of the CAPM under the assumption of constant asset betas and time-varying financial leverage. In the second part, the data sources for mapping out the capital structure of the firm are described. Summary statistics are provided for the data and compared under various assumptions about the capital structure. In Section 3, I provide formal tests of the conditional versions of the CAPM, highlighting the use of leverage in developing the conditional model, and show the sources of the improvements. Section 4 looks at the underlying mechanisms of risks among high book-to-market firms within the framework of leverage and time-varying asset betas. Section 5 concludes.

2 Preliminaries

2.1 Motivating Theory

Although the idea that a change in leverage affects the firm's equity beta has been known for decades (e.g., Hamada (1972), Black and Scholes (1973) and Galai and Masulis (1976)), its implications for asset pricing tests have not been explored in the literature.[6] In this section, I provide a

[6] Although there are previous studies such as Hecht (2004) and Charoenrook (2004) that use firms' asset returns, they do not look at the impact of time-varying leverage on the unconditional alphas. Their focus is on whether

simple model of time-varying beta under the assumption of a constant firm beta and time-varying leverage. The goal is to show that the conditional beta can change due to changes in expected returns.

Consider a world where the conditional CAPM holds for firms' asset returns. The expected return on the firm's asset is determined by the beta of the firm, which is assumed to be constant. One can view this as an economy where the firms have production-side investment opportunities that are priced by the market portfolio.

Let firm i's asset value be A_t^i and the market be M_t and assume that both follow the diffusion processes:

$$\frac{dA_t}{A_t} = \mu_t^A dt + \beta^A \sigma_t^M dW_t^M + \sigma_t^I dW_t^I \tag{1}$$

$$\frac{dM_t}{M_t} = \mu_t^M dt + \sigma_t^M dW_t^M \tag{2}$$

The superscript i is omitted when obvious. There are both systematic (dW_t^M) and idiosyncratic (dW_t^I) shocks. The innovation on the market return is $\sigma_t^M dW_t^M$ and β^A is the constant beta of the firm's assets. The market volatility σ_t^M and the idiosyncratic volatility σ_t^I along with their drift terms μ_t^A and μ_t^M can be time varying in general and I do not assume any particular functional structure on the drift and volatility parameters except they are linked through the CAPM.

Now consider the righthand side of the firm's balance sheet. Assume that the firm issues debt and equity to finance their projects (investment opportunities) and therefore the accounting identity $A_t = E_t + D_t$ holds where E_t and D_t are equity and debt amounts issued by the firm. Because the firm's equity is a contingent claim on its underlying assets, E_t also follows a diffusion process

$$\frac{dE_t}{E_t} = \mu_t^E dt + \beta_t^E \sigma_t^M dW_t^M + \sigma_t^{E,I} dW_t^{E,I} \tag{3}$$

where β_t^E is the levered beta, μ_t^E is the drift rate (conditional mean), $\sigma_t^{E,I}$ is the idiosyncratic volatility of equity and $dW_t^{E,I}$ is an idiosyncratic shock orthogonal to the systematic shock, dW_t^M.

Since volatility risk is not priced, from the application of Ito's lemma and Girsanov's theorem we get the following conditional CAPM representation

$$\mu_t^E - r^f = \frac{\partial E_t}{\partial A_t}\frac{A_t}{E_t}\beta^A(\mu_t^M - r^f) = \eta_t \beta_A(\mu_t^M - r^f) \tag{4}$$

firm characteristics are priced at the asset level using Fama-Macbeth regressions.

where the equity elasticity to assets $\eta_t \equiv \frac{\partial E_t}{\partial A_t}\frac{A_t}{E_t}$ and the conditional beta of equity is given as

$$\beta_t = \eta_t \beta_A \tag{5}$$

It is well known that we can get a closed form solution for the term $\frac{\partial E}{\partial A} = 1 - \frac{\partial D}{\partial A}$ using the Black-Scholes formula when the volatilities σ_t^M and σ_t^I are constant (Galai and Masulis (1976)). In fact, a straight zero-coupon corporate bond can be replicated by being long in a riskless bond and short in a put option on the underlying firm value (Merton (1974)). In option-pricing language, $\frac{\partial D}{\partial A}$ is called the delta (of the short position in the put option) and is given as $\frac{\partial D}{\partial A} = 1 - N(d_1)$, where $N(\cdot)$ is the cumulative normal distribution function, $d_1 = \frac{\log\left(\frac{A_t}{F}\right)+\left(r^f+\frac{1}{2}\sigma_a^2\right)(T-t)}{\sigma_a\sqrt{T-t}}$, F is the face value of debt, $T-t$ is the time to maturity of debt, and the volatility of the firm's assets $\sigma_a \equiv \sqrt{{\beta^A}^2{\sigma^M}^2 + {\sigma^I}^2}$.

The parameter d_1 proxies for the credit quality of the firm and is also known as the distance-to-default. It is increasing in the firm's asset ratio to face value ($\frac{A_t}{F}$) and the time to maturity $(T-t)$ and decreasing in the volatility of assets (σ_a).[7] For firms with good credit quality, the distance-to-default is high, the delta, $\frac{\partial E}{\partial A}$, is close to one and, therefore, $\eta \approx \frac{A}{E}$.

A special case is when the debt is riskless. In that case, the change in the asset value and equity value is one-to-one ($\frac{\partial E}{\partial A} = 1$) and therefore (5) becomes[8]

$$\beta_t^E = \frac{A_t}{E_t}\beta^A = (1 + l_t)\beta^A \tag{6}$$

The interesting implication of this time-varying beta model based on leverage is that the conditional beta of equity is a function of the *firm's* expected return. When the firm's discount rate for future cash flows is high, the firm value A_t will drop, everything else being equal. The reduction in firm value will affect equity and debt differently. Because the firm's equity is a levered claim, the corresponding percentage decrease in equity is larger than that of debt and, therefore, the leverage ratio l_t increases.

Not only is there a positive relationship between the expected equity return and the leverage ratio, but also the leverage ratios of highly levered firms increase more than those of less levered ones when there are positive shocks in the firms' discount rates.[9] In my framework, this implies

[7]This is when the σ_a is not too large. For some large values of σ_a, the distance to default is an increasing function of σ_a.

[8]Although (6) can be seen as a special case of (5), one does not need the constant volatility assumption to derive (6).

[9]The proof of this statement under the Merton model assumptions is provided upon request.

that highly levered firms' stocks become riskier in bad times, when the market risk premium is high. When there is an increase in the risk premium and a corresponding increase in the firms' discount rates, it is the stocks with high leverage ratios that are hardest hit. Therefore, the leverage ratios of highly levered firms shoot up and their equity betas will increase in bad times.

Given the above links between the conditional beta and the market risk premium, the question to ask is what implications this has for the empirical testing of asset pricing models. In the later sections, I show that the pricing errors (alphas) that have been observed in book-to-market–sorted portfolios could be driven by the relationships between the conditional beta and the risk premium.

2.2 Data

For the empirical tests in the later sections, I construct the return and value series on firms' assets. Because no single dataset has a complete picture of the market value of the capital structure, a number of datasets have to be combined. I use the EJV database and FISD from Mergent for corporate bonds, Yield Book from Citigroup for bond indices, Dealscan and the mark-to-market pricing service from Loan Pricing Corporation for loans and Compustat quarterly and annual database for the face value of debt and other accounting information. In the following subsections I explain the corporate bond and bank loan datasets in detail.

2.2.1 Corporate Bond Data

In this paper, the primary data source for corporate bond prices is the Fixed Income Database provided by EJV. The prices are collected from the major dealers in the market and reflect the market valuation of the bid side as of 3 PM for each trading day. It covers terms and conditions, credit ratings, daily pricing and historical amount outstanding. There are more than 72,000 U.S. corporate bond issues in the dataset for the period from July 1991 to December 2007. Because the analysis of this paper is based on firms' asset returns and leverage, I select bonds issued by nonfinancial firms with matching CRSP stock returns and Compustat accounting information. The resulting sample has 3,328 issuers with 18,730 bonds. Table A-2 provides summary statistics on the sample.

As with other corporate bond datasets based on dealer quotes, it is possible that my pricing data are a mix of actual trader quotes and so-called matrix prices. Although there are tens of thousands of bonds outstanding, only a few thousand bonds are traded on a given day. When there are no traded prices or dealer quotes available, matrix prices are computed from proprietary algorithms by the pricing services. This could result in excessive comovement in the price data when dealers or the pricing service update the bond prices following transactions of bonds in the same industry and ratings category. Another potential issue with the prices based on dealer quotes is price staleness. When bonds trade infrequently, dealers update their price quotes only when they receive orders, and the quotes do not necessarily have the current information in the market. Price staleness can also arise from the use of matrix pricing because matrix prices do not necessarily reflect the current price levels where bonds might actually trade, and the mispricings might be corrected with some time lags through later transactions or client feedback.

To mitigate these issues inherent in the database, month-end bond prices and returns are used throughout the study rather than those at a higher-frequency. End-of-month prices are generally considered to be close to the actual market prices because firms perform more careful checks on their book value at the end of month (Warga (1991)). And, the effect of time delays in information updating will be lessened at monthly frequencies. In addition, returns are based on value-weighted averages in all of the analyses in this paper. Because bonds with large notional amounts tend to trade more frequently, the impact of matrix prices and quotes that are not updated will be minimized by value-weighting.

To further examine this issue, I perform the analysis of price staleness based on autocorrelations and cross-correlations in Table A-1 in the appendix. If prices are stale, the returns of individual securities will be negatively auto-correlated and portfolio returns will be positively autocorrelated (Scholes and Williams (1977)). Moreover, price staleness will also cause stock returns to lead bond returns because stocks are traded more frequently. The results suggest that the staleness in bond prices is not severe at the monthly frequency, in contrast to the daily and weekly frequencies. For example, at the higher frequencies the cross-correlations of high-yield bond returns with corresponding lagged stock returns are all positive up to lag 5, whereas in monthly returns, the cross-correlations die out after lag 1. This suggests that, in weekly and daily returns, the prices are stale and the news in stock returns are reflected in the dealer quotes with lags of several weeks.

2.2.2 Bank Loan Data

Another important piece of firms' capital structures is bank loans. The bank loan market has grown dramatically over the past decades and has become one of the most flexible financing alternatives available in corporate finance. Annual loan originations exceed US$1 trillion and annualized trading volume has grown at an annual rate of 25% since 1990, exceeding $160 billion as of 2005. According to Thomas and Wang (2004), the liquidity of the market is comparable to that of the high-yield bond market after 1993. The loan market is composed of two parts: the primary market and the secondary market. The primary market is for loan syndication and origination. After origination, loans are traded on the secondary market. Because loans are categorized as private instruments, participants in secondary market transactions are banks and non-bank financial institutions. It is generally considered an informationally more efficient market than equity markets because it excludes uninformed noise traders.[10]

The primary loan market data are from Dealscan. It is a comprehensive dataset on loan origination, covering over 155,000 primary market loan and bond transactions since 1987. For market prices of bank loans in the secondary market, I use the Mark-to-Market Pricing Service from Loan Syndications and Trading Association (LSTA) and Loan Pricing Corporation (LPC). The service has daily bid and ask quotes from major dealers in the market and covers the period from November 1999 to December 2004. The entire dataset obtained from combining the primary and secondary markets has 65,039 observations, with 4,424 loan facilities and over 1,500 borrowers. After the sample is mapped to CRSP and Compustat, there are 42,276 observations, 2,487 facilities and 717 borrowers. Some descriptive statistics of the sample are given in Table 1. Most of the firms and loan facilities are in the high-yield rating group, showing that the majority of the trading volume is in distressed loans. Typical facility size varies between \$150 million and \$1.1 billion, with investment-grade firms issuing a larger amount of loans.

Because the price data from LSTA are also based on dealer quotes, the quality of the dataset can be an issue. In order to analyze the quality of the pricing data, LSTA initiated the annual Trade Data Study in 2002 to compare the mean of dealer marks and actual traded prices (Taylor and Sansone (2007)). The mean absolute price difference was 1.5% in 2002 and decreased to less than 1% in 2004. The median was around 0.5% in 2002 and less than 0.25% in 2004. Considering that the average bid-ask spread over the study period was around 1.25%, the prices in the dataset reflect the actual transaction prices reasonably well. The data-collecting policies of LSTA also assure the quality of the data. On a daily basis, a series of price accuracy audits govern the data collection procedures. Any observations that look suspicious, such as large price movements or stale prices, are reviewed and confirmed by LSTA analysts (see Taylor and Sansone (2007) for details). In all, the results of the study by LSTA indicate that the quality of the loan data does not seem an issue.

[10]Refer to Allen and Gottesman (2006) for a detailed description of the syndicated bank loan market.

Table 1: Summary Statistics for Loan Sample

For the period from November 1999 to December 2004, sample statistics for issuer rating-based group are reported. No. of Firm is the average number of firms in each rating group. No. of Facilities is the average number of loan facilities. Loan Amount per Firm is the total loan amount issued by a borrower, in billions of dollars. Mean and Median Facility Amounts are the average and the median size of facilities, in billions of dollars. Average Spread is the mean spread over the benchmark rates. Mean TTM and Median TTM are the average and the median times-to-maturity of loan facilities. Fraction of Revolver is the percentage of revolving loan observations to the total.

	AAA – A	BBB	BB	B	CCC	Unrated
No. Firm	3.12	19.38	89.25	56.68	20.22	34.02
No. Facility	10.03	46.50	239.98	178.40	68.13	99.43
Loan Amount per Firm(B)	2851.75	2349.09	887.00	787.19	885.20	424.81
Mean Facility Amount(B)	2040.20	1455.92	428.91	368.86	424.23	224.02
Median Facility Amount(B)	1148.29	513.17	272.54	250.03	281.04	156.59
Mean Spread (bps)	203.50	201.48	268.59	303.99	273.14	293.51
Mean Spread	178.50	173.44	270.31	299.02	284.17	302.60
Mean TTM	4.30	3.14	4.26	4.48	3.61	4.09
Median TTM	4.15	3.06	4.40	4.63	3.67	4.15
Fraction of Revolver	16.1%	22.9%	15.8%	12.5%	18.2%	11.4%

2.3 Variable Construction

2.3.1 Mapping the Capital Structure

In order to construct the firm-level data, I first map out each firm's capital structure month by month using the aforementioned datasets. However, the mapping-out process is not a simple task due to the dynamic nature of firms' capital structures. For example, the bond amount outstanding can change over time for variety of reasons[11] and the datasets sometimes do not agree on the changes. In those cases, I manually collect Bloomberg's corporate actions item or 10-K filings to decide which data point is the right one. There are other complications in the mapping, which are explained in detail in the appendix.

