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WP 2009-23
June 2009

Working Paper

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Is Unlevered Firm Volatility Asymmetric?

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This version: May 21, 2008

Abstract

Asymmetric volatility refers to the stylized fact that stock volatility is negatively correlated to stock returns. Traditionally, this phenomenon has been explained by the financial leverage effect. This explanation has recently been challenged in favor of a risk premium based explanation. We develop a new, unlevering approach to document how well financial leverage, rather than size, beta, book-to-market, or operating leverage, explains volatility asymmetry on a firm-by-firm basis. Our results reveal that, at the firm level, financial leverage explains much of the volatility asymmetry. This result is robust to different unlevering methodologies, samples, and measurement intervals. However, we find that financial leverage does not explain index-level volatility asymmetry, which is consistent with theoretical results in Aydemir, Gallmeyer and Hollifield (2006).

JEL Classification: G12
Keywords: Volatility asymmetry; Financial leverage.

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I. Introduction

Asymmetric volatility refers to the stylized fact that stock volatility is negatively correlated to stock returns. Traditionally, this phenomenon has been explained by the financial leverage effect (Black (1976) and Christie (1982a)). The financial leverage hypothesis posits that as the price of a firm's stock decreases, that firm's financial leverage increases, leading to a higher volatility of equity. Indeed, this leverage effect explanation is so dominant that it has become synonymous with asymmetric volatility.[1]

However, Pindyck (1984) and French, Schwert and Stambaugh (1987) have challenged the financial leverage hypothesis with the risk premium hypothesis and, subsequently, this challenge has been supported by many major studies.[2] The risk premium hypothesis, also known as the volatility feedback effect, proposes that an increase in unexpected volatility will increase expected future volatility. The resulting increase in expected returns will cause prices to drop and this will lead to volatility asymmetry. As a result, it appears that financial leverage does not play much of a role in explaining volatility asymmetry.

Using a new, intuitive, approach that utilizes the concept of unlevering, we examine whether the financial leverage explanation should be rejected in favor of the risk premium hypothesis. Interestingly, we find that the leverage effect plays an important role in explaining volatility asymmetry. In fact, at the firm level, financial leverage explains much of volatility asymmetry. This result is robust to different unlevering methodologies, different samples, and different measurement intervals, applies to firms of different sizes and in different industries, and is the same whether we examine the panel data set or just the cross section of firms. We find that financial leverage is more important than size, beta, book-to-market, or operating leverage in explaining volatility asymmetry at the firm level.

The reason that we find a significant role for financial leverage is that we conduct a firm-level analysis rather than the portfolio- or index-level analyses which have been used in most recent studies.[3] Our unlevering approach makes it possible to examine volatility asymmetry on a firm-by-firm basis using a broad cross section of firms. Equity volatility is first transformed by stripping out the effect of financial leverage. The reduction in volatility asymmetry subsequent to this operation indicates the strength of the effect of financial leverage. This approach allows us to examine the reasons for volatility asymmetry among a broad cross section of firms.

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[1] For instance, the parameter that captures the covariance of expected returns and volatility in GARCH is called "leverage effect."

[2] Glosten, Jagannathan and Runkle (1993), Campbell and Hentschel (1992), Bekaert and Wu (2000), Tauchen (2005) and Dennis, Mayhew and Stivers (2006).

[3] The exception is Dennis, Mayhew and Stivers (2006). Dennis, Mayhew and Stivers (2006) examine implied volatilities on indices and stocks and conclude that the risk premium effect is important. However, they do not examine financial leverage.

The next task is to use the unlevering approach to find out whether financial leverage is as important at the index level as it is at the firm level. The unlevering approach allows us to remove financial leverage from each component firm before different firms' returns are aggregated into an index. In contrast to the result found at the firm level, at the index level, a large portion of volatility asymmetry persists even after unlevering. In other words, even unlevered index-level returns have higher volatility when the index goes down than when it goes up. Hence, financial leverage alone explains only a small portion of the index-level volatility. To sum up, we find that the leverage effect is extremely important in explaining volatility asymmetry at the firm level, but it is not important in explaining index-level asymmetry.

The paper makes three main contributions to the volatility asymmetry literature. First, we develop the unlevering approach that helps us to examine the leverage effect on a firm-by-firm basis. This approach opens up opportunities to empirically document the effect of financial leverage on a broad cross section of firms over time. We find that the financial leverage hypothesis is by far the most important explanation for volatility asymmetry at the firm level. Second, as Aydemir, Gallmeyer and Hollifield (2006) point out, "any study of the effect of financial leverage on volatility should use market debt valuations, which are difficult to obtain in practice." As a result of this difficulty, no previous work has allowed for market price of debt in computing financial leverage. When we strip out financial leverage, we account for market price of debt either through a Merton-KMV model or a procedure that matches the bond prices with bonds with similar credit ratings. Third, we find that volatility asymmetry at the market level and at the firm level have different causes. While financial leverage accounts for most of the firm-level asymmetry, it does not explain index-level asymmetry.

Our empirical finding is consistent with the theoretical results developed in Aydemir, Gallmeyer and Hollifield (2006). While Campbell and Hentschel (1992), Wu (2001), and Tauchen (2005) make important theoretical contributions concerning the modeling of asymmetric volatility at a market level, the Aydemir, Gallmeyer and Hollifield (2006) model is particularly relevant in our case because it includes firm-level as well as market-level asymmetries. It incorporates both the leverage effect and a time-varying risk premium in a dynamic general equilibrium economy with debt and equity claims. Under a representative agent model with habit formation preference, financial leverage is linked endogenously to interest rates, prices of risk and volatility. At the market level, financial leverage is driven by the aggregate risk in the economy. As a result, risk premium rather than financial leverage explains the market-level volatility asymmetry. At the firm level, however, the equity portion of financial leverage is driven by idiosyncratic risk shocks, in addition to aggregate risk shocks. Hence, financial leverage could have a substantial impact on firm-level volatility asymmetry, although it contributes very little to market-level stock return volatility.