The firms' assets are divided into three claims: equity, public debt and private debt. It is assumed that public debt is proxied for by the corporate bonds issued by the firm and private debt by the bank loans. The mapping is first done with the corporate bond dataset. Firm by firm and month by month, the book value of long-term debt and debt in current liabilities is mapped to the bond amount outstanding. The bond mapping results are given in Table A-3. On average, 50% of long-term debt and debt in current liabilities is mapped to the corporate bond

[11] To name a few: issue-called, issue-converted, over-allotment, sinking fund provision, issue-tendered, issue exchange in case of Rule 144A securities and so on.

Table 2: Descriptive Statistics for Firm Return/Leverage Sample

For each issuer rating group, the sample statistics are reported for the period from July 1991 to December 2007. No. Firms is the average number of firms in each rating group. Mean and Median Leverage are average and median values of market debt to market equity ratios. Equity, bond, loan and firm values are market size of each value in billions of dollars. Volatilities are standard deviation of the monthly returns.

	AAA	AA	A	BBB	BB	B	CCC~	Unrated
No. Firms	8.9	36.8	165.3	226.6	208.4	180.7	38.6	256.7
Mean Leverage	0.20	0.22	0.43	0.71	1.21	2.46	6.83	1.41
Median Leverage	0.07	0.14	0.31	0.51	0.76	1.35	3.82	0.60
Mean Equity Value(B)	117.256	41.889	13.598	5.913	1.904	0.959	0.685	1.184
Median Equity Value(B)	102.426	31.343	6.430	2.925	0.935	0.389	0.211	0.455
Mean Bond Value(B)	3.733	1.867	1.338	1.211	0.542	0.391	0.294	0.366
Median Bond Value(B)	0.870	0.923	0.593	0.503	0.240	0.173	0.125	0.112
Mean Loan Value(B)	31.368	3.895	3.042	1.827	0.874	0.698	0.594	0.293
Median Loan Value(B)	7.777	1.623	0.694	0.560	0.245	0.128	0.161	0.086
Mean Firm Value(B)	149.286	47.660	17.813	8.835	3.314	2.106	1.804	1.714
Median Firm Value(B)	117.459	34.927	8.618	4.537	1.581	0.833	0.579	0.744
Mean Firm Volatility	5.53%	5.67%	5.88%	6.16%	7.65%	9.16%	9.40%	9.61%
Median Firm Volatility	5.72%	5.51%	5.60%	5.90%	6.80%	7.72%	7.94%	8.40%
Mean Equity Volatility	6.33%	6.92%	8.02%	9.71%	13.66%	18.32%	22.10%	15.71%
Median Equity Volatility	6.15%	6.58%	7.62%	9.15%	12.85%	17.02%	21.36%	14.20%
Mean Equity Excess Return	0.71%	0.59%	0.58%	0.57%	0.55%	0.59%	-1.08%	0.34%
Mean Firm Excess Return	0.46%	0.46%	0.42%	0.37%	0.33%	-0.07%	-0.45%	0.21%

amount outstanding. Once the mapping to the bond dataset is done, the remaining portion of book debt is mapped out to bank loans. Combining the bond and the loan amounts, the datasets cover on average 94% of the book value of long-term debt, which shows that the mapping is fairly representative of firms' capital structure.

2.3.2 Firm Level Variables

Using the mapping of the capital structure from above, I construct the two most important variables in this study: the monthly firm returns and the market values of the firms' capital structure. The leverage ratios are calculated from the equity value and the sum of public and private debt value, and the firm returns are calculated from value-weighting equity and debt returns by their market values. I exclude financial firms from the sample, following the convention in the literature. For details of the variable construction procedures, refer to the appendix.

I report several characteristics of firm returns and leverage in Table 2. Investment-grade firms account for most of the sample, both in terms of size and number. As is expected, lower-rated

Table 3: Coverage of Sample to CRSP/Compustat Universe

Column Number reports the average number of firms in my sample for each year. Total Size Ratio is the ratio of total equity size in my sample to the total equity size of the CRSP/Compustat universe.

Year	Number	Total Size Ratio
1991	333	43.6%
1992	490	57.4%
1993	710	62.7%
1994	825	64.5%
1995	902	64.5%
1996	975	66.7%
1997	1034	67.0%
1998	1075	71.0%
1999	1103	71.0%
2000	1107	71.7%
2001	1074	76.4%
2002	1074	79.5%
2003	1063	78.3%
2004	1111	79.6%
2005	1097	79.0%
2006	1096	85.3%
2007	1085	79.1%
Average	963	70.4%

firms have higher leverage and firm return volatility than investment grade firms. For example, B-rated firms have mean leverage of 2.46 and firm volatility of 9.4%, whereas A-rated firms have mean leverage of 0.43 and firm volatility of 5.88%. Notably, lower-rated firms, especially CCC and lower, have smaller firm and equity returns, -1.08% and -0.45%, respectively. This is consistent with the results of Campbell et al. (2008) in which they report that stocks with high default risk earn lower returns.

Sample statistics on the final sample are in Table 3. The sample length is 198 months, spanning the period from July 1991 to December 2007. On average there are 963 firms monthly, covering approximately 70% of the total stock market of the CRSP universe.[12] The correlation between the aggregate stock returns from the sample and the CRSP universe is 0.95 and increases to 0.99 including no-debt firms, which also indicates that the sample is fairly representative.

[12]This statistic understates the actual coverage of the sample because the zero-leverage firms are not included in calculating the coverage. In the main empirical analyses, they will also be added into the sample.

3 Impact of Leverage in Tests of the CAPM

Given the tight link between book-to-market and leverage shown in the introduction, it is possible that the large positive alphas from the high-book-to-market portfolios come from financial leverage. When the risk premium is high, high-book-to-market firms' equity betas tend to increase more than those of low-book-to-market firms, through the mechanism outlined in the previous section. Because the conditional beta is high when the risk premium is high, the average price of a high-book-to-market firm's equity can be very low.

In order to see how much leverage alone can explain in tests of the conditional CAPM, I examine the average of the conditional alphas by computing them from the following time series model

$$R^i_{t+1} = \alpha_t + \beta_t R^M_{t+1} + \epsilon^i_{t+1} \tag{7}$$

in which R^i_{t+1} and R^M_{t+1} are the excess equity and market return, respectively. The conditional beta, β_t, is either based on the Merton model assumption, (5), or on the riskless debt assumption, (6), and asset betas are assumed to be constant[13]. The market portfolio is the usual value-weighted stock market return.[14] In the next sections, I explain the beta estimation methodology and provide the empirical results.

3.1 Beta Estimation Methodology

In the estimation of portfolio betas and alphas, running time-series regressions on portfolio returns has become a standard procedure in asset pricing tests. Instead of this conventional "top-down" approach, throughout this paper the main methodology used to estimate alphas and betas is the "bottom-up" approach of Elton et al. (2007). The top-down approach is not available for my purposes because the leverage ratio of a portfolio does not make economic sense unless all the firms in the portfolio have the same firm return volatility and are perfectly correlated. Furthermore, the bottom-up approach estimates the alphas and the betas more precisely, as is shown by Elton et al. (2007).

The first step of the approach is to obtain the conditional betas at the individual-firm level using the firms' asset betas and leverage. To estimate the asset betas, a regression of firm returns on the

[13] The constant asset beta assumption will be relaxed later

[14] There is a question of what the market portfolio is when the CAPM holds at the asset level. A couple of unlevered market returns, constructed from the asset return sample and from bond indices, are also tried and the results are qualitatively the same. For the remainder of the paper, the CRSP value-weighted returns are used throughout.

market return, $R^i_{A,t+1} = \beta^i_A R^M_{t+1} + \epsilon_{t+1}$, is run for firms with more than six months of observations available.[15] Then, the time-varying β^i_t for each firm's equity is obtained by multiplying the market leverage ratio $(1 + l^i_t)$ by the asset beta β^i_A.[16] The second step is to calculate the portfolio beta by value-weighting the individual conditional betas; $\beta^{pf}_t = \Sigma_{i\in X_t} w^i_t \beta^i_t$ where w^i_t is the weight for firm i and X_t is the set of firms in the portfolio for month t. This cross-sectional aggregation of individual firm betas will reduce the effect of the estimation error from the first-stage regression. In the last step, the portfolio alpha for month t is calculated as the difference between the portfolio equity excess return R^{pf}_{t+1} and the expected portfolio equity excess return $\beta^{pf}_t R^M_{t+1}$.[17]

The estimation of the conditional beta based on Merton's model, (5), requires the estimates for the elasticity, η^i_t, which requires the following parameters: (i) current asset value, (ii) face value of debt, (iii) interest rate, (iv) time to maturity and (v) asset volatility. (i) is obtained from the sample and (iii) is set to the 1-year treasury constant maturity yield. For (iv), I calculate the average of the bonds' maturities weighted by the amount outstanding. The last piece left is the firm's asset volatility. I assume that the volatility of the firm is constant and compute the sample volatility using the whole time series of firm returns.

The bottom-up betas have the following characteristics compared to the top-down betas. First, even though the betas of individual firms are constant, the bottom-up betas of portfolios can be time-varying because the portfolio betas change when the weighting variable w^i_t changes. Second, the portfolio betas can change by a large amount when the portfolio is reformulated. As can be seen from the definition of the portfolio beta, $\beta^{pf} = \Sigma_{i\in X_t} w^i_t \beta^i$, a change in the composition of portfolio X_t can change the portfolio beta.

The portfolio formation procedure is the standard one (see Fama and French (1993) for details). At the end of June of each year, I form 10 book-to-market–decile portfolios according to the firms' book-to-market ratio in December of the previous year.

[15] The empirical results are robust to the choice of the minimum sample length.

[16] There is an alternative method. One can estimate the asset beta by running $R^i_{E,t+1} = \beta^i_A(1 + l^i_t)R^M_{t+1} + \epsilon_{t+1}$ using equity returns alone. This estimate of the asset beta is less accurate, because this regression is based on a misspecified asset beta model.

[17] To be exact, $\alpha_t + \epsilon_{t+1} = R^{pf}_{t+1} - \beta^{pf}_t R^M_{t+1}$.

3.2 Results

3.2.1 Dynamics of Conditional Betas

Before turning to the conditional alpha results, I provide in Figure 2 the time-series plot of the conditional betas, the unconditional betas and the firms' asset betas of the low and high decile portfolios. Note that unconditional betas can vary through time in the bottom-up method when portfolios are reformulated or portfolio weights change. The unconditional betas of assets and equity are also estimated with the bottom-up approach. The two figures show remarkable differences between the betas of the two portfolios. For the low book-to-market decile portfolio in the top figure, there are almost no differences between the unconditional and the conditional betas and the betas are relatively stable.

In contrast, the betas of the high book-to-market portfolio show very different patterns from its low book-to-market counterpart. First, the changes in the betas due to the reformulation are distinct and large, showing that the stocks in the portfolio have different betas year by year. This raises a question about the credibility of the conventional top-down approach to estimate the beta of the value portfolio by treating it as stable over the full sample period. Second, the conditional betas tend to be volatile and large in economic downturns compared to the unconditional betas. The shaded periods (years 1991 and 2001) are NBER recessions. Around the mid-1990s they are as low as 0.5 but go up to 2 in 1991 and 2003. This is consistent with the previous findings by Lettau and Ludvigson (2001) and Petkova and Zhang (2005) that high book-to-market portfolios have higher equity betas in bad times.

3.2.2 Pricing Errors

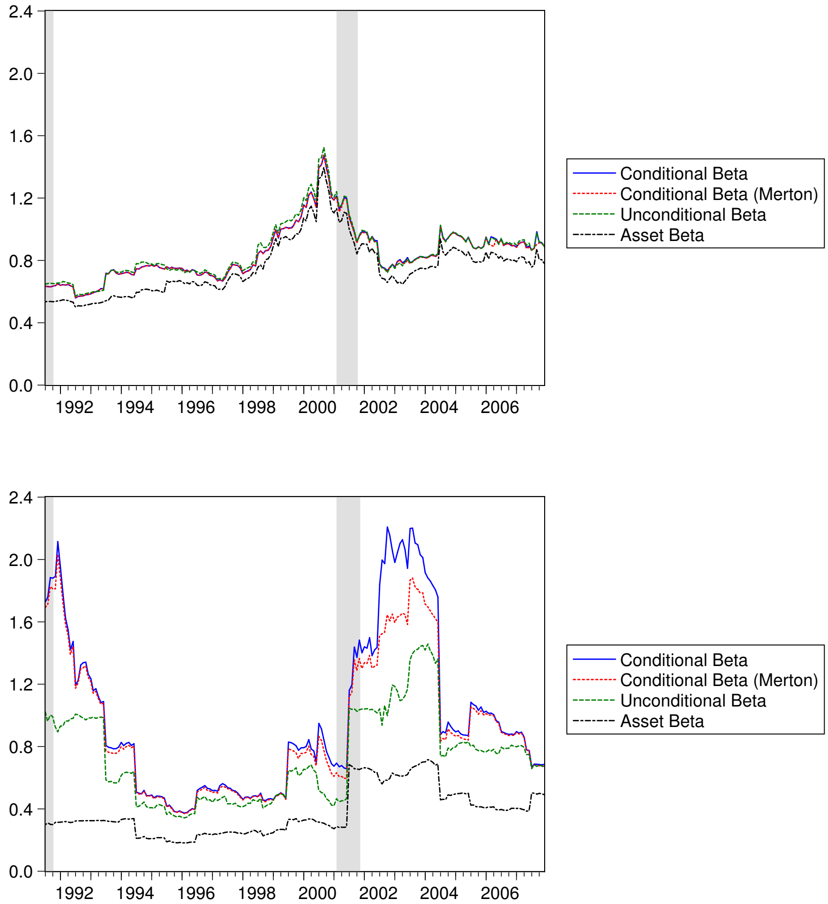
In Table 4, I provide results of the pricing errors from the unconditional and the conditional betas above. The reported alphas are the mean of the monthly pricing errors, and the t-statistics of the alphas are based on the standard deviations of the sample means, which are robust to the conditional heteroskedasticity.[18] Because the results from the two time-varying beta models—one with riskless debt and the other with the Merton model assumption—are similar, I focus on explaining the results from the riskless debt assumption in the following.

Looking at the unconditional alphas in panel A, it is clear that the alphas are greater among

[18] The standard errors are not corrected for serial correlation as in Lewellen and Nagel (2006). The alphas each month, α_t, do not appear autocorrelated in the sample with an estimated autocorrelation of less than 0.01.