Our paper is related to Bekaert and Wu (2000), a major study of index- and firm-level volatility in the Japanese stock market. Using the market portfolio and portfolios with different leverage constructed from Japanese Nikkei stocks, Bekaert and Wu reject the leverage effect in favor of the volatility feedback hypothesis. Their result is not consistent with our finding for the following reasons. First, our samples are different. Bekaert and Wu use 172 Japanese stocks from 1986 to 1995, while we examine thousands of US stocks from 1986 to 2003.[4] Second, Bekaert and Wu conduct their analysis by aggregating stocks into portfolios, while we examine firm-level asymmetry directly, based upon firm-level data. As we will show in this paper, leverage effect is extremely important on the firm level but diminishes after stocks are aggregated into portfolios.

Our finding is also related to the empirical phenomenon of covariance asymmetry. Erb, Harvey, and Viskanta (1994), Bekaert and Wu (2000), Ang and Chen (2005), and Ang, Chen, and Xing (2006) find that covariance for stocks is higher in a down market. We find that unlevered stock returns also have higher covariance when the market index goes down. While firm-level unlevered volatility stays the same in a down market, index-level unlevered volatility
is higher due to higher covariance between stocks.

Other papers propose alternative explanations of asymmetry volatility. Cheung and Ng (1992) show that volatility asymmetry is much stronger for small stocks. Bekaert and Wu (2000) propose that the risk premium effect behind volatility asymmetry will be more pronounced for firms with higher covariance with the market. Kogan (2004) develops a production economy model which implies that firm investment activity and firm characteristics, particularly the market-to-book ratio, or q, might lead to volatility asymmetry. Christie (1984b) proposes that operating leverage affects volatility asymmetry. Finally, Duffee (1995) proposes that volatility asymmetry at the firm-level could be due to a positive contemporaneous relation between returns and volatility. We empirically examine these explanations and conclude that firm-level volatility asymmetry is due to financial leverage rather than size, beta, book-to-market ratio, operating leverage, or a positive contemporaneous relationship between returns and volatility.

The remainder of the paper proceeds as follows. Section II presents the unlevering methodology. Section III presents data and summary statistics. Sections IV and V present results using pooled firm-month observations and a cross section of firms. Section VI shows the market-level versus firm-level asymmetry. Finally, section VII offers conclusions.

[4] Wu (2001) also finds leverage play a role in the US market index, which is different from Bekaert and Wu's (2000) finding on Japanese stocks.

II. Methodology For Unlevering Volatility

In this section, we propose a methodology that transforms equity volatility to extract from it the effect of financial leverage. This is done by using an equation that expresses the volatility of equity in terms of a volatility that is not affected by financial leverage.

A. Effect of financial leverage

We account for the effect of financial leverage through three different methodologies. First, we compare volatility asymmetries for firms with the highest value of book debt, lowest value of book debt and the median value of book debt. Second, we adopt the approach developed by Merton (1974) and implemented by KMV (Crosbie and Bohn (2001)). Vassalou and Xing (2004), Campbell, Hilscher and Szilagyi (2007) and Bharath and Shumway (2004) have also recently applied the Merton-KMV model in the context of examining firm-level default risk. Third, we unlever using the Schwert (1989) formula that has been used in this literature. To improve on this method, we use the bond index prices for different credit rating classes instead of face value to approximate market value of debt. We will describe the methodologies in this section.

First, we examine volatility asymmetry based on sub-samples of firms with different levels of book leverage. In particular, we report the volatility asymmetry of the firm-months with lowest 1% leverage, median (49-51%) leverage, and highest 1% leverage. We will report the change in raw volatilities together with the returns for firms with different leverage levels in figure 3. To preview the results, we find that all three methodologies provide similar conclusions.

Second, we unlever firm volatilities based on Merton-KMV models. In the Merton-KMV model, the equity of the firm is a call option for the underlying value of the firm with a strike price equal to the face value of the firm's debt. The model recognizes that neither the underlying value of the firm nor its volatility are directly observable but they can be inferred from the value of equity, the volatility of equity and several other observable variables by solving two nonlinear simultaneous equations (see Bharath and Shumway (2004) for details of the procedure and computer code). In this paper, we are interested in inferring the volatility of the value of the firm.

The Merton-KMV model makes two important assumptions. The first is that the total value of a firm will follow geometric Brownian motion,

$$dV = \mu V\,dt + \sigma_V V\,dW, \qquad (1)$$

where V is the total value of the firm, μ is the expected continuously compounded return on V, σ_V is the volatility of firm value and dW is a standard Weiner process. The second important assumption of the Merton-KMV model is that the firm has issued just one discount bond maturing in T periods. Under these assumptions, the equity of the firm is a call option for the underlying value of the firm, with a strike price equal to the face value of the firm's debt and a time-to-maturity of T. Moreover, the value of equity as a function of the total value of the firm can be described by the Black-Scholes-Merton Formula. By put-call parity, the value of the firm's debt is equal to the value of a risk-free discount bond minus the value of a put option written on the firm, again with a strike price equal to the face value of debt and a time-to-maturity of T.