Figure 2: Betas for the Low and the High Book-to-Market Decile Portfolios

For the low (top) and high (bottom) book-to-market decile portfolios, four kinds of betas are plotted: asset beta, unconditional equity beta, conditional beta based on the riskless debt assumption and conditional beta based on Merton model assumption. The asset beta and unconditional beta for each portfolio is obtained from the bottom-up method by Elton et al. (2007). The conditional betas are also from the bottom-up mothod, in which the individual betas are obtained by multiplying leverage ratio ($\frac{A}{E}$) or equity sensitivity implied by Merton model ($\frac{\partial E}{\partial A}\frac{A}{E}$) to the individual firm asset betas. Note that unconditional betas can vary through time in the bottom-up method when portfolios are reformulated or portfolio weights change. The shaded periods are NBER recessions.



higher book-to-market portfolios.[19] In the high book-to-market decile portfolio, the alpha is 0.54% monthly and statistically significant at the 10% level. The difference in alphas between the high and the low decile portfolios is quite large—0.59% monthly—and also statistically significant at the 10% level. In unreported results, the same test is performed on the CRSP universe and the results are similar. In summary, in my 17-year sample, in which we have firms' asset return data available, the value premium is present and significant both statistically and economically.

[19]The alphas do not have to be centered around zero because my sample does not include all the firms in the CRSP/Compustat universe. In conventional top-down regressions on the same 10 book-to-market–sorted portfolios, I obtain similar figures for alphas and betas as in Panel A of Table 4.

Table 4: Pricing Errors of Book-to-Market-Sorted Portfolios

Alphas from the three different models–the unconditional CAPM and the two conditional CAPMs with riskless debt and the Merton model assumptions–are reported in panels A, B, and C, respectively. The test portfolios are 10 book-to-market-sorted portfolios. The first two rows of each panel show the average and the t-statistics of the monthly pricing errors. The next two rows report the average and the standard deviation of betas obtained from the bottom-up approach by Elton et al. (2007). The standard errors used to calculate the t-statistics are robust to the conditional heteroskedasticity. I use *, **, and *** to denote significance for F-statistics at the 10% level, 5% level and 1% level, respectively.

Panel A : Unconditional CAPM

	Book-to-Market Decile										
	Low	2	3	4	5	6	7	8	9	High	$H_0 : \alpha_{high} = \alpha_{low}$
α	-0.05%	0.18%	0.01%	0.19%	0.16%	0.30%	0.30%	0.24%	0.28%	0.54%	F-stat : 2.66*
$t(\alpha)$	-0.30	1.25	0.06	1.00	0.92	1.61	1.64	1.06	1.46	1.79	
β	0.86	0.94	0.94	0.88	0.89	0.83	0.74	0.69	0.74	0.73	
$std(\beta)$	0.18	0.10	0.10	0.08	0.14	0.13	0.16	0.19	0.21	0.29	

Panel B : Conditional CAPM with the riskless debt assumption ($\beta_t = (1 + lev_t)\beta^A$)

	Low	2	3	4	5	6	7	8	9	High	$H_0 : \alpha_{high} = \alpha_{low}$
α	-0.05%	0.18%	0.00%	0.17%	0.11%	0.25%	0.28%	0.21%	0.22%	0.32%	F-stat : 1.04
$t(\alpha)$	-0.31	1.28	-0.03	0.91	0.66	1.38	1.54	0.91	1.10	1.06	
β	0.85	0.91	0.94	0.89	0.92	0.86	0.76	0.73	0.81	0.92	
$std(\beta)$	0.18	0.10	0.10	0.10	0.15	0.12	0.15	0.23	0.31	0.52	

Panel C : Conditional CAPM with the Merton model ($\beta_t = \eta_t\beta^A$)

	Low	2	3	4	5	6	7	8	9	High	$H_0 : \alpha_{high} = \alpha_{low}$
α	-0.05%	0.18%	0.00%	0.18%	0.12%	0.26%	0.29%	0.22%	0.23%	0.36%	F-stat : 1.36
$t(\alpha)$	-0.29	1.31	0.01	0.93	0.70	1.44	1.59	0.96	1.18	1.24	
β	0.84	0.91	0.94	0.88	0.91	0.85	0.75	0.71	0.79	0.87	
$std(\beta)$	0.18	0.10	0.10	0.10	0.15	0.12	0.15	0.23	0.31	0.52	

In panels B and C, we find that the conditional alphas are much smaller than the unconditional ones, especially in the high decile portfolio. For example, the alpha of the high decile portfolio is 0.32% in the first row of panel C, less than 60% of the unconditional alpha of 0.54%. In terms of the differences in the alphas between the high and the low deciles, their magnitude is 66% of that from the unconditional CAPM. Furthermore, the F-statistics for the hypothesis of $\alpha_{high} = \alpha_{low}$ are not rejected at the 10% level. With leverage being the only time-variation, the results are more supportive of the CAPM than previously documented in the literature.

In conclusion, considering time variation caused by change in leverage improves the time-series pricing errors. Although the value premium is not explained fully, time variation in leverage alone is responsible for approximately 40% of the unconditional alphas; the literature has been silent on this issue. In the next section, I provide breakdowns of the unconditional alphas and examine the sources of the performance enhancement.

3.3 Error Breakdowns

The results in the previous section are in contrast to those of Lewellen and Nagel (2006) who argue that the conditional CAPM does not explain the value premium. Their reasoning is based on the following decomposition of unconditional pricing errors:

$$\alpha^u = cov(\beta_t, E_t[R^M_{t+1}]) + E[R^M_{t+1}](E[\beta_t] - \beta^u) \tag{8}$$

when the true data generating process follows the conditional CAPM, as in (7). Using short window regressions with high frequency data to estimate conditional betas and alphas, they show empirically that (i) the mean of the conditional alphas is as large as the alphas from the unconditional regressions and (ii) the covariance term of the conditional beta and the time-varying risk premium, $cov(\beta_t, E_t[R^M_{t+1}])$, is too small to explain the unconditional alphas. However, the tests based on the short-window regressions are still unconditional tests of the CAPM and can be misleading because the bias in the conditional alphas and the covariance between the beta and the risk premium can be quite large.[20] When this is the case, the estimate for the second term in (8) can be biased downward as well, which is ignored in their analysis.

The intuition of the theory in the preliminary section predicts the sign and the magnitude of the two terms. A shock in the risk premium $E_t[R^M_{t+1}]$ translates to an increase in the discount rate and a corresponding increase in leverage. Therefore the first term is positive and larger for highly levered firms. The second term also tends to be positive and larger for highly levered firms for the following reasons. It is shown in the appendix that

$$E[R^M_{t+1}](E[\beta_t] - \beta^u) \approx -\frac{E[R^M_{t+1}]}{var(R^M_{t+1})} cov(\beta_t, E_t[{R^M_{t+1}}^2]) \tag{9}$$

Since a firm's stock is a call option and its debt is a negative put option on the underlying assets, leverage is negatively related to volatility. The term $E_t[{R^M_{t+1}}^2]$ largely captures market volatility and, therefore, the second term in (8) will be positive and larger for highly levered firms.[21] Given

[20] Using simulation exercises, Choi (2008) shows that the short-window regressions can lead to large biases in the conditional alphas and in the covariance between the conditional beta and the risk premium, when portfolio reformulation changes the mean of portfolio betas.

[21] One could argue that the effects of the risk premium and the volatility tend to cancel each other, referring to the positive risk–return relationship implied by the CAPM. However, the empirical evidence on the relationship is ambiguous, for example, French et al. (1987), Campbell and Hentschel (1992), Brandt and Kang (2004) and Guo and Whitelaw (2006). Ultimately, it is an empirical question as to how large the terms, α_1 and α_2, would be.

Table 5: Breakdowns of Unconditional Pricing Errors

For the book-to-market decile portfolios, this table reports the breakdowns of the unconditional alphas. The first row, α, and the second row, α_t, are the respective unconditional and conditional alphas from Table 4. The conditional alphas are from the riskless debt-based model. The third and fourth rows, $cov(\beta_t, E_t[R^M_{t+1}])$ and $E[R^M_{t+1}](E[\beta_t] - \beta^u)$, report the unconditional pricing errors implied by conditioning down in (8).

	Book-to-Market Decile									
	Low	2	3	4	5	6	7	8	9	High
α	-0.05%	0.18%	0.01%	0.19%	0.16%	0.30%	0.30%	0.24%	0.28%	0.54%
α_t	-0.05%	0.18%	0.00%	0.17%	0.11%	0.25%	0.28%	0.21%	0.22%	0.32%
$cov(\beta_t, E_t[R^M_{t+1}])$	0.01%	0.02%	0.01%	0.01%	0.03%	0.02%	0.01%	0.01%	0.02%	0.09%
$E[R^M_{t+1}](E[\beta_t] - \beta^u)$	-0.01%	-0.02%	0.01%	0.01%	0.02%	0.02%	0.01%	0.02%	0.04%	0.13%

that book-to-market and market leverage are tightly linked at the portfolio level, the two terms in (8) will generate positive unconditional pricing errors.

In Table 5, I quantify how much of the unconditional pricing errors in Table 4 are attributed to the conditioning–down by calculating the two terms in (8) and the mean of the conditional alpha in the case of the leverage-based conditional beta model in (6). Moving from the low to the high decile, we find that a greater fraction of the unconditional pricing errors are from the two terms in (8). In the lower decile portfolios (which also have small pricing errors), most of the pricing errors are from the errors of the conditional model. For example, almost 100% of the pricing errors originate from the conditional alphas in the low and the second decile portfolios. However, the fractions explained by the conditioning-down become more important in the high decile portfolios.

Of the two sources of unconditional alphas from the conditioning down, what is the major contributor to the errors? Lewellen and Nagel (2006) find that the covariance between the beta and the risk premium, α_1, explains, on average, less than 10% of the difference between the pricing errors of the high and the low book-to-market decile portfolios, depending on estimation methods. I find a slightly greater figure in Table 5, 0.08% monthly, from the difference between the high and low book-to-market decile portfolios. On the other hand, the second component, $cov(\beta_t, E_t[R^M_{t+1}])$, is 0.13%, which is estimated to be very small and ignored in the analysis of LN. It is estimated to be greater than the other term and is about 23% of the difference in pricing errors between the high and the low book-to-market portfolios.

3.4 The CAPM at the Asset Level

The results in the previous sections suggest that leverage alone can explain a large part of the unconditional alphas, especially for high book-to-market portfolios. What, then, is the relationship between leverage and book-to-market so that the former seems to explain the value premium? We have seen in Figure 1 that they are linked cross-sectionally at the portfolio level. I further investigate the link between the two and show that they are tightly related in time-series and at the individual firm level. I then test the CAPM on asset returns, which represent the fundamental business of firms, to see whether the value premium is just an artifact of leverage. If one can find a value premium at the asset return level as well, then book-to-market is related to something more than leverage, as discussed in a later section.

3.4.1 The Link between Leverage and Book-to-Market

Leverage and book-to-market are related through the following identity:

$$\log\left(\frac{BE}{ME}\right) = \log\left(\frac{MD}{ME}\right) - \log\left(\frac{BD}{BE}\right) - \log\left(\frac{MD}{BD}\right) \tag{10}$$

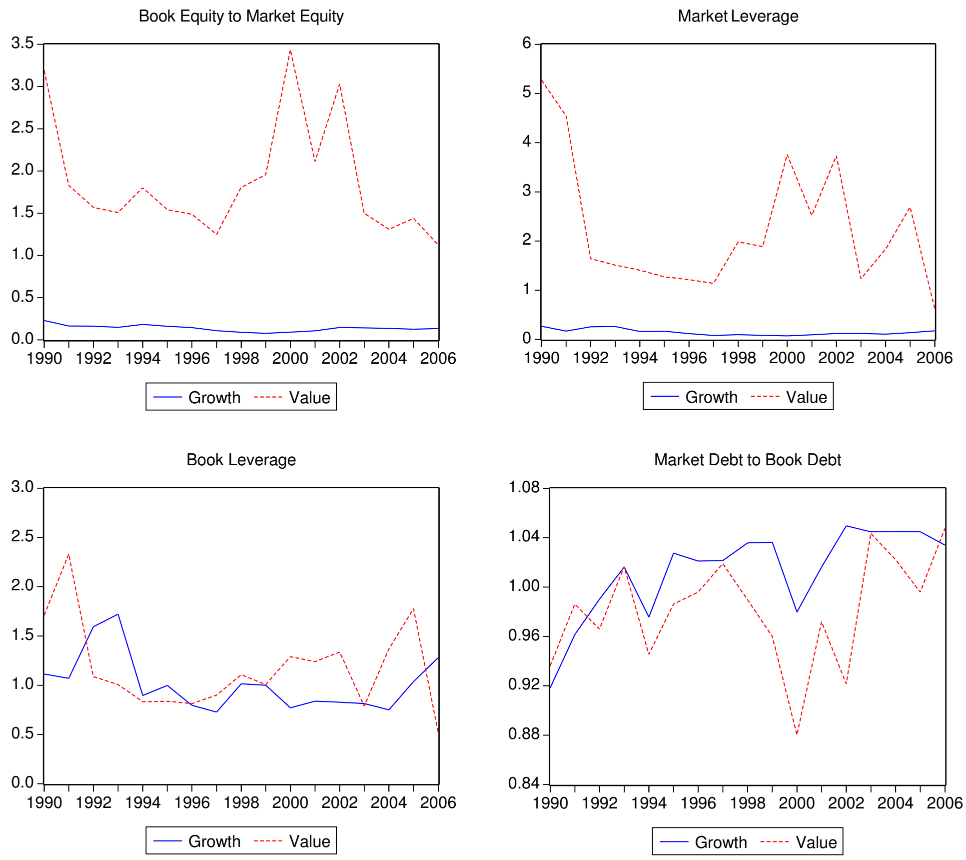
where BE, BD, ME and MD are the book equity, the book debt, the market equity and the market debt, respectively. Because the term $\log\left(\frac{MD}{BD}\right)$ is usually very small, the book-to-market ratio can be viewed as the distance between market leverage $\frac{ME}{MD}$ and book leverage $\frac{BE}{BD}$. By investigating (10) empirically, we can verify the relationship between book-to-market and leverage.

In fact, there is a theoretical study by Asness (1993) that proposes a model based on (10) and then studies its implications for asset pricing through simulation exercises. Specifically, he assumes that the firm's asset returns are governed by the unconditional CAPM similar to my framework. He further posits that firms' target leverage ratios are set to their book leverage ratios and do not vary over time. Under this assumption, the book-to-market ratio is mechanically a measure of the market leverage ratio from (10). Given this relationship, he shows through simulations that the book-to-market ratios are priced, whereas the market leverage ratios $\frac{MD}{ME}$ are not. This is because book-to-market combined with the unconditional beta is a better proxy for the conditional beta than leverage and the unconditional beta combined, because book-to-market measures the deviation of the conditional beta from its mean.

Whether firms set their target leverage to book leverage or not, book-to-market will be closely related to market leverage if book leverage does not depend on book-to-market. In Figure 3, I

Figure 3: Book-to-Market Ratio Decomposition

For the low book-to-market (growth) and the high book-to-market (value) decile portfolios, annual values of book-to-market $\frac{BE}{ME}$, market leverage $\frac{MD}{ME}$, book leverage $\frac{BD}{ME}$ and market-debt-to-book-debt $\frac{MD}{BD}$ are plotted. Each ratio is obtained from end-of-December values of previous years and is value-weighted by market equity, market equity, book equity and book debt, respectively.



provide the time-series evidence for this link. For the low (growth) and high (value) book-to-market-decile portfolios, I plot the time-series of value-weighted book-to-market, market leverage and book leverage. From the two figures at the top, we see the remarkable resemblance between book-to-market and market leverage. On the other hand, the graph for book leverage shows that there does not seem to exist any link between book leverage and book-to-market over the sample period. Together with Figure 1, this evidence suggests that the two variables are linked very tightly in the cross-section and time-series.

The results above shows the link at the portfolio level. Next, I examine what the main driver is for changes in book-to-market at the individual firm level. Specifically, I examine whether it is an increase in market leverage or a decrease in book leverage that drives the rise in book-to-market at the firm level. In each year, firms are ranked in book-to-market quintiles, market leverage deciles and book leverage deciles, separately. When firms enter a higher book-to-market, the changes in their market leverage and book leverage deciles are counted.

The results are provided in Figure 4, which shows that the book-to-market changes are mostly driven by changes in market leverage. For example, given an increase in book-to-market by one quintile (top graph), book leverage does not change for most of the firms, and the increases and the decreases in book leverage occur with similar frequency. On the other hand, there are more occurrences of increases in market leverage than no changes. These results suggest that firms become high book-to-market firms mainly because their market leverage rises or because their equity value falls after negative shocks. These results are quite surprising considering the fact that the variation in individual firms' book leverage is, on average, greater than that of market leverage. The mean of the quarterly standard deviation of the log of book leverage is 0.21, whereas the market leverage counterpart is 0.15.

The link between the two variables also has theoretical support in previous studies. For example, Myers (1977) argues that growth options are likely to be financed with equity. Jensen (1986) predicts that debt helps to reduce the agency costs associated with assets-in-place that generate free cash flow. Assuming that book-to-market proxies for growth options, it is therefore expected that book-to-market and market leverage have a positive relationship. On the other hand, book leverage, which represents the relative amount of debt to assets-in-place, will have no reason to be related to book-to-market because more growth options (higher book-to-market) do not change assets-in-place or debt amount issued.[22] If book leverage is the same for growth and value firms, then book-to-market is linked to market leverage very tightly according to (10).

3.4.2 Testing the CAPM with Asset Returns

Given this link between leverage and book-to-market and stable asset returns across book-to-market-decile portfolios shown in Figure 1, I test the CAPM at the asset level to see whether the value premium is an artifact of leverage or it originates from the economics of the underlying business of firms.[23]

The pricing errors from the 10 book-to-market–sorted portfolios are shown in Table 6. To be

[22]In fact, Barclay et al. (2006) argue that the debt capacity of growth options is not zero, but negative. Their empirical results are statistically significant, but the economic magnitude of the negative debt capacity is very small: in the regression of book leverage on book-to-market, they report that the coefficient is approximately 0.01.

[23]Hecht (2004) and Charoenrook (2004) also look at the CAPM at the asset level and find favorable results to the CAPM. But their studies do not focus on the time-series intercepts and are not free from Lewellen et al. (2008) criticisms.

Figure 4: Change of Book Leverage and Market Leverage Given Change in Book-to-Market

In each year, firms are ranked in book-to-market quintiles, market leverage deciles and book leverage deciles, separately. The ratios are obtained from end-of-December values. Then changes in market leverage and book leverage deciles are examined when firms enters a higher book-to-market quintile. For firms whose book-to-market quintile increases, the changes in the book leverage and market leverage decile are counted. For example, the top histogram shows the frequency of changes in book leverage or market leverage quintile given an increase in book-to-market quintile.

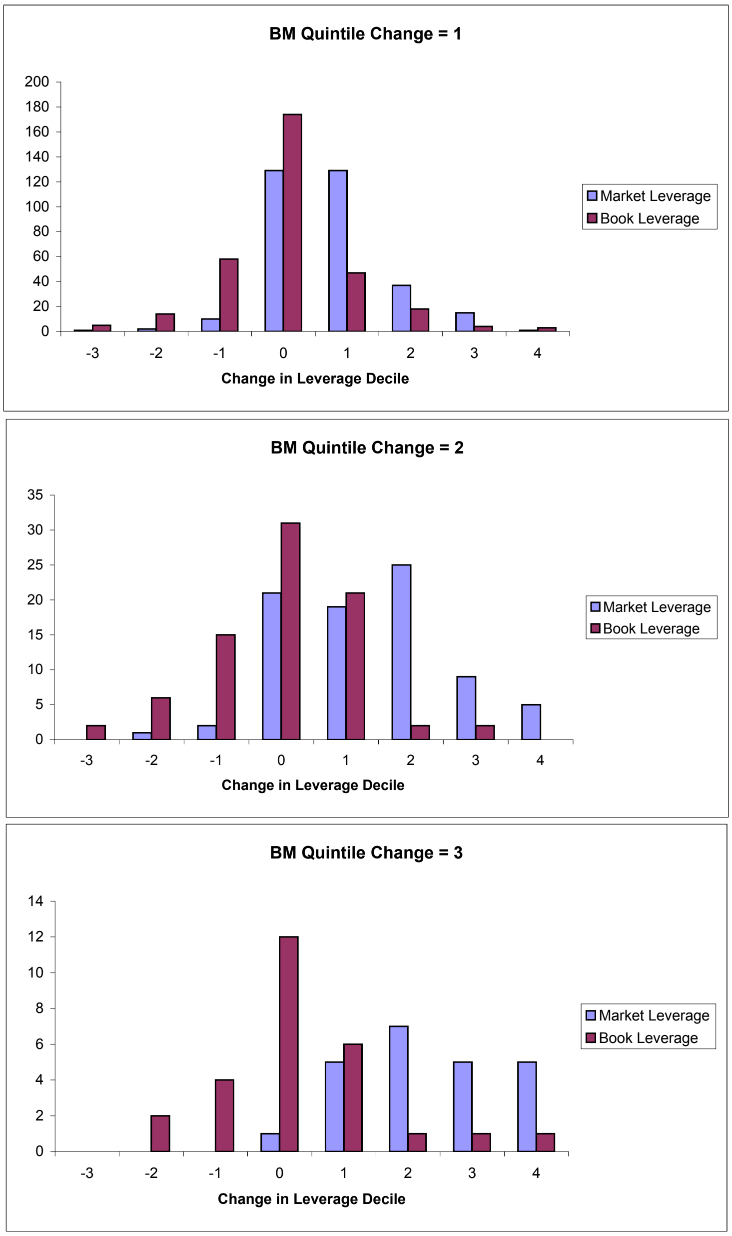


Table 6: Alphas from the Unconditional CAPM at the Asset Level

Alphas from the bottom-up approach at the asset return level are reported for the book-to-market decile portfolios. The first two rows show the average and the t-statistics of the monthly pricing errors. The next two rows report the average and the standard deviation of betas obtained from the bottom-up approach by Elton et al. (2007). The standard deviations used to calculate the t-statistics are robust to the conditional heteroskedasticity. I use *, **, and *** to denote significance for F-statistics at the 10% level, 5% level and 1% level, respectively.

	Book-to-Market Decile										
	Low	2	3	4	5	6	7	8	9	High	$H_0 : \alpha_{high} = \alpha_{low}$
α	-0.03%	0.16%	0.01%	0.19%	0.12%	0.21%	0.24%	0.16%	0.13%	0.24%	F-stat : 1.92
$t(\alpha)$	-0.24	1.40	0.15	1.37	1.03	1.76	2.09	1.18	1.27	1.91	
β	0.76	0.74	0.69	0.66	0.61	0.55	0.47	0.40	0.44	0.38	
$std(\beta)$	0.18	0.11	0.10	0.08	0.13	0.11	0.12	0.14	0.15	0.15	

consistent with the previous analysis, I use the bottom-up approach in estimating portfolio betas and alphas. Comparing the results to those of the unconditional CAPM in Table 4, I find that the magnitudes of the alphas are not as large as those from the equity counterparts. Although the alpha in the high book-to-market decile portfolio is statistically significant at the 10% level, it magnitude is just 0.24%, which is less than half that from equity returns. The value spread, which is the alpha difference between the high and the low deciles, is just 0.27%, is not statistically significant at the 10% level. Although the magnitudes of the alphas increase slightly for the high book-to-market portfolios, the results are more favorable to the CAPM.

In order distinguish the leverage effect and the value premium, I also consider an extreme case of leverage/book-to-market 4-by-4 double-sorted portfolios. Because book-to-market and leverage are highly correlated, the double sorts are dependent ones, meaning that the firms are sorted first into leverage quartiles and then into book-to-market quartiles within each leverage portfolio. If the value premium is mainly driven by a leverage effect, then the alphas within the same leverage quartile portfolio will not increase across the book-to-market quartiles.

The results are given in Table 7. For comparison, the alphas for the unconditional CAPM at the equity level and the two conditional CAPMs with the riskless debt and the Merton model assumptions are reported as well. The pricing errors for the CAPM at the asset level are in the top left panel. Although the magnitudes of the alphas are not very large and most of them are statistically insignificant, they are increasing across the book-to-market quartiles. The value premium is most pronounced and statistically significant in the high leverage quartile. The pricing error for the high leverage/high book-to-market quartile is 0.36%, and the F-statistic is significant at the 5% level for the difference between the high and the low book-to-market quartiles within the high leverage quartile.

Not only at the asset level, but also at the equity level, both unconditional and conditional, the CAPM performs poorly, especially in the high leverage quartile. In all three of the cases, the magnitudes of the alphas are large and the F-statistic are reject the null at the 10% level for the high leverage quartile. These results suggest that high book-to-market firms do earn higher returns and the CAPM does not work very well, especially for highly levered/high book-to-market firms.

Overall, the leverage story alone is not a complete answer for the value premium, and book-to-market is related to something that a constant beta of assets and time-varying leverage do not capture. In the next section, I delve deeper into this issue and provide an answer to why book-to-market seems to explain expected returns better despite leverage being the factor that changes the risks according to my theory.

4 Time-Varying Asset Betas and Financial Leverage

To isolate the impact of time-varying leverage, I have assumed constant asset betas in the previous sections. Although the constant asset beta framework has advantages in its simplicity, there are theoretical and empirical reasons to believe that the asset beta is time varying. First, the evidence from Choi and Richardson (2008) that the volatility of assets moves around a lot suggests that asset betas also change over time. Second, there are previous theoretical studies showing that firms' asset betas should change depending on the history of their investment decisions and the market environment. For example, Carlson et al. (2004) demonstrate that firms with a lot of assets-in-place have high operating leverage and their asset betas rise when they are distressed. Zhang (2005) shows the mechanism through which the same type of firms will be riskier in bad times than firms with abundant growth opportunities due to costly reversibility and the counter-cyclical price of risk.

If the asset beta varies over time with financial leverage in a systemic way, the firm's equity can be very risky. To understand the mechanism, consider a diagram in Figure 5. Firms will correspond to one of the four rectangles according to their asset beta and financial leverage and will move around the rectangles as their leverage and asset betas vary over time. Firms in the low leverage/low asset beta rectangle are the ones with the safest equity returns, and those in the high leverage/high asset beta rectangle are the ones with the riskiest equity returns. I explain below that the relationship between asset beta and leverage is guided by economic theories.

Table 7: Test of the CAPM with 4-by-4 Leverage/Book-to-Market–Sorted Portfolios

Four models are examined: the two unconditional CAPMs at the asset and the equity level and the two conditional CAPMs based on the riskless debt assumption and on the Merton model assumption. The alphas and the betas are estimated from the bottom-up method by Elton et al. (2007) and their average values are reported. The standard deviations used to calculate the t-statistics are robust to the conditional heteroskedasticity. The test portfolios are 4-by-4 dependent-sort leverage/book-to-market portfolios. I use *, **, and *** to denote significance for F-statistics at the 10% level, 5% level and 1% level, respectively.