The Merton model stipulates that the equity value of a firm satisfies

$$S = V\,N(d_1) - e^{-rT}\,FN(d_2), \tag{2}$$

where S is the market value of the firm's equity, F is the face value of the firm's debt, r is the instantaneous risk-free rate, $N(\cdot)$ is the cumulative standard normal distribution function, d_1 is given by

$$d_1 = \frac{\ln\left(V/F\right) + \left(r + 0.5\sigma_V^2\right)T}{\sigma_V \sqrt{T}}, \tag{3}$$

and $d_2 = d_1 - \sigma_V\sqrt{T}$. Under Merton's assumptions, the value of equity is a function of the value of the firm and time, so it follows directly from Ito's lemma that

$$\sigma_S = \left(\frac{V}{S}\right)\frac{\partial S}{\partial V}\sigma_V\,. \tag{4}$$

In the Black-Scholes-Merton model, it can be shown that $\partial S/\partial V = N(d_1)$, so that under the Merton model's assumptions, the volatility of the firm and its equity are related by $\sigma_S = \left(\frac{V}{S}\right)N\left(d_1\right)\sigma_V$. In other words,

$$\sigma_V = \left(\frac{S}{V}\right)\frac{1}{N\left(d_1\right)}\sigma_S\,. \tag{5}$$

The most significant step in implementing the model is to solve equations (2) and (5) numerically for values of V and σ_V. Simultaneously solving equations (2) and (5) is a reasonably straightforward thing to do. However, Crosbie and Bohn (2001) explain that "in practice the market leverage moves around far too much for [equation (5)] to provide reasonable results." To resolve this problem, we adopt an iterative procedure used in Bharath and Shumway (2004). First, we use an initial value of $\sigma_V = \sigma_S\,[S/(S + F)]$. This value of σ_V is used in conjunction with equation (3) to infer the market value of each firm's assets every day for the previous year. We then calculate the implied log return on assets each day and use that returns series to generate new estimates of σ_V and μ. We iterate on σ_V in this manner until it converges (so that the absolute difference in current and previous value of σ_V is less than 10^{-3}). Following Bharath and Shumway (2004), we assume a forecast horizon of one year (T=1) and take the book value of debt as the face value of the firm's debt.

Third, we also adopt a simple unlevering approach, recognizing that the Merton model has its limitations. To compare our results with previous literature, we unlever using the same formula that is used in this literature (see for example Schwert (1989)). The volatility of the return to the assets of the firm σ_V is

$$\sigma_V = \left(\frac{S}{V}\right)\sigma_S . \qquad (6)$$

where $\left(\frac{S}{V}\right)$ represents the fraction of the market value of the firm due to stocks, and σ_S is the volatility of the return to the stock. We call this method simple unlevering. While previous papers use a firm's book debt as a proxy of its market debt, we make an improvement by using bond index prices for different credit risk categories instead of face value to approximate market value of debt.

Comparison of (5) and (6) shows that the Merton-KMV method is different from the simple unlevering method by a factor of $N(d_1)$, which can be interpreted as an adjusted default probability. This is because the Merton-KMV method captures the fact that the debt may default in the future.

In this paper, we examine two versions of volatility. We first report the raw stock volatility σ_S without any adjustment. We then examine the stock volatility after unlevering for financial leverage σ_V. This is done by using either the Merton-KMV method in equation (5) or the simple unlevering in equation (6).

III. Data and Volatility Asymmetry Metrics

A. Data

We merge all firms in the intersection of COMPUSTAT industrial and research files and the CRSP database. The data period is from January 1986 to December 2003. Because leverage takes on a different meaning in financial firms, we remove stocks of financial firms from the sample.

For book value of debt, we use quarterly data from COMPUSTAT by adding total liabilities (#54) and preferred stock carrying value (#55). The market price of debt is implied by the option pricing formula in the Merton-KMV model. As a proxy for equity value, we multiply monthly stock prices from CRSP by common shares outstanding. Then, we compute a monthly asset-to-equity ratio. To facilitate estimation of a robust model, we drop firms with prices below $3 per share. We also eliminate firms with negative book value (defined as common equity), and any firms missing price or accounting data that is needed for the estimation regression. After these screens, the number of firms range from 1456 in 1987 to 2448 firms in 2003, for a total of 767268 firm-month observations.

When we unlever using the simple unlevering method instead of the Merton-KMV method, we use proxies for the market value of debt. To obtain such proxies, we require that the firms have credit ratings data from COMPUSTAT. We construct market value of debt based on book value of debt along with Lehman Brothers Corporate Bond Index of different credit ratings. Returns data for the Lehman Brothers Corporate Bond Index for these rating classes has to be available for those years. We assume that the initial book value of debt is evaluated at market price and that, subsequently, the price of the debt follows the movement of bonds with the same credit ratings. The requirement for the availability of credit rating data reduces the sample substantially when we use simple unlevering method. But, as we will see, the results are very similar when we unlever using the Merton-KMV method or the simple unlevering method.

First, we calculate the variance of stock returns for every month as the variance of daily returns in the month:

$$\sigma_{s,t}^2 = \frac{1}{(N_t - 1)} \sum_{i=1}^{N_t} (r_{i,t} - \overline{r}_t)^2, \qquad (7)$$

where there are N_t daily returns $r_{i,t}$ in month t. Using non-overlapping samples of daily data to estimate the monthly variance creates an estimation error that is uncorrelated through time. We take the square root to obtain the standard deviation (i.e. volatility) of the stock returns.

We investigate the robustness of our results in relation to a firm's size, beta, book-to-market, and operating leverage. As mentioned before, a firm's size (i.e. market capitalization) is calculated by multiplying monthly stock prices by common shares outstanding. Beta is based upon a rolling regression of stock returns on the S&P 500 index on a firm-by-firm basis. Book-to-market ratio is computed by dividing a firm's book equity by its market capitalization. The degree of operating leverage (OL) is the percentage change in EBIT (earnings before interest and taxes) for a given percentage change in sales revenue i.e. $\left(1+\mathrm{OL}\right) = \frac{\%\Delta EBIT}{\%\Delta sales}$. Following Mandelker and Rhee (1984), we compute operating leverage by running the following regression for each firm j:

$$\ln EBIT_{jt} = a_j + b_j \ln Sales_{jt} + \varepsilon_{jt}$$

The coefficient b_j is the operating leverage for firm j.[5] Table 1 reports the summary statistics for our main variables of interest: volatility, monthly returns, financial leverage, market capitalization, beta, book-to-market, and operating leverage.

[5] We also conduct a robustness check, in which we estimate industry-wide operating leverage and use that as a firm's operating leverage. The results remain the same.

B. Volatility Asymmetry Metrics

To examine volatility asymmetry, we adopt a regression approach that allows both clean graphical evidence as well as statistical inference. The general form of the regression model is the following:

$$\ln \frac{\sigma_{k,t}}{\sigma_{k,t-2}} = \sum_{i=1}^{d} \beta_i D_{i,t-1} + \varepsilon_t. \qquad (8)$$

where $k = S$ or V. These two specifications pertain to log changes in monthly standard deviations of stock returns before any transformation σ_S and log changes in monthly standard deviations with financial leverage removed σ_V. $D_{i,t-1}$ is a dummy variable that equals 1 if returns at t-1 fall within the range, and d is the number of sets of returns that are created by partitioning the space of returns. We partition the stock returns into ten intervals (i.e. d = 10), each of which is represented by a dummy variable in the following way: D_1 for returns less than –0.20; D_2 for returns between –0.20 and –0.15; D_3 for returns between –0.15 and –0.10; D_4 for returns between –0.10 and –0.05; D_5 for returns between –0.05 and 0; D_6 for returns between 0 and 0.05; D_7 for returns between 0.05 and 0.10; D_8 for returns between 0.10 and 0.15; D_9 for returns between 0.15 and 0.20; and D_{10} for returns larger than 0.20.[6]

The independent variables are dummy variables, representing returns of different signs and magnitude. This gives us the mean response of the change in volatility to returns of differing signs and magnitudes. In this model, an asymmetric relation would be assessed by examining the response of volatility to returns of the same magnitude but with opposite signs. This functional form is close in spirit to the news impact curve in Engle and Ng (1993)[7]. It has the appealing features of simplicity (linear least squares) and flexibility (allowing different parameter values for different return categories). It also allows for the well known ARCH effect, where volatility increases following both large negative and large positive returns. We should note that the leverage effect does not mean that leverage is the main determinant of the movement of volatility. The large ARCH literature has shown that the magnitude of lagged return has the most explanatory power for volatility changes. The response of volatility to returns therefore has the shape of a parabola. The leverage effect tilts this parabola to the right by making the reaction of volatility to large negative returns more pronounced than that from large positive returns. Figlewski and Wang (2000) investigate the leverage effect but do not account for this ARCH effect.[8]

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[6] All of our results are robust to alternative partitions with different d's.

[7] Engle and Ng (1993) derive a procedure that plots the implied relation between the conditional variance from an Asymmetric GARCH model and lagged residuals. They explore the curve pattern of many models, and assess how well these models fit the data. They also propose a partially non-parametric news impact curve.

[8] Figlewski and Wang (2000) find that volatility increases even when stock price increases. They call this a "reverse" leverage effect and consider this evidence against the leverage effect. However, they do not account for the ARCH effect. When positive returns are large, ARCH effect pushes volatility higher while the leverage effect

Following Petersen (2007) and Vuolteenaho (2002), we use Rogers's (1983, 1993) robust standard error methodology in order to calculate cross-sectional correlation consistent standard error. In order to run a statistical test on the level of volatility asymmetry, we develop a new metric for volatility asymmetry, which describes how much of the asymmetry is explained by each competing hypothesis. The metric in question is based on the difference between the "left tail" and the "right tail" of the curve in the graphs. The left tail is the response of volatility to negative shocks, and the right tail is the response of volatility to positive shocks. If the two tails are exactly the same, then there is no asymmetry. If the two tails are very dissimilar, then there is strong asymmetry. The sign of the asymmetry in this case will depend on which tail of the curve is higher than the other, on average.

The metric formalizes the above intuition by summarizing the degree of asymmetry by a single number. We resort to the concept of integration which can be seen in Figure 1. Figure 1 left panel plots the change of stock volatility (on the y-axis) against stock returns (on the x-axis). Picture the two tails of the curve superimposed with absolute returns on the x-axis as in Figure 1, right panel. The area between the two tails can be used as a measure of asymmetry. If there is no asymmetry, the two tails of the curve are identical. In such a case, superposing the two tails provides a single curve with no area in it, and the asymmetry metric has a value of zero. On the other hand, if there is strong asymmetry, then the area between the two tails becomes very large, and the asymmetry metric has a large value. We adopt the convention that the area is negative (positive) if there is negative (positive) asymmetry.

To compute the asymmetry metric from our coefficients, we approximate the (signed) area described above by summing the difference between the two (superposed) tails of the curve for each category of absolute returns. We give standard errors around the metric in the brackets following the point estimate. The standard errors are derived from one million replications of Monte Carlo Integration of the area underlying the asymmetry metric. We refer to this first volatility asymmetry metric as the U-shaped metric, because a symmetric relationship looks like a capital letter U.