Panel A: Unconditional CAPM at the Asset and the Equity Level

	Asset Returns					Equity Returns				
	α					α				
Leverage	BM Quartile				F-stat	BM Quartile				F-stat
Quartile	Low	2	3	High	$\alpha_{high} = \alpha_{low}$	Low	2	3	High	$\alpha_{high} = \alpha_{low}$
1	0.28%	-0.06%	0.11%	0.26%	0.00	0.28%	-0.05%	0.09%	0.26%	0.00
2	-0.06%	0.09%	0.06%	0.23%	1.98	-0.08%	0.10%	0.04%	0.25%	1.91
3	0.00%	0.15%	0.19%	0.09%	0.41	-0.03%	0.17%	0.24%	0.09%	0.37
4	0.08%	0.22%	0.19%	0.36%	4.45**	0.16%	0.38%	0.47%	0.76%	3.96**
	$t(\alpha)$					$t(\alpha)$				
1	0.65	-0.16	0.27	0.82		0.65	-0.14	0.23	0.81	
2	-0.39	0.64	0.46	1.61		-0.45	0.61	0.25	1.45	
3	-0.03	0.95	1.43	0.58		-0.17	0.75	1.14	0.41	
4	0.75	1.95	1.75	2.95		0.74	1.51	2.01	2.76	
	β					β				
1	1.60	1.49	1.40	1.28		1.61	1.50	1.42	1.30	
2	0.66	0.77	0.74	0.73		0.74	0.92	0.89	0.88	
3	0.55	0.57	0.48	0.47		0.80	0.82	0.72	0.68	
4	0.48	0.37	0.32	0.32		1.02	0.77	0.64	0.68	

Panel B: Conditional CAPM

	Riskless Debt Model					Merton Model				
	α					α				
Leverage	BM Quartile				F-stat	BM Quartile				F-stat
Quartile	Low	2	3	High	$\alpha_{high} = \alpha_{low}$	Low	2	3	High	$\alpha_{high} = \alpha_{low}$
1	0.28%	-0.06%	0.11%	0.26%	0.00	0.28%	-0.05%	0.10%	0.26%	0.00
2	-0.08%	0.09%	0.04%	0.25%	1.80	-0.08%	0.10%	0.04%	0.25%	1.85
3	-0.06%	0.14%	0.23%	0.07%	0.37	-0.06%	0.15%	0.24%	0.08%	0.41
4	0.08%	0.30%	0.38%	0.59%	2.70*	0.11%	0.32%	0.40%	0.64%	2.99*
	$t(\alpha)$					$t(\alpha)$				
1	0.65	-0.15	0.26	0.82		0.65	-0.13	0.26	0.82	
2	-0.44	0.58	0.24	1.42		-0.44	0.61	0.26	1.44	
3	-0.31	0.61	1.12	0.30		-0.31	0.63	1.14	0.34	
4	0.37	1.20	1.58	2.03		0.49	1.28	1.69	2.29	
	β					β				
1	1.61	1.50	1.40	1.29		1.61	1.49	1.40	1.29	
2	0.72	0.90	0.88	0.88		0.72	0.89	0.88	0.88	
3	0.80	0.83	0.71	0.70		0.79	0.83	0.70	0.70	
4	1.12	0.85	0.78	0.86		1.08	0.82	0.75	0.86	

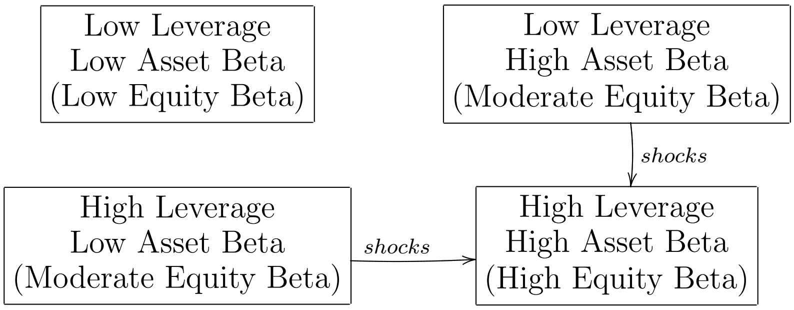


Figure 5: Leverage and Asset Beta Diagram

In normal times, asset beta and leverage tend to be negatively related and firms will tend to be in the off-diagonal rectangles: low asset beta, high leverage and high asset beta, low leverage. This is because the cost of financial distress is high for firms with high systematic risk (high asset betas) and vice versa. Therefore, those firms with high asset betas will try to have low leverage, whereas firms with low asset beta will take on large amounts of debt to enjoy the benefits of financial leverage.

The argument above is based on the idea that systematic risk matters more than total risk in gauging the cost of financial distress. There are a few previous studies that support this view. For example, Almeida and Philippon (2007) show that the risk-adjusted cost of financial distress is much higher than the expected cost because default risk is systematic. It follows then from the trade-off theory of capital structure that firms with high asset betas tend to have low leverage and vice versa. Another line of research, based on the story of Shleifer and Vishny (1992), suggests that loss given default will be higher in bad times and firms with high systematic risks will have a high cost of financial distress. Altman et al. (2005) and Acharya et al. (2007) document that loss given default is indeed high in recessions or when the industry of the defaulted firms are in distress.

When negative shocks hit the economy, the risk exposure of firms (asset beta) will change along with leverage. Leverage will tend to rise because equity will fall more than debt given a bad shock. Asset betas will also vary, but their direction of change depends on the characteristics of firms' underlying business, which are determined by the history of the firms' investment decisions. If both leverage and asset beta rise at the same time, the risk of equity will shoot up because the equity beta is the product of the two. Furthermore, if firms with low asset betas that take on large amounts of debt experience increases in both leverage and asset betas, they are the ones most likely to have extremely risky equity returns because the increase in leverage is higher.

Table 8: Betas of Leverage- and Book-to-Market-Sorted Portfolios

For each set of book-to-market-sorted-decile portfolios and leverage-sorted-decile portfolios, several statistics, including asset-to-equity ratios , book-to-market (BM) and the betas of equity and assets are reported. The betas are obtained from the OLS regressions of value weighted returns on the market portfolio returns.

Panel A : Market Leverage Decile Portfolios										
	Low	2	3	4	5	6	7	8	9	High
Asset/Equity	1.00	1.07	1.18	1.27	1.37	1.49	1.65	1.88	2.33	4.22
BM	0.24	0.23	0.35	0.40	0.51	0.63	0.73	0.81	0.84	0.91
Equity Beta	1.63	0.89	0.91	0.91	0.74	0.81	0.77	0.69	0.75	1.18
Asset Beta	1.63	0.84	0.78	0.73	0.55	0.55	0.49	0.38	0.35	0.34
Panel B : Book-to-Market Decile Portfolios										
	Low	2	3	4	5	6	7	8	9	High
Asset/Equity	1.13	1.25	1.38	1.44	1.57	1.60	1.73	1.85	1.95	2.61
BM	0.14	0.27	0.37	0.46	0.55	0.65	0.76	0.91	1.13	2.04
Equity Beta	1.00	0.92	0.95	0.85	0.95	0.69	0.70	0.65	0.71	0.73
Asset Beta	0.91	0.75	0.73	0.64	0.62	0.46	0.43	0.36	0.39	0.35

What kind of firms, then, will be the ones with counter-cyclical asset betas and high levels of leverage? As briefly mentioned above, existing theories suggest that firms with large assets-in-place are the ones with counter-cyclical asset betas, due to lack of flexibility coming from high operating leverage or costly reversibility. It is high book-to-market firms, then, that have counter-cyclical asset betas because they typically have large assets-in-place relative to their market value. Furthermore, they are highly levered, as is seen from the link in the previous sections, and therefore their equity betas are likely to increase rapidly in bad times.

In the following sections, I empirically demonstrate the intuition outlined above. I first look at the cross-sectional distributions of leverage and asset betas and then the time-series changes in the two.

4.1 Distribution of Leverage and Asset Betas: Cross-Section and Time-Series

If firms' financial distress costs are high when they have high asset betas, there will be a negative cross-sectional relationship between leverage and asset betas. To examine this relationship, I form 10 leverage-sorted portfolios and estimate their asset betas, shown in the top panel of Table 8. All the zero-leverage firms are assigned to the low leverage portfolio and the rest of the firms are allocated to nine leverage-sorted portfolios.

Confirming my intuition on leverage and financial distress costs, the relationship between leverage and asset beta is monotonic. Low leverage decile portfolios have higher asset betas than high leverage portfolios. On the other hand, the equity betas are in a similar range across the leverage decile portfolios,[24] which may suggest that firms lever up their equity betas to similar levels with their peers in other leverage groups. The empirical relationship is also consistent with the model in Gomes and Schmid (2007): highly levered returns' assets are safe and therefore their equity is not very risky.

We have seen previously that book-to-market and financial leverage are linked very tightly. Then it is natural to conjecture that the same negative cross-sectional relationship exists between book-to-market and asset betas.[25] From the results in the bottom panel of Table 8, we find that the relationship is negative as well: high book-to-market portfolios have lower asset betas and vice versa. From these cross-sectional results, we confirm that high book-to-market firms have low systematic risk on average. On the other hand, the equity betas are not increasing across the book-to-market decile portfolios, which is another aspect of the value premium.

Even though high book-to-market firms' equity betas are not high on average, if high book-to-market firms' asset betas vary over time, then their equity risks can shoot up because they have taken on a large amount of debt. This counter-cyclical pattern in high book-to-market firms' asset betas has theoretical support, such as the studies by Carlson et al. (2004) and Zhang (2005). But most of these studies are missing the role financial leverage plays in amplifying the risks of the firms' business.[26]

In order to verify this time-series pattern in asset betas, I estimate a time-varying beta model, following the specification of Petkova and Zhang (2005):

$$R_{i,t+1} = \alpha_i + \beta_{i,t} R_{M,t+1} + \epsilon_{i,t+1} \tag{11}$$

where

$$\beta_{i,t} = b_{i0} + b_{i1} DIV_t + b_{i2} DEF_t + b_{i3} TERM_t + b_{i4} + TB_t \tag{12}$$

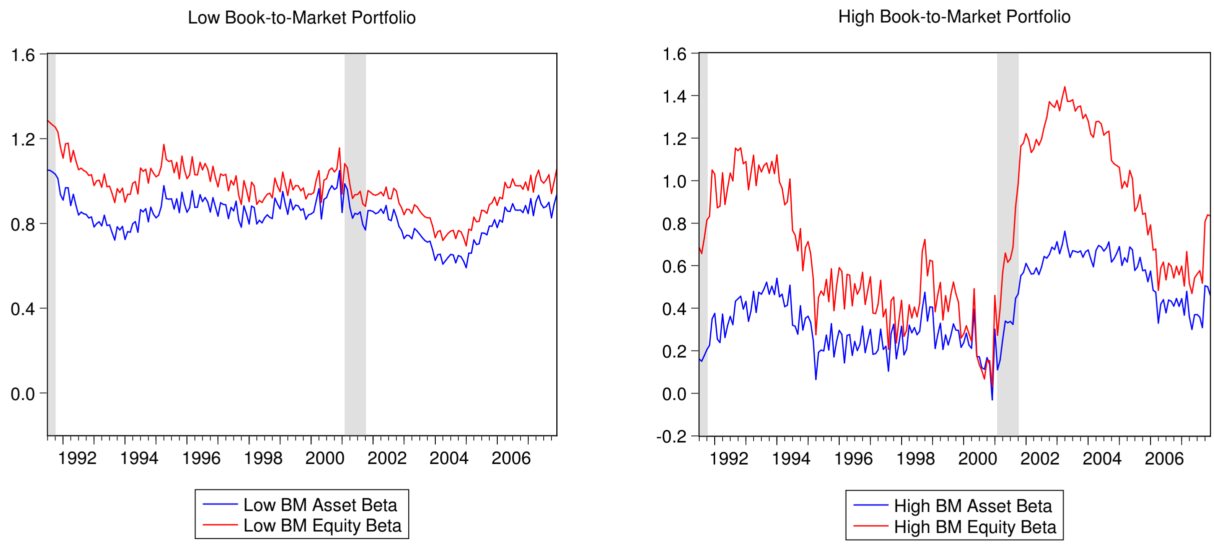
[24]The low leverage decile portfolio has a very high equity beta. This is due to the internet bubble in the sample period. Most of the zero-leverage firms have extreme returns during the sample period, and the estimated equity beta is very high compared to other portfolios.

[25]There is an alternative story for this. Firms with high assets-in-place tend to have stable cash flows and low asset betas. A large amount of assets-in-place will cause the free cash flow problem by Jensen (1986) and therefore it is optimal for those firms to issue more debt. High-book-to-market firms typically have more assets-in-place and low asset betas and therefore have high leverage.

[26]An exception is Gomes and Schmid (2007). They explore a theoretical model in which mature firms have low asset betas and high leverage, and show that highly levered firms do not earn high equity returns.

Figure 6: Time-Varying Asset and Equity Betas

For the low quintile (left) and the high quintile (right) book-to-market-sorted portfolios, the regression, $R_{i,t+1} = \alpha_i + (b_{i0} + b_{i1}DIV_t + b_{i2}DEF_t + b_{i3}TERM_{t+b_i4} + TB_t)R_{M,t+1} + \epsilon_{i,t+1}$, is estimated for asset and equity returns. The fitted beta is then plotted from $\beta_t = b_{i0} + b_{i1}DIV_t + b_{i2}DEF_t + b_{i3}TERM_{t+b_i4} + TB_t$.



The conditioning variables are the dividend yield (DIV), the default spread (DEF), the term spread ($TERM$), and the short-term Treasury bill rate (TB), which are known in the literature to capture the time-varying risk premium.

I first plot the fitted time-varying asset and equity betas for the low and the high quintile of the book-to-market-sorted portfolios, in Figure 6. The left graph has the asset and equity betas of the low book-to-market portfolio. Notably, the equity and the asset betas are very similar due to the low level of leverage and there is no counter-cyclical tendency in the asset betas around recessions.

In contrast, the figure on the right shows a remarkably different pattern for the high book-to-market portfolio. On average, the asset beta is not very high, in the range of 0.2 to 0.6 for most of the time, which is consistent with the cross-sectional relationship shown above. However, the asset beta exhibits substantial variations compared to the low-book-to-market asset beta in the top figure and is high around and after recessions. Furthermore, the variation in equity beta are much larger and amplified, especially in those periods, combined with counter-cyclical leverage. For a robustness check, I also estimate the conditional betas using the diagonal VECH model of Bollerslev et al. (1988). Although not reported here for the sake of brevity, the estimated asset and equity betas follow a similar pattern to those using the conditioning variables.

In order to formally examine the counter-cyclicality of the high-book-to-market portfolio's asset beta, I estimate the following equations together with (11) and (12) using GMM as in Petkova and Zhang (2005):

$$R_{M,t+1} = \delta_0 + \delta_1 DIV_t + \delta_2 DEF_t + \delta_3 TERM_t + \delta_t TB_t + e_{m,t+1} \tag{13}$$

$$\hat{\beta_{i,t}} = c_i + \phi_i \hat{\gamma_t} + \eta_{i,t} \tag{14}$$

where $\hat{\beta_{i,t}}$ and $\hat{\gamma_t}$ are the estimated beta and risk premium, respectively, from (12) and (13). A positive slope coefficient ϕ_i implies that the corresponding beta varies counter-cyclically. The theory predicts that the slope coefficient ϕ_i will be positive for the high book-to-market portfolio's asset beta. Moreover, equity betas will tend to have greater ϕ_i than asset betas because leverage is a counter-cyclical variable.

The results from the GMM estimation are in Table 9 and confirm the intuition above. Although they are not statistically significant, the economic magnitudes are in the right direction. The slope coefficient ϕ for the low book-to-market portfolio is estimated to be negative and the ϕ for the high is positive, which indicate that the asset beta of the high book-to-market portfolio is counter-cyclical. On the other hand, the slope coefficients for equity betas are all positive due to the counter-cyclicality in leverage. Moreover, the high book-to-market portfolio has a much higher slope coefficient than the low book-to-market portfolio, which shows the amplification through the high level of leverage.

In summary, the results show that the high book-to-market portfolios' asset beta is counter-cyclical. Furthermore, combined with the high levels of financial leverage that high book-to-market firms take on in good times, the results indicate that such firms' equity can be extremely risky in economic downturns.