The second volatility asymmetry metric is based on a simplified version of equation (8):

$$\ln\frac{\sigma_{k,t}}{\sigma_{k,t-2}} = \beta_{-} D_{-,t-1} \ln\frac{S_t}{S_{t-1}} + \beta_{+} D_{+,t-1} \ln\frac{S_t}{S_{t-1}} + u_t, \qquad (9)$$

where $D_{-,t-1}$ ($D_{+,t-1}$) is a dummy variable that takes on a value of 1 when t-1 returns are negative (positive), and 0 otherwise. This model fits a linear regression for negative returns and positive returns separately. It is similar to equation (8) except that it uses a line instead of a curve to fit the volatility changes. The difference in areas between the "negative" segment and the "positive" segment is a measure of volatility

pushes volatility lower. Since ARCH is the dominant effect, volatility increases. It does not mean that the leverage effect is not important. Our methodology makes it easy to see if the magnitude of the tilt in the parabola corresponds to what is expected given the magnitude of the change in leverage.

asymmetry (see Figure 2, right panel). We refer to this second volatility asymmetry metric as the V-shaped metric, because a symmetric relationship looks like a capital letter V. We show our results based on both the U- and the V-shaped metrics. While equation (8) provides clear graphical evidence and statistical inference for volatility asymmetry, it requires that a wide range of returns are observed. The metric based on equation (9) has the advantage that it can be calculated even when a stock does not have returns within a certain range. For some of the later analysis, we use only the V-shaped metric because of this data limitation. We will explain this in more detail later.

In the remainder of the paper, we will present results on volatility asymmetry. First, we will examine the role of financial leverage based on pooled firm-month observations (Section IV). Second, we will examine the financial leverage, risk premium and other hypotheses using a cross section of firm-level volatility asymmetries (Section V). Third, we will relate firm-level volatility asymmetry to index-level volatility asymmetry (Section VI).

IV. Results Using Pooled Firm-Month Observations

A. Assessing the effect of leverage on the relation between volatility and returns for stocks

We first examine volatility asymmetry based on a sub-sample of firms with different levels of book leverage.[9] In particular, we report the volatility asymmetry of the firm-months with lowest 1% leverage, median (49-51%) leverage, and highest 1% leverage. We plot the change in raw volatilities together with the returns for firms with different leverage levels.

Panels A, B, and C in Figure 3 show the results in three graphs, for firms with low, median and high leverage, respectively. The graphs show that volatility asymmetry is substantially higher for firms with high leverage, while firms with the lowest leverage have minimal volatility asymmetry. The U-shaped volatility asymmetry metric is -0.98 for firms with low leverage, -2.9 for firms with median leverage, and -4.3 for firms with high leverage.

Table 2 shows results based on the unlevering approach using the Merton-KMV model, through equation (5). Table 3 reports the regression results in (6) for stock volatility by removing the financial leverage via the simple unlevering approach. We also report robustness checks for different firm sizes and industry groups.

Table 2, Panel A, shows the result for raw (i.e. untransformed) stock volatility σ_S and unlevered volatility σ_V. The volatility asymmetry metric is negative and significant at -2.94 (t-statistic -4.00). After unlevering, the volatility asymmetry metric is substantially reduced to -0.23 (t-statistic -0.31). The change from stripping out financial leverage is 2.71 (2.94 minus 0.23). In other words, financial leverage

[9] Book leverage is used instead of market leverage in this section because our focus is on firms with close to zero leverage. Our sample of firms with market leverage requires credit ratings of firms. Usually only firms with substantial leverage have credit ratings.

accounts for 92% of the change in asymmetry.[10] Table 2, Panel B shows the result using the V-shaped volatility asymmetry metric. The result is similar to that in the first panel. Volatility asymmetry drops from -2.41 (t-stat -8.65) to -0.19 (t-stat -1.92). Again, after unlevering, a vast majority (92%) of the volatility asymmetry is gone, although in this case the asymmetry is still statistically significant.

Figure 4 displays graphically the results in Table 2, Panel A. The band around the curves is a two standard error confidence interval. The graph on the left shows the results related to raw stock volatility σ_S. The response of volatility change to returns exhibits a substantial negative asymmetry. Large negative returns lead to a large increase in volatility. On the other hand, positive returns in general lead to a small decrease in volatility. The graph on the right shows the curve related to the unlevered volatility σ_V using the Merton-KMV unlevering method in equation (5). As one can tell, after taking out financial leverage, there is very little negative volatility asymmetry left.[11] This offers strong support for the firm-level financial leverage effect and mirrors the volatility asymmetry metric results in showing that most of the negative asymmetry has disappeared after accounting for financial leverage. Since the results in Panel B are the same, we do not report the graph separately.

Table 3 presents results from using the simple unlevering method in equation (6) to account for risky corporate debt. As can be seen, even with a different unlevering approach, the results are very similar to our previous results. Table 3, Panel A shows the results for the U-shaped volatility asymmetry metric. After unlevering, volatility asymmetry drops from -4.15 (t-statistics -5.65) to -0.72 (t-statistics -0.96). Around 83% of the volatility asymmetry is removed after financial leverage is taken out.[12] Figure 4 shows the results from this unlevering procedure. Table 3, Panel B, shows that the V-shaped volatility asymmetry metric also drops substantially. Approximately 89% of the volatility asymmetry is removed after unlevering.

B. Robustness Checks with Different Firm Sizes and Industry Groups

We investigate the robustness of our results for firms in different size quintiles or industries. Cheung and Ng (1992) examine the volatility asymmetry for individual stocks from 1962 to 1989 and show that volatility asymmetry is much stronger for small stocks. In this section, we check whether stocks of different sizes or industries behave differently.

[10] As the asymmetry metric is the measure of a (signed) area, the change in the area due to the removal of a specific effect divided by the total change in the area will give the percentage of the asymmetry effect attributable to a specific explanation.

[11] Even if leverage effect is the only explanation for volatility asymmetry, the asymmetry curve based on KMV-Merton unlevering will not be flat but will be U-shaped since the pure Merton model does not capture the ARCH effect. For the same reason, the levered curve is downward sloping but not linear as in a pure Merton leverage model.

[12] To identify whether our market debt assumption makes a big difference in the results, we repeat our analysis in Table 3 using book debt data. Most (84%) of the volatility asymmetry is removed after adjusting for financial leverage.

We examine the volatility asymmetry metrics for different size quintiles. We find significant negative asymmetry across all size quintiles (ranging from -2.69 to -3.52 for U-shaped asymmetries). More importantly, regardless of the size quintiles and metrics, volatility asymmetries drop dramatically after unlevering. After unlevering, volatility asymmetry is reduced by 85% (size 5 quintile) to 97% (size 1 quintile). The results for V-shape volatility asymmetry results are broadly similar.

We also check the volatility asymmetry metric for different industry groups. The industry grouping is the same as in Griffin and Karolyi (1998). Again, we find significant negative asymmetry across all industry groups. After taking out financial leverage, volatility asymmetries drop by 88% or more in all industries. Thus, the financial leverage effect is strong in all industry groups.

C. Timing issue

We present the main results using the change of volatility from t-2 to t because Duffee (1995) conjectures that the negative volatility asymmetry documented in the literature is largely due to a positive contemporaneous relation between firm stock returns and firm stock return volatility. Essentially, using the change in volatility between t and t-1 as a dependent variable might induce the regression to pick up the positive contemporaneous relation. Given this possibility, finding negative volatility asymmetry might be a spurious result (see Duffee (1995) for more details). To address Duffee's (1995) valid point, we use a specification that can show that volatility asymmetry is a pervasive phenomenon that is not limited only to the t-1 specification. Throughout the paper, we use the change in volatility between times t and t-2 as the dependent variable instead of that between times t and t-1. This specification is in the spirit of event study methodologies in which a normal period is used as a benchmark, excluding the window of data that contains the event.

As a robustness check, we examine results with the specification for change in volatility that uses month t-1 instead of t-2. Following Duffee (1995), we conduct the following linear regression: $\ln\frac{\sigma_{s,t}}{\sigma_{s,t-1}} = \beta_0 + \beta_1 \ln\frac{S_t}{S_{t-1}} + \varepsilon_t$. The negative asymmetry is revealed when β_1 is found to be negative. We find a β_1 coefficient of -0.41 (t-statistic of -45.91), which reveals significant negative asymmetry. When we use $\ln\frac{\sigma_{s,t}}{\sigma_{s,t-2}}$ as the dependent variable, we find a β_1 coefficient of -0.53 (t-statistic of -55.35), which confirms that negative asymmetry is a pervasive phenomenon that holds for more than the t-1 specification.

To examine this further, we estimate a modified version of equation (8) with a one-month lag (from t-1 to t) instead of a two-month lag as before.

$$\ln\frac{\sigma_{k,t}}{\sigma_{k,t-1}} = \sum_{i=1}^{d} \beta_i \,.\, D_{i,t-1} + \varepsilon_t\,. \qquad (10)$$

Table 4 Panel A reports the results. The raw return volatility asymmetry is statistically significant, and the negative asymmetry goes away when we remove leverage using the Merton-KMV model.[13] This is confirmed in Table 4 Panel B.

V. Results Using the Cross Section of Firm-Specific Volatility Asymmetry

This section reports the results from the cross-sectional analysis of volatility asymmetry for different firms. We run a time-series regression (9) for each firm in our sample and construct a volatility asymmetry metric for each firm. We then relate the cross section of firm volatility asymmetries to different firm-level variables. This allows us to examine the financial leverage hypothesis, the risk premium hypothesis and other potential explanations of volatility asymmetry. We focus, here, on the V-shaped volatility asymmetry instead of the U-shaped volatility asymmetry. The U-shaped volatility asymmetry is calculated based upon the regression in equation (8). However, not every firm has the entire range of returns necessary to allow us to run the regression. In a case in which a stock never showed returns in a particular interval, the U-shaped volatility asymmetry would be undefined.

A. Cross-Sectional Distribution of Volatility Asymmetries

In Figure 6, we plot the distribution of the volatility asymmetry metric for our firms. Looking at the distribution of volatility asymmetries before unlevering, it is clear that the distribution is mostly in the negative range (solid line). This shows that, on average, firms exhibit negative volatility asymmetry. However, after the Merton-KMV unlevering procedure, the unlevered volatility seems to be equally distributed between positive and negative values (dotted line). This again indicates that the original negative asymmetry is, to a large extent, accounted for by financial leverage.

B. Volatility Asymmetry based on Different Financial Leverage, Beta, Book-to-market and Operating Leverage Quintiles

In Table 5, we assess the effect of financial leverage as compared to the effect of the risk premium and other hypotheses. We compute each firm's financial leverage, beta, book-to-market, and operating leverage based on its time-series data. Stocks are then sorted into quintiles based on the cross section of these variables. In each quintile, the average volatility asymmetry for stocks is computed.

Table 5, Panel A presents results from sorting on financial leverage. There is a clear negative monotonic relation between the volatility asymmetry metric and financial leverage. A test of difference in

[13] When we examine the coefficients in Panel A, we notice that large returns for either sign are associated with a large decrease in volatility. The reason for this is selection bias, as in Duffee (1995). A month with a large absolute return is associated with a large standard deviation. Since this regression uses the change in standard deviation as the dependent variable, an abnormally large return will be associated with a decrease in volatility since the following month's standard deviation will likely be lower. Because of this problem, we choose to use the change in volatility between month t and month t-2 in this paper.

the volatility asymmetry metric between the first and fifth quintile yields a p-value of 0.001. This shows that financial leverage is a driver of volatility asymmetry.