4.2 Individual Firm Level Analysis

4.2.1 Time-Varying Asset Beta

We have seen in the previous section that the high-book-to-market portfolio has a high beta of assets in bad times and its equity beta shoots up. However, the analysis was done at the portfolio level and does not confirm that individual firms in the portfolio have counter-cyclical asset betas. In other words, it is possible that individual firms' asset betas are relatively stable through the peaks and the troughs of the economic cycles and the high book-to-market portfolio just picks

Table 9: GMM Estimation Results.

Using GMM, the equations (11), (12), (13) and (14) are estimated simultaneously. The reported coefficients are for the time-varying beta equation in (12) and for the sensitivity of beta to the risk premium, ϕ.

Panel A : Firm Returns						
	Low Book-to-Market Quintile Portfolio					
	$Const$	DIV	DEF	$TERM$	TB	ϕ
β_t	0.87	-11.28	-5.22	3.57	61.99	-3.92
t-stat	27.87	-2.04	-0.48	0.85	2.63	-1.14
	High Book-to-Market Quintile Portfolio					
	$Const$	DIV	DEF	$TERM$	TB	ϕ
β_t	0.37	24.64	34.05	-11.13	-180.95	5.11
t-stat	7.05	3.27	2.58	-2.33	-5.86	0.78
Panel B : Equity Returns						
	Low Book-to-Market Quintile Portfolio					
	$Const$	DIV	DEF	$TERM$	TB	ϕ
β_t	0.99	-2.29	-12.48	1.71	38.52	0.71
t-stat	36.32	-0.32	-0.98	0.35	1.34	0.17
	High Book-to-Market Quintile Portfolio					
	$Const$	DIV	DEF	$TERM$	TB	ϕ
β_t	0.62	37.08	34.64	-4.03	-282.19	13.42
t-stat	5.09	2.42	1.70	-0.38	-4.32	1.01

high asset beta firms in bad times and low asset beta firms in good times.

To address this possibility, I examine the change in asset beta before and after firms enter the high book-to-market portfolio. For each December of year t, I rank firms in quintile groups according to the book-to-market ratios known at the time. The firms newly coming into the high-quintile portfolio would have been hit by bad shocks in year t, because the increase in book-to-market is typically driven by the increase in market leverage, as we have seen in the previous section. For those firms, I estimate asset betas for the 2-year windows $[t-2, t-1]$ and $[t+1, t+2]$, separately. Year t is not included because the firms have experienced bad returns in year t and including it might cause an ex post conditioning bias. By comparing the averages of the individual firms' asset betas, we can verify if the individual firms' asset betas increase after bad shocks. The estimation errors in the first-stage time-series regressions are considered when the statistical significance is examined.[27]

The results are plotted in Figure 7. In the top and bottom figures, the asset betas and leverage of low book-to-market firms do not move in a systemic way before and after the portfolio rankings.

[27]If the idiosyncratic errors of the firms are positively correlated cross-sectionally, then the variance of the mean of the slope coefficients will be greater than simple variance estimates.

Figure 7: Betas and Leverage Before and After Book-to-Market Rankings

The changes in the betas of assets (solid line) and equity (dotted line) are plotted before and after the firms enter the high and low book-to-market decile portfolios. The top and middle graphs are for firms entering the low and high book-to-market-quintile portfolios, respectively, while the bottom graph is the change in leverage for firms in the top and the middle graphs. For each t, the change in averages of betas for firms entering the two extreme decile portfolios, are estimated using the 2-year windows, $[t-2, t-1]$ and $[t+1, t+2]$. To be included in the estimation, firms need to have more than 18 months of observations in each 2-year window.

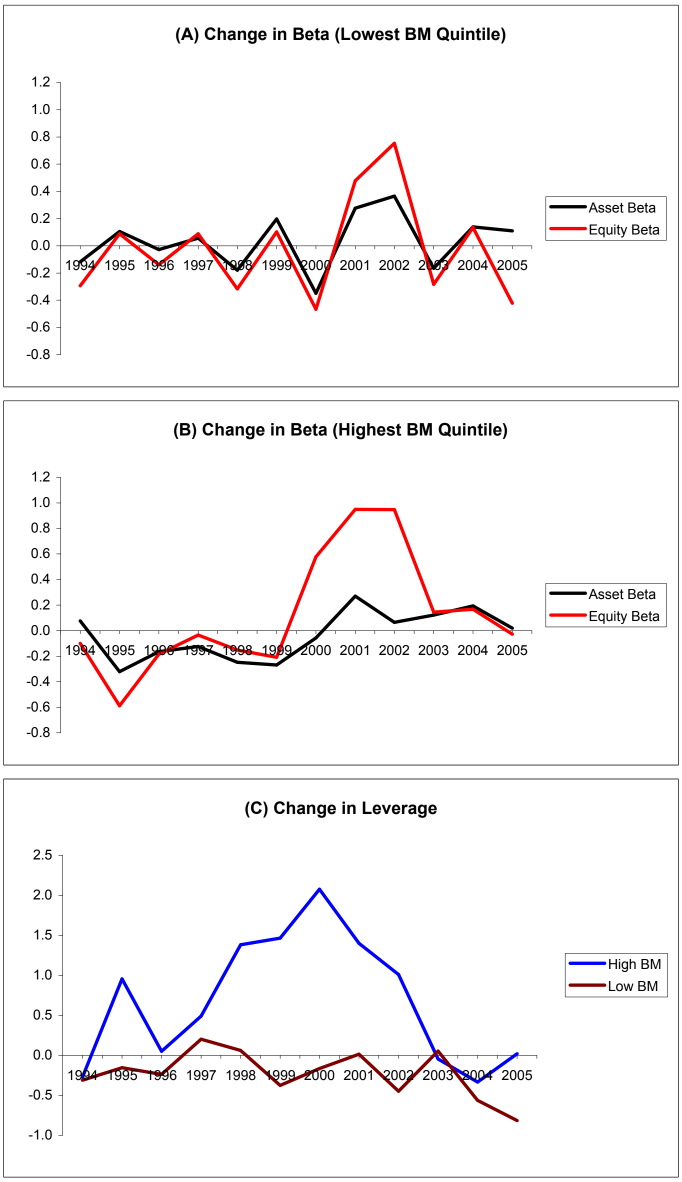


Table 10: Changes in Betas and Leverage Before and After Book-to-Market Rankings

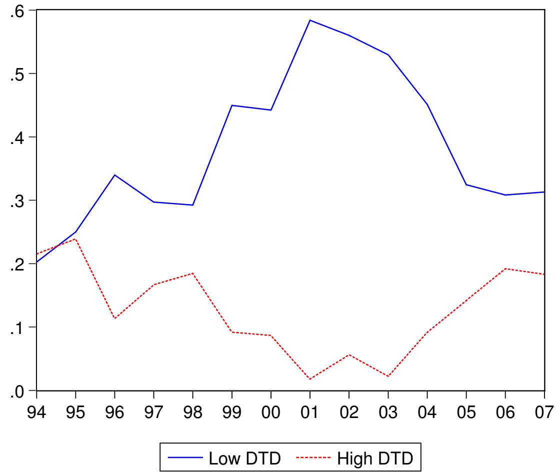
Changes in the betas of assets (solid line) and equity (dotted line) are reported before and after firms enter the book-to-market portfolios. The t-statistics are corrected for the first-stage estimation errors in the betas. I use *, **, and *** to denote significance for t-statistics at the 10% level, 5% level and 1% level, respectively.

	Low Book-to-Market				High Low Book-to-Market			
	Asset Beta		Equity Beta		Asset Beta		Equity Beta	
year	Change	t(diff)	Change	t(diff)	Change	t(diff)	Change	t(diff)
1994	-0.12	-1.54	-0.29	-2.90***	0.08	0.88	-0.10	-0.62
1995	0.10	1.24	0.09	0.79	-0.32	-2.77***	-0.59	-2.54**
1996	-0.03	-0.26	-0.14	-1.07	-0.16	-1.96**	-0.18	-1.21
1997	0.06	0.48	0.09	0.49	-0.12	-0.88	-0.03	0.12
1998	-0.18	-1.46	-0.32	-1.77*	-0.25	-1.49	-0.15	-0.45
1999	0.20	0.94	0.10	0.33	-0.27	-1.95*	-0.21	-0.70
2000	-0.35	-1.42	-0.47	-1.33	-0.06	-0.26	0.58	1.20
2001	0.28	1.74*	0.48	2.27**	0.27	2.04**	0.95	3.17***
2002	0.37	2.14**	0.75	2.63***	0.06	0.55	0.95	4.82***
2003	-0.17	-0.72	-0.28	-0.98	0.12	1.20	0.14	0.86
2004	0.14	1.16	0.13	0.76	0.19	1.83*	0.17	0.98
2005	0.11	0.85	-0.42	-2.42**	0.02	0.23	-0.03	-0.20

In contrast, the figure in the middle shows that the changes in high book-to-market firms' betas of assets have a clear counter-cyclical pattern. From 1995 to 2000, firms have lower asset betas once they get hit by negative shocks and enter the high book-to-market portfolio. Because the asset betas are lower, their equity betas are not necessarily high after the increase in leverage from the negative shocks. In 1994 and from 2001 on, the betas of assets are higher after they suffer from negative shocks.

Then, what role does leverage play in changing the systematic risk of equity given the change in asset betas? The answer in Figure 7 is similar in spirit to those from the previous results. Entry into the high book-to-market portfolio usually comes with an increase in market leverage. Combined with high asset betas around the recession period, this increase in leverage amplifies the risk of high book-to-market firms' equity. In contrast, the equity betas are not particularly high in the other periods and even become much smaller around year 1995. This is because high levels of leverage among high book-to-market firms are amplifying the decrease in asset betas. In Table 10, I report t-statistics of the same changes plotted in Figure 7. The results show that changes in equity betas are larger and have greater statistical significance, which also suggests the role of leverage in amplifying the risk in equity.

Figure 8: Fraction of High Book-to-Market Firms in Low and High Distance-to-Default Quintile
The solid and dotted lines are the respective fractions of high book-to-market quintile firms in the low and high distance-to-default quintiles. In December of each year, firms are sorted into book-to-market and distance-to-default quintiles independently. Then, for firms in the high book-to-market quintile, the fraction in the low and high distance-to-default quintiles are plotted. Firms in the low distance-to-default are the most financially distressed.



4.2.2 Measure of Financial Distress: Distance-to-Default

Vassalou and Xing (2004) show that the book-to-market effect is largely due to financial distress. My results up to this point also suggest the possibility of financial distress for high book-to-market firms because the cost of financial distress will rise when their asset betas increase. The unique prediction of my theory different from Vassalou and Xing (2004) is that high book-to-market firms are *not always* in financial distress. Only in recessions are they likely to be financially distressed.

To investigate this issue, I look at the distance-to-default, which is given as

$$d_1 = \frac{\log\left(\frac{A_t}{F}\right) + \left(r^f + \frac{1}{2}\sigma_a^2\right)(T-t)}{\sigma_a\sqrt{T-t}} \tag{15}$$

As in Section 2.1, F is the face value of debt, $T-t$ is the time to maturity of debt and σ_a is the volatility of the firm's assets, which is estimated using the past two years of firms' asset returns.

In order to examine how many of the firms in the high book-to-market quintile are distressed, I double-sort firms independently into 4-by-4 book-to-market/distance-to-default portfolios. For each year from 1994 onward, I calculate what fraction of the firms in the high book-to-market portfolio is in the low distance-to-default quartile portfolio. The higher the fraction, the more firms are in financial distress.

The results are plotted in Figure 8. Around the beginning and end of the period, there are a comparable number of firms in the high and the low distance-to-default quartiles, meaning that the high book-to-market firms are not typically distressed in good times. In contrast, approximately 60% of the high book-to-market firms are in the low distance-to-default decile in 2001, which shows that high book-to-market firms are typically financially distressed.

In summary, the results indicate that high book-to-market firms' equity betas are amplified and their stocks become very risky in economic downturns: so-called value firms have low asset risks and can afford a large amount of debt. Then, a negative shock hits the economy and market leverage rises. What is special about the value firms is that they have counter-cyclical asset betas. Combined with the counter-cyclicality of market leverage, this pattern in the asset betas makes the value firms' equity betas shoot up in bad times. It is unfortunate that there is only one recession in the sample, but the advantage of this paper is that all the results are in the same direction and guided by the theory.

4.3 Conditional CAPM: Time-Varying Asset Beta and Leverage

Having seen that high book-to-market firms' equity betas can be very high in bad times, I revisit the test of the conditional CAPM using the time-varying asset beta model and compare the results with those from the constant asset beta model. Specifically, I compare the pricing errors when time-variation in both asset betas and leverage is considered to those when time variation in asset betas is ignored. If high book-to-market proxies for this systemic pattern in the risk of equity that can be captured by the time-varying beta of assets and financial leverage, the conditional CAPM allowing for time-varying asset betas should perform well on book-to-market-sorted portfolios. I use the specification in (12) to obtain the time-varying beta of assets and the bottom-up approach in Section 3.1 to obtain the time-varying equity beta. The 4-by-4 leverage-/book-to-market-sorted portfolios are used to distinguish the effects of leverage and book-to-market.

The results are given in Table 11. Pricing errors are compared for the three sets of models: the CAPM at the asset return level and the conditional CAPMs with the riskless and the Merton model assumptions. Each panel has the alphas from the time-varying asset beta model on the left and the constant asset beta model on the right. At the asset return level, considering time-variation in asset betas improves the alphas, especially in the high leverage-quartile portfolios, which are the portfolios where the CAPM performed the worst in the previous section. Although the value spread between the high and the low book-to-market portfolios is still significant at the 10% level, this fact shows that accounting for time variation in asset beta helps at the asset level,

Table 11: Test of the CAPM with the Conditioning Variables

Three models are examined: the conditional CAPM using the conditioning variables at the asset level and the two conditional CAPMs based on the riskless debt assumption and on the Merton model assumption. Once the asset beta is estimated using (12) for each firm, the bottom-up method is used to obtain corresponding portfolio betas. Portfolios are constructed by ranking firms according to the market leverage ratios first and then sorting by book-to-market within each leverage quartile. I use *, **, and *** to denote significance for F-statistics at the 10% level, 5% level and 1% level, respectively.