Table 5, Panel B presents results from sorting on beta. As Bekaert and Wu (2000) indicate, the risk premium effect will be more pronounced for firms with higher covariance with the market. The cross-sectional implication is that firms with higher beta will have higher risk premia. This is because beta is defined as the covariance divided by the variance of the market (which does not vary in the cross-section). In contrast to the results for financial leverage, there does not seem to be any recognizable pattern that relates beta and volatility asymmetry. The difference in the volatility asymmetry metric between the first and fifth quintile is negative (p-value of 0.065). This is the opposite of the prediction from the risk premium story. This indicates that risk premium does not explain volatility asymmetry in the cross section.

Table 5, Panel C shows the results from sorting on book-to-market. Kogan (2004) develops a model of a production economy in which real investment is irreversible and subject to convex adjustment costs. An implication of his model is that firm investment activity and firm characteristics, particularly the market-to-book ratio, or q, might lead to volatility asymmetry. Also, book-to-market is often considered a factor underlying the risk premium that is separate from beta (Fama and French (1993)). We find no discernible pattern across the quintiles. The difference between the first and fifth book-to-market quintile is insignificant. This shows that it is financial leverage, and not book-to-market, that drives volatility asymmetry.

Finally, Table 5 Panel D presents results from sorting on operating leverage. Operating leverage is the degree to which a firm is committed to fixed production costs. A firm with low (high) fixed costs will have low (high) operating leverage. Theoretically, as Christie (1984b) shows, operating leverage can cause volatility asymmetry. A forecast of lowered cash flows can result in an immediate fall in stock prices. Cash flows, and stock prices, become more volatile when their levels decrease because fixed costs act like a lever in the sense that a small percentage change in operating revenue can be magnified into a large percentage change in operating cash flow. There is some evidence that many aggregate economic series are more volatile during recessions (Schwert (1989)). However, the effect of operating leverage on stock-market volatility asymmetry has not been tested empirically. Therefore, we examine operating leverage in addition to financial leverage. We find that there does not seem to be any recognizable pattern that relates operating leverage and volatility asymmetry.

C. Cross-Sectional Regressions of Firm-Level Volatility Asymmetry

Table 6 presents cross-sectional regressions of the firm volatility asymmetry metric on the explanatory variables used above. Following Petersen (2007), we calculate robust standard errors with firm clustering to correct for cross-sectional correlation in all regressions. Column 1 shows the results for financial leverage. Column 2 shows the results for beta. Column 3 shows the results for book-to-market. Column 4 shows the results for operating leverage. Columns 5, 6, and 7 show the results when we include financial leverage along with the competing variable, i.e. beta, book-to-market and operating leverage. Column 8 shows the multivariate regression with financial leverage, beta, book-to-market and operating leverage.

Our results in the first two columns show that the coefficient of financial leverage is negative and significant at the 1% level. However, the coefficient of firm beta is of the wrong sign. More importantly, when we run multivariate regressions with financial leverage and beta, the coefficient of firm beta is insignificant and of the wrong sign.

The book-to-market factor and operating leverage are insignificant in both univariate regressions and multivariate regressions with financial leverage. This shows that volatility asymmetry is driven by financial leverage but not by book-to-market or operating leverage. We also replace firm beta with covariance of firm returns with the index (results available upon request). The covariance factor is not significant.

Overall, our empirical results confirm our conclusions. Firms with higher financial leverage have more negative volatility asymmetry. On the other hand, the risk premium explanation for individual firm negative volatility asymmetry is not supported. Furthermore, neither the book-to-market or the operating leverage explanations for volatility asymmetry are supported.

VI. Market-Level Versus Firm-Level Asymmetry

Our results so far suggest that financial leverage explains most firm-level volatility asymmetry. In this section, we examine the impact of financial leverage on market-level volatility asymmetry. We find that volatility asymmetry is more pronounced at the market level than at the firm level. Interestingly, we find that financial leverage has little effect on market-level volatility asymmetry.

A. Market-Level vs. Firm-Level Volatility Asymmetry

We first construct an equal-weighted market index based on stocks in the Standard and Poor's (S&P) mid-cap 400 and small-cap 600 indices, as well as the S&P 500 index. We first compare the raw and unlevered volatility asymmetry of the index to that of the individual stocks that compose the index.

The results are reported in Table 7 and Figure 7. Table 7, Panel A shows the volatility asymmetry results for the index, while Panel B shows the results for the component stocks. Figure 7 graphically depicts the results.

We find that both the market index and component stocks show significant negative asymmetry, but the asymmetry for the market is much larger than that for the individual stocks. The V-shaped asymmetry metric for the market index is -14.49, compared to -3.77 for the component stocks. In other words, the market-level volatility asymmetry is 3.84 times that of the firm-level volatility asymmetry.

Our regressions show that, on average, market volatility rises by 4.64% more when return drops by 1%, as compared to a case in which return rises by 1%.[14] In contrast, firm volatility rises by only 1.21% more when return drops by 1%, as compared to a case in which return rises by 1%. This finding is qualitatively similar to the ones based on implied volatility in Dennis, Mayhew and Stivers (2006), and on return skewness on equity options in Bakshi, Kapadia and Madan (2003).

To understand what drives the difference in market-level and firm-level asymmetry, we use the unlevering approach. The daily returns of each stock are first unlevered based on an equation similar to equation (6).[15] The unlevered market return and volatility are then computed based on the unlevered returns of the component stocks. Even after unlevering, index volatility remains highly asymmetric. The volatility asymmetry is -12.89 with a t-statistic of -3.05. In contrast, the volatility asymmetry metric for the component stocks is -0.85 with a t-statistic of -1.58. Only 11% of the index volatility asymmetry is removed after unlevering, while 77% of the component stock volatility asymmetry is removed after unlevering.