Panel A: CAPM at the Asset Level

	Time-Varying Asset Beta					Constant Asset Beta				
	α					α				
Leverage	BM Quartile				F-stat	BM Quartile				F-stat
Quartile	Low	2	3	High	$\alpha_{high} = \alpha_{low}$	Low	2	3	High	$\alpha_{high} = \alpha_{low}$
1	0.58%	0.06%	0.16%	0.17%	0.67	0.28%	-0.06%	0.11%	0.26%	0.00
2	-0.17%	-0.01%	-0.03%	0.14%	2.34	-0.06%	0.09%	0.06%	0.23%	1.98
3	-0.11%	0.07%	0.09%	0.02%	0.90	0.00%	0.15%	0.19%	0.09%	0.41
4	0.06%	0.16%	0.11%	0.30%	3.39*	0.08%	0.22%	0.19%	0.36%	4.45**
	$t(\alpha)$					$t(\alpha)$				
1	1.36	0.17	0.40	0.56		0.65	-0.16	0.27	0.82	
2	-1.13	-0.09	-0.25	0.98		-0.39	0.64	0.46	1.61	
3	-0.92	0.48	0.71	0.15		-0.03	0.95	1.43	0.58	
4	0.64	1.44	1.11	2.57		0.75	1.95	1.75	2.95	

Panel B: Conditional CAPM with Riskless Debt Model

	Time-Varying Asset Beta					Constant Asset Beta				
	α					α				
Leverage	BM Quartile				F-stat	BM Quartile				F-stat
Quartile	Low	2	3	High	$\alpha_{high} = \alpha_{low}$	Low	2	3	High	$\alpha_{high} = \alpha_{low}$
1	0.58%	0.06%	0.15%	0.17%	0.67	0.28%	-0.06%	0.11%	0.26%	0.00
2	-0.21%	-0.03%	-0.07%	0.14%	2.07	-0.08%	0.09%	0.04%	0.25%	1.80
3	-0.21%	0.02%	0.07%	-0.05%	0.68	-0.06%	0.14%	0.23%	0.07%	0.37
4	0.05%	0.15%	0.19%	0.45%	1.83	0.08%	0.30%	0.38%	0.59%	2.70*
	$t(\alpha)$					$t(\alpha)$				
1	1.36	0.18	0.39	0.55		0.65	-0.15	0.26	0.82	
2	-1.22	-0.17	-0.47	0.78		-0.44	0.58	0.24	1.42	
3	-1.19	0.10	0.37	-0.24		-0.31	0.61	1.12	0.30	
4	0.23	0.62	0.82	1.67		0.37	1.20	1.58	2.03	

Panel C: Conditional CAPM with Merton Model

	Time-Varying Asset Beta					Constant Asset Beta				
	α					α				
Leverage	BM Quartile				F-stat	BM Quartile				F-stat
Quartile	Low	2	3	High	$\alpha_{high} = \alpha_{low}$	Low	2	3	High	$\alpha_{high} = \alpha_{low}$
1	0.58%	0.06%	0.15%	0.17%	0.67	0.28%	-0.05%	0.10%	0.26%	0.00
2	-0.21%	-0.03%	-0.07%	0.14%	2.11	-0.08%	0.10%	0.04%	0.25%	1.85
3	-0.21%	0.03%	0.08%	-0.04%	0.73	-0.06%	0.15%	0.24%	0.08%	0.41
4	0.07%	0.17%	0.21%	0.51%	2.13	0.11%	0.32%	0.40%	0.64%	2.99*
	$t(\alpha)$					$t(\alpha)$				
1	1.36	0.19	0.39	0.56		0.65	-0.13	0.26	0.82	
2	-1.23	-0.17	-0.45	0.80		-0.44	0.61	0.26	1.44	
3	-1.19	0.13	0.40	-0.20		-0.31	0.63	1.14	0.34	
4	0.35	0.70	0.94	1.93		0.49	1.28	1.69	2.29	

especially for the high leverage portfolios.

When time-variation in leverage is also considered, how does the model perform in a test of the conditional CAPM? The panels in the middle and the bottom show that the results are better than when ignoring time-variation in asset betas. None of the differences in alphas between the high and the low book-to-market portfolios is statistically significant at the 10% level. The improvement in performance is especially concentrated in the high leverage quartile, in which the value premium appears strongly when asset betas are assumed to be constant. In summary, combining the time-variation in asset betas and leverage together does a much better job in a test of the conditional CAPM.

5 Conclusion

Although there are a number of new explanations for the value premium, most of them are ex post in the sense that they resort to specific settings to match the observed empirical findings. This paper proposes a simple structural model in which a firm's equity beta is decomposed into the product of financial leverage and its asset beta. Then, the link between leverage and the conditional beta is mechanical, and it also implies an interaction between the risk premium and the conditional beta. Furthermore, combined with the change in the asset beta, leverage can have a large, amplifying impact on the risk of equity.

From this simple framework and using a unique dataset on firms' asset returns, I find the following empirical results. First, leverage alone can explain a substantial portion of the alphas in book-to-market-sorted portfolios. Second, there is a tight link between book-to-market and leverage, which explains why leverage can help explain the value premium. Third, high book-to-market firms have counter-cyclical asset betas and, combined with high levels of financial leverage, their equity becomes extremely risky in economic downturns.

Appendix

Quality of Bond Price Data

I analyze the degree of staleness in bond prices in this appendix. For this purpose, the autocorrelation coefficients of daily, weekly and monthly bond returns and the cross-correlations with their equity counterparts are estimated. If prices are stale, then individual bond returns will have negative autocorrelations and bond portfolios will tend to have positive autocorrelations, and lagged equity returns will have predicting power for current and future bond returns. I perform the analysis with individual returns and portfolio returns based on issuer ratings.[28]

The estimated autocorrelations and cross-correlations are in Table A-1 of the appendix. As expected, the staleness of monthly prices is not severe, as shown in panel A. The mean of autocorrelations is 0.08 and the cross-correlation with equity returns is 0.23 and 0.06 with contemporaneous and one-month lagged equity returns, respectively. In weekly and daily individual bond returns there is some evidence of stale prices, as we see from the negative autocorrelations, -0.04 and -0.10, respectively. The contemporaneous correlations are 0.16 and 0.12 for weekly and daily returns, respectively, which are lower than the monthly cross-correlation, 0.23. This could be because of the noise or the staleness in the high-frequency data. Moreover, the weekly and daily cross-correlations across all lags are positive, although the magnitudes are small, showing the possibility of staleness in the bond prices. For instance, the cross-correlation results with the daily returns imply that news today can be updated in the bond prices more than five trading days later.

Panel B and C of Table A-1 also confirm that the staleness problem with monthly returns is not severe. Although the monthly autocorrelations are positive, their magnitudes are small in investment-grade portfolios. In the high-yield portfolio it is 0.16 but, considering that the autocorrelation of its equity counterpart is around 0.10, the magnitude does not raise a serious doubt on the quality of the dataset. The unrated portfolio autocorrelation is not a concern either because the amount of unrated portfolio is approximately 2% of the total bond amount outstanding (see Table A-2). On the other hand, panel C shows that the staleness persists for a few periods among weekly and daily returns, especially in high-yield and unrated portfolios. The weekly and daily cross-correlations with lagged equity returns are all positive up to lag 8 in the high-yield and the unrated portfolios. The higher contemporaneous cross-correlations in monthly returns than weekly and daily returns also indicates that monthly observations are less noisy and stale.

Constructing Firm Return Data

This appendix explains in detail how the firm return series are built up using corporate bond and loan datasets.

Debt Return Construction

The first step in building up the public debt return series is to map out bond amounts to each firm and compare them to the book value of long-term debt and debt in current liabilities. Because the return of public debt is the value-weighted average of bond returns issued by a firm, it is crucial to have data on the

[28] The reason for the issuer ratings portfolios is that the matrix prices are typically updated against the benchmark bond rating index. The returns can look uncorrelated spuriously when the portfolios are formed based on the issue ratings.

Table A-1: Autocorrelations and Cross-correlations for Bond and Equity Returns

For the entire sample period from July 1991 to December 2007, autocorrelations and cross-correlations with equity returns are calculated on individual- and portfolio-level bond returns. In panel A, the mean of autocorrelations and cross-correlations are reported from the estimates on individual bond returns. In panels B and C, value-weighted portfolios are formed based on the ratings of issuers. The cross-correlations in panel C are between bond portfolio returns and contemporaneous (lag 0) and lagged equity returns of the corresponding portfolio.

Panel A : Individual Bond Returns

Autocorrelation		Crosscorrelation						
	Lag1		Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
Monthly	0.08	Monthly	0.23	0.06	-0.01	0.01		
Weekly	-0.04	Weekly	0.16	0.06	0.03	0.00	0.02	
Daily	-0.10	Daily	0.12	0.03	0.02	0.01	0.01	0.01

Panel B : Autocorrelations of Bond Portfolios

		Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
AAA - A	Monthly	0.09	-0.11	0.07	-0.13	-0.04
	Weekly	-0.06	0.05	0.03	0.00	-0.02
	Daily	0.01	0.01	-0.03	-0.02	0.01
A- BBB-	Monthly	0.09	-0.14	0.07	-0.14	0.01
	Weekly	-0.06	0.06	0.03	0.01	-0.03
	Daily	0.09	0.02	0.00	-0.01	0.02
High Yield	Monthly	0.16	-0.05	0.00	-0.09	0.01
	Weekly	0.10	0.10	0.05	0.03	-0.02
	Daily	0.04	0.08	0.06	-0.01	0.03
Unrated	Monthly	0.20	0.05	0.05	-0.03	-0.07
	Weekly	-0.05	0.03	0.05	0.03	-0.05
	Daily	-0.04	0.00	0.02	-0.03	0.00

Panel C : Crosscorrelations of Bond Portfolios Returns with Lagged Equity Returns

		Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7	Lag 8
AAA - A	Monthly	0.10	-0.15	-0.02	-0.02	-0.11	0.02			
	Weekly	0.11	-0.09	0.07	-0.06	0.00	-0.03	0.00		
	daily	0.06	0.02	-0.01	-0.02	-0.02	0.01	-0.01	-0.02	-0.01
A- BBB-	Monthly	0.22	-0.10	-0.06	-0.03	-0.13	0.02			
	Weekly	0.08	-0.02	0.08	-0.03	0.03	-0.02	-0.03		
	daily	0.07	0.04	0.01	-0.01	-0.01	0.02	0.00	-0.01	0.01
High Yield	Monthly	0.54	0.10	-0.09	-0.07	-0.06	0.03			
	Weekly	0.48	0.22	0.11	0.05	0.03	0.01	0.07		
	daily	0.30	0.18	0.10	0.05	0.03	0.08	0.06	0.03	0.01
Unrated	Monthly	0.62	0.12	-0.05	-0.08	-0.11	-0.02			
	Weekly	0.50	0.11	0.05	0.07	0.06	0.00	0.01		
	daily	0.47	0.08	0.02	0.03	0.03	0.05	0.00	0.01	0.01

bond amount outstanding. The amount outstanding can change over time for a variety of reasons[29] and the firm's capital structure can be significantly altered. The changes are recorded both in EJV and FISD. When the bond amount outstanding does not match in the two datasets, I use Bloomberg's corporate actions item to decide which data point is the right one.

[29]To name a few, issue-called, issue-converted, over-allotment, sinking fund provision, issue-tendered, issue exchange in case of Rule 144A securities and so on.

Table A-2: Summary Statistics for Bond Sample

For the four issuer-level rating groups, time series averages are computed for each item for the period from July 1991 to December 2007. Total Amount is the sum of bond amounts outstanding, in billions of dollars. Fraction is the ratio of each portfolio's Total Amount to the sum of the four Total Amounts. Number of Issues excludes bonds with face values less than 20 million dollars. Mean and Median TTM are average and median time-to-maturity. Coupons are value-weighted by the amount outstanding and include floating rate coupon bonds.

Rating Group	AAA – A	A- – BBB-	High Yield	Unrated
No. Firms	104.3	209.4	177.8	34.9
Total Amount(B)	123	232	114	10
Fraction	0.32	0.48	0.17	0.02
Mean No. Issue	3.94	3.55	2.21	1.58
Median No. Issue	2.63	2.28	1.05	1.02
Mean TTM	15.70	13.59	9.75	10.82
Median TTM	14.20	12.26	8.74	8.32
Mean Coupon	6.91	7.29	8.01	6.56
Median Coupon	7.08	7.43	8.41	6.59
Mean Principal Amount(M)	274.1	248.2	247.4	178.7
Median Principal Amount(M)	209.1	192.4	178.8	144.2

In mapping corporate bonds to the issuing firm, there are several complications that need cautions. One example is the Rule 144A securities and cusip identifier change. Many firms in the database issue unregistered bonds (Rule 144A securities) and exchange them later with identical but registered ones. Another example is the change of cusip identifiers. In these cases, it is possible that there are identical observations with different bond identifiers. Therefore I identify them carefully and avoided the double-counting of bond amount outstanding. Another example is merger and acquisition, especially when the issuing firms are acquired and the bonds are not bought back. In this case I track the surviving firms from the CRSP event file.

After the mapping is ready, I pile up all the corporate bonds available in EJV issued by a firm to get the total face value of the public bond amount outstanding for a given month and given firm. Since discount bonds appear in the balance sheets at discount, I take the issue price of bonds as the book value of the bonds and assume the discount amortizes linearly until maturity. The market value of bonds can simply calculated from the marked-to-market bond prices and face values.

Once the bond amounts are piled up for each firm, I map the amounts to the book value of long-term debt and debt in current liabilities from Compustat Quarterly. The mapping results are in Table A-3. On average 50% of book debt is public debt and more than 5% of firms have only public debt on their balance sheets. Although the corporate bond amount in our data set is mapped to the significant portion of book debt, the public bond amount obtained from EJV could be less than the actual bond amount issued by firms. To check the severity of this problem, I compare the number and the amount of bonds issued for each company in EJV to that in FISD, which is a comprehensive database on corporate bonds issue information. The results are in Table A-4. All firms are categorized into decile groups based on the amount of bonds issued. The EJV database covers around 90% of bonds in FISD and the under-coverage is not systematic in that it is consistent across all deciles. I conclude that the mapping of the corporate bonds based on the EJV database is quite representative of the actual corporate bond amount in balance sheets.

Once I have the market value of public bond amount outstanding, I get the public debt returns by

Table A-3: Ratio of EJV Bond Amount to Book Value of Debt

For each firm, the total corporate bond amount outstanding is mapped to the book value of long-term debt and debt in current liabilities. The mean, median and 95'th percentile of the ratios of the total bond amount to the book value of debt are reported.

Year	Mean	Median	95'th Percentile
1990	0.34	0.26	0.89
1991	0.36	0.28	0.92
1992	0.40	0.33	0.99
1993	0.45	0.42	1.00
1994	0.47	0.45	1.00
1995	0.47	0.44	1.00
1996	0.47	0.45	1.00
1997	0.47	0.44	0.99
1998	0.48	0.46	1.00
1999	0.49	0.46	1.00
2000	0.49	0.45	1.00
2001	0.52	0.48	1.01
2002	0.57	0.57	1.04
2003	0.60	0.62	1.05
2004	0.61	0.63	1.06
2005	0.59	0.61	1.04
2006	0.57	0.58	1.03
2007	0.58	0.60	1.03
Average	0.50	0.47	1.0

value-weighting the individual bond returns. Specifically, the bond returns from clean prices and accrued interests are given by

$$R_{t+1}^{bond} = \frac{P_{t+1} + AI_{t+1} + C_{t+1} - (P_t + AI_t)}{P_t + AI_t} \tag{16}$$

where P_t is the quoted price, C_t the coupon, and AI_t the accrued interest. When there is a bond pricing missing for a month, I interpolate the price assuming that the bond price change is linear in duration. I use the price change of other bonds for the firm and calculated the missing bond price in proportion to durations of the bonds. First I calculate the average per-duration price change by calculating the value-weighted average of the per-duration price changes of bonds whenever available. Then I multiply the duration of the missing bond by the average per-duration price change to interpolate the missing price. When the interpolation is impossible due to the lack of other bond prices, I treat the firm observation as missing for the month. This procedure is not expected to change the qualitative results because the total number of interpolated prices is 8098 out of 885,670 data points, which is about 0.91% of the total bond prices.

The next step is to construct private debt return series. I assume the remaining part of book value of debt that is not mapped out by the corporate bond amounts in the EJV is private debt and can be proxied by bank loans. In order to see how much of the remainders is actually bank loans, I map the bank loan amount issued by each firm obtained from Dealscan database to the remaining book debt. As opposed to the corporate bond case, the mapping is not straight forward due to the instituional structure[30]. There are many types of bank loan, among which the most common ones are amortizing loans and revolving loans[31]. In amortizing loans, borrowers make small principal payments along with

[30]For details, see Taylor and Sansone (2007).

[31]Other types of typical bank loan include a letter of credit (LOC) and and acquisition or equipment line (a delayed-draw term loan)

Table A-4: Ratio of EJV Bond Amount to FISD Bond Amount

For each firm, the number and amount of bonds in EJV to those in FISD are compared. Firms are ranked in 10 groups in terms of the bond amount issued for the period from July 1991 to December 2007. For each decile, the ratio of the number and the amount of bonds issued in EJV to FISD is calculated. Equally weighted average and bond amount-weighted averages are calculated.

Bond Amount Decile	EW number of bonds	VW number of bonds	EW Ratio	VW Ratio
1	0.90	0.92	0.92	0.94
2	0.91	0.92	0.92	0.93
3	0.89	0.89	0.91	0.91
4	0.88	0.88	0.90	0.90
5	0.89	0.89	0.91	0.90
6	0.90	0.90	0.92	0.92
7	0.87	0.87	0.90	0.89
8	0.90	0.90	0.92	0.92
9	0.90	0.90	0.91	0.91
10	0.88	0.86	0.91	0.91

coupon(fee) payments and make a one-time lump-sum payment at maturity. In revolvers, borrows can draw down up to the credit line and pay commitment fee along with interests for the amount withdrawn. Another characteristics of bank loans are prepayment options. Borrowing firms can prepay the loan when the firms' financing condition improves. And the typical bank loans are floating rate loans; the fees are set as some spreads over benchmark rates. Some loans are perfomance sensitive; Rates are reset according to the credit risk of the borrowers. Unfortunately the Dealscan database does not have all the information on these complications. For example, we do not know how much of the loans are repaid and withdrawn.

To get around this issue, I assume that the term loans are amortized in a linear fashion over time and all paid out after five years. For revolvers, I assume that 20% is withdrawn. For the sample year of 2003, on average 88% of the book value of long-term debt and debt in current liabilities net of corporate bond amounts is mapped to the loans under these assumptions. In all, approximately 94% of book value of debt is mapped to the bond and loan amounts in our data sets.

For the sample period where the loan data are available, the return on private debt can be calculated in a similar fashion as in (16).[32] Unfortunately, the sample of loan returns is limited compared to the EJV database. Instead, I use an alternative approach to get a broader and longer sample. Since both the bonds and loans can be seen as contingent claims on the firm's underlying asset, I approximate bank loan returns R_{t+1}^{loan} using the predictions from the following regressions for each firm :

$$R_{t+1}^{loan} - R_{t+1}^{F} = a + b\left(R_{t+1}^{bond} - R_{t+1}^{F}\right) + c\left(R_{t+1}^{treasury} - R_{t+1}^{F}\right) + \epsilon_{t+1} \tag{17}$$

where R_{t+1}^{F} is the risk free return and $R_{t+1}^{treasury}$ is the return on a one-year treasury bond return. The treasury return on the righthand side is to correct for the difference in the interest sensitivity of the bond and the loan return.[33] I try various specifications for the regression in Table A-5. The coefficients from the Panel IV, which are from the rating portfolio regressions, are used throughout the paper and the

[32] The difference is that there is no distinction between dirty and clean prices in loan returns. Returns are simply calculated the sum of the next period's price and the interest for the period divided by the current price.

[33] Bank loans are floating rate instruments whereas typical corporate bonds pay fixed rate coupons. If the change in the bond price is due to the change in the term structure, it will not affect the price of bank loans.

Table A-5: Regression of excess loan returns on excess bond returns.

For the model $R^{loan}_{t+1} - R^F_{t+1} = b\left(R^{bond}_{t+1} - R^F_{t+1}\right) + c\left(R^{treasury}_{t+1} - R^F_{t+1}\right) + \epsilon_{t+1}$, four types of regressions are run. The first panel (Model I) shows the mean coefficients from the individual-firm-level regressions. Equally weighted average and Model II is a panel regression with all firms. Model III is three separate panel regressions for rating category groups. Group A is ratings higher than Ba2, Group B is between Ba2 and B1, and Group C is lower than B1. Model IV is a portfolio-level regression for the same rating groups. The numbers in parenthesis are t statistics.

Model I : Individual Firm Regression	
b	0.06
	(7.01)
c	-1.29
	(-38.87)

Model II : Panel Regression		
b	c	R^2
0.15	-1.12	0.19
(36.45)	(-2.90)	

Model III : Panel with Ratings								
Group A			Group B			Group C		
b	c	R^2	b	c	R^2	b	c	R^2
0.07	-0.46	0.08	0.15	-0.84	0.23	0.13	-2.16	0.17
(10.58)	(-3.69)		(27.46)	(-2.99)		(16.23)	(-2.06)	

Model IV : With Rating Portfolios								
Group A			Group B			Group C		
b	c	R^2	b	c	R^2	b	c	R^2
0.14	-0.63	0.32	0.18	-2.06	0.28	0.18	-3.91	0.30
(4.92)	(-3.09)		(3.91)	(-2.11)		(3.88)	(-2.63)	

results are robust to the choice of coefficients. Finally, the firm returns are obtained by

$$R^{Asset}_{t+1} = \frac{E_t}{E_t + B_t + L_t} R^{Equity}_{t+1} + \frac{B_t}{E_t + B_t + L_t} R^{Bond}_{t+1} + \frac{L_t}{E_t + B_t + L_t} R^{Loan}_{t+1} \tag{18}$$

where E_t is the market value of equity, B_t the market value of bond and L_t the market value of Loan. And market leverage can be calculated by $\frac{B_t + L_t}{E_t}$.

Proofs

Proof of the equation (9). In population,

$$\begin{aligned} cov(R^i, R^M) &= cov(\beta_t R^M + \epsilon, R^M) \\ &= E[\beta_t {R^M}^2] - E[\beta_t R^M]E[R^M] \\ &= cov(\beta_t, {R^M}^2) + E[\beta_t]E[{R^M}^2] - E[R^M]\Big(cov(\beta_t, R^M) + E[\beta_t]E[R^M]\Big) \end{aligned}$$

$$= \quad E[\beta_t]var(R^M) + cov(\beta_t, {R^M}^2) - E[R^M]cov(\beta_t, R^M)$$

Therefore

$$E[R^M]\left(E[\beta] - \beta^u\right) = \frac{E[R^M]^2}{var(R^M)}cov(\beta_t, R^M) - \frac{E[R^M]}{var(R^M)}cov(\beta_t, {R^M}^2)$$

Since the squared of Sharpe Ratio is very small (≈ 0.02), the approximation in (9) is obtained.

References

Acharya, V., Bharath, S., and Srinivasan, A. (2007). Does industry-wide distress affect defaulted firms? evidence from creditor recoveries. *Journal of Financial Economics*, 85(3):787–821.

Allen, L. and Gottesman, A. A. (2006). The informational efficiency of the equity market as compared to the syndicated bank loan market. *Journal of Financial Services Research*, 30(1):5–42.

Almeida, H. and Philippon, T. (2007). The risk-adjusted cost of financial distress. *Journal of Finance*, 62(6):2557 – 2586.

Altman, E. I., Brady, B., Resti, A., and Sironi, A. (2005). The link between default and recovery rates: Theory, empirical evidence and implications. *Journal of Business*, 78:2203–2227.

Asness, C. (1993). Do empirical results reject the CAPM? *University of Chicago*.

Banz, R. W. (1980). The relative efficiency of various portfolios: Some further evidence: Discussion. *Journal of Finance*, 35(2):281–283.

Barclay, M. J., Smith, C. W., and Morellec, E. (2006). On the debt capacity of growth options. *Journal of Business*, 79(1):37–59.

Berk, J. B., Green, R. C., and Naik, V. (1999). Optimal investment, growth options and security returns. *Journal of Finance*, 54:1153–1607.

Black, F. and Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy*, 81(3):637–654.

Bollerslev, T., Engle, R. F., and Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances. *Journal of Political Economy*, 96(1):116–131.

Brandt, M. W. and Kang, Q. (2004). On the relationship between the conditional mean and volatility of stock returns: A latent var approach. *Journal of Financial Economics*, 72:217–257.

Campbell, J. and Hentschel, L. (1992). No news is good news. *Journal of financial Economics*, 31:281–318.

Campbell, J., Hilscher, J., and Szilagyi, J. (2008). In search of distress risk, forthcoming. *Journal of Finance*.

Carlson, M., Fisher, A., and Giammarino, R. (2004). Corporate investment and asset price dynamics: Implications for the cross-section of returns. *Journal of Finance*, 59:2577–260.

Charoenrook, A. (2004). The role of capital structure in cross-sectional tests of equity returns. *Working Paper*.

Choi, J. (2008). The conditional CAPM does not explain asset-pricing anomalies: A comment. *Working Paper*.

Choi, J. and Richardson, M. (2008). The volatility of the firm's assets. *Working Paper*.

Dybvig, P. H. and Ross, S. A. (1985). Differential information and performance measurement using a security market line. *Journal of Finance*, 40(2):383–399.

Elton, E. J., Gruber, M. J., and Blake, C. R. (2007). Monthly holdings data and the selection of superior mutual funds. *Working Paper*.

Fama, E. F. and French, K. R. (1992). The cross-section of expected stock returns. *Journal of Finance*, 47(2):427–465.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 10:3–56.

Ferson, W. and Harvey, C. R. (1999). Conditioning variables and cross-section of stock returns. *Journal of Finance*, 54:1325–1360.

French, K. R., Schwert, G. W., and Stambaugh, R. F. (1987). Expected stock returns and volatility. *Journal of financial Economics*, 19:3–30.

Galai, D. and Masulis, R. W. (1976). The option pricing model and the risk factor of stock. *Journal of Financial Economics*, 3(1-2):53–81.

Gomes, J. F. and Schmid, L. (2007). Levered returns. *Working Paper*.

Guo, H. and Whitelaw, R. F. (2006). Uncovering the risk–return relation in the stock market. *Journal of financial Economics*, 61(3):1433–1463.

Hamada, R. S. (1972). The effect of the firm's capital structure on the systematic risk of common stocks. *Journal of Finance*, 27(2):435–452.

Hecht, P. (2004). The cross section of expected firm (not equity) returns. *Harvard Business School Working Paper Series*.

Jagannathan, R. and Wang, Z. (1996). The conditional capm and the cross-section of expected returns. *Journal of Finance*, 51(1):3–53.

Jensen, M. (1986). Agency costs of free cash flow, corporate finance and takeovers. *American Economic Review*, 76:323–329.

Lettau, M. and Ludvigson, S. (2001). Resurrecting the (C)CAPM: A cross-sectional test when risk premia are time-varying. *Journal of Political Economy*, 109:1238–1287.

Lewellen, J. and Nagel, S. (2006). The conditional CAPM does not explain asset-pricing anomalies. *Journal of Financial Economics*, 82(2):289–314.

Lewellen, J., Nagel, S., and Shanken, J. A. (2008). A skeptical appraisal of asset pricing tests. *Journal of Financial Economics*, Forthcoming.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics*, 47(1):13–37.

Lustig, H. N. and Van Nieuwerburgh, S. G. (2005). Housing collateral, consumption insurance, and risk premia: An empirical perspective. *Journal of Finance*, 60(3):1167–1219.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance*, 29(2):449–470.

Myers, S. C. (1977). Interactions of corporate financing and investment decisions–implications for capital budgeting: Reply. *Journal of Finance*, 32(1):218–220.

Petkova, R. and Zhang, L. (2005). Is value riskier than growth? *Journal of Financial Economics*, 78:187–202.

Santos, T. and Veronesi, P. (2006). Labor income and predictable stock returns. *Review of Financial Studies*, 19(1):1–44.

Scholes, M. and Williams, J. (1977). Estimating betas from nonsynchronous data. *Journal of Financial Economics*, 5:309–327.

Sharpe, W. F. (1964). A capital asset pricing model with time-varying covariances. *Journal of Finance*, 19(3):425–442.

Shleifer, A. and Vishny, R. W. (1992). Liquidation values and debt capacity: A market equilibrium approach. *Journal of Finance*, 47(4):1343–1366.

Taylor, A. and Sansone, A. (2007). *The Handbook of Loan Syndications and Trading*. McGraw-Hill, New York.

Thomas, H. and Wang, Z. (2004). The integration of bank syndication loan and junk bond markets. *Journal of Banking and Finance*, 28(2):299–329.

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

Warga, A. D. (1991). Corporate bond price discrepancies in the dealer and exchange markets. *Journal of Fixed Income*, 1(3).

Zhang, L. (2005). The value premium. *Journal of Finance*, 60(1):67–103.