Figure 7 plots this result. Unlevered market-level volatility still exhibits considerable negative asymmetry (Figure 7, Panel A, dotted line). However, unlevered firm-level volatility has no significant negative asymmetry (Figure 7, Panel B, dotted line).

In summary, our findings are as follows. Volatility asymmetry for the market index is much higher than firm-level asymmetry. As expected, we find that, after financial leverage is removed, firm-level volatility asymmetry is reduced to an insignificant level. However, even after financial leverage is removed from the component firms, market-level volatility asymmetry is still very substantial. This means that, while leverage explains firm-level asymmetry, it does not explain market-level volatility asymmetry.

Our finding is consistent with Aydemir, Gallmeyer and Hollifield (2006), in which the representative agent has a Campbell-Cochrane (1999) type preference. In their model, leverage effect is explicitly modeled and volatility is endogenously determined along with interest rates and time-varying risk premiums. On the market level, financial leverage is solely driven by aggregate risk and does not affect volatility beyond risk premium. On the firm level, leverage is influenced by idiosyncratic risk and may have a substantial impact on firm-level volatility asymmetry. Through simulations Aydemir et al. find that financial leverage is important for firm-level but not market-level volatility asymmetry. Our empirical work shows that financial leverage indeed accounts for a vast majority of firm-level volatility asymmetry although it does not account for market-level volatility asymmetry.

B. Relation to Covariance Asymmetry

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[14] This equals $\beta_{-} + \beta_{+}$ =-2.85 -1.79 = -4.64.

The difference in unlevered volatility asymmetry between the index and the component stocks is related to the empirical finding of covariance asymmetry. To better understand this, we calculate a diversification factor which also shows the average correlation of firm returns. A diversification factor can be defined as the ratio of the equal-weight-index return variance to the firm-level return variance (see for example Elton et al. (2003) and Vuolteenaho (2002)). Formally, the diversification factor is written as

$$\text{Diversification factor} = \frac{\operatorname{var}\left(\frac{1}{n}\sum_{i=1}^{n} r_i\right)}{\frac{1}{n}\sum_{i=1}^{n}\operatorname{var}(r_i)}, \qquad (12)$$

where r_i are the firms' returns, var is the variance, and n is the number of firms in the market portfolio. There is less diversification in the equal weighted index as the diversification factor increases.

The variance of equal-weight index returns can be expressed as a function of the elements of the cross-sectional covariance matrix:

$$\operatorname{var}\left(\frac{1}{n}\sum_{i=1}^{n} r_i\right) = \frac{1}{n^2}\sum_{i=1}^{n}\operatorname{var}(r_i) + \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1, j\neq i}^{n}\operatorname{cov}(r_i, r_j) = \frac{1}{n}\overline{\operatorname{var}} + \frac{n-1}{n}\overline{\operatorname{cov}}. \qquad (13)$$

where average variance and covariance are denoted by $\overline{\operatorname{var}}$ and $\overline{\operatorname{cov}}$. Defining the average correlation as $\overline{corr} \equiv \overline{\operatorname{cov}} / \overline{\operatorname{var}}$, the diversification factor can then be written as:

$$\frac{\operatorname{var}\left(\frac{1}{n}\sum_{i=1}^{n} r_i\right)}{\frac{1}{n}\sum_{i=1}^{n}\operatorname{var}(r_i)} = \frac{1}{n} + \left(\frac{n-1}{n}\right)\overline{corr}. \qquad (14)$$

From equation (14), it can be seen that for relatively large n, the diversification factor equals the average correlation.

A portfolio is said to display a negative asymmetric diversification factor if

$$\frac{\operatorname{var}\left(\frac{1}{n}\sum_{i=1}^{n} r_i \middle| r_m < 0\right)}{\frac{1}{n}\sum_{i=1}^{n}\operatorname{var}(r_i | r_m < 0)} > \frac{\operatorname{var}\left(\frac{1}{n}\sum_{i=1}^{n} r_i \middle| r_m > 0\right)}{\frac{1}{n}\sum_{i=1}^{n}\operatorname{var}(r_i | r_m > 0)}. \qquad (15)$$

This means that the diversification factor is higher when stocks are down than when stocks are up. We compute the diversification factors based on unlevered returns. This allows us to examine the difference in asymmetry between unlevered volatility of index and unlevered volatility of firms.

[15] Book value of debt is used here due to the absence of daily corporate bond index prices.

We find that the diversification factor is 0.38 when lagged returns are negative, and 0.29 when lagged returns are positive, i.e. diversification is worse in bad times than in good times. This means that the market portfolio displays a negative asymmetric diversification factor. This finding is consistent with our finding that market-level unlevered asymmetry is more negative than firm-level unlevered asymmetry. This also means that average correlation is higher when stocks are down than when stocks are up.

Because of the increase in correlation when returns are lower, there is market-level volatility asymmetry, even though there is no firm-level volatility asymmetry. Indeed, we have seen earlier that, after negative returns, average firm-level unlevered volatility does not increase (see Figure 7, Panel B, dotted line). However, the average unlevered correlation between firms increases, which implies an increase in unlevered covariance (i.e. covariance asymmetry). This causes the unlevered volatility of the market-level portfolio to increase, even though the average firm-level unlevered volatility does not. Notice that the covariance asymmetry we find is based upon unlevered returns rather than levered returns. In other words, we find that, on an unlevered basis,

$$\operatorname{var}\left(\frac{1}{n}\sum_{i=1}^{n} r_i \middle| r_m < 0\right) > \operatorname{var}\left(\frac{1}{n}\sum_{i=1}^{n} r_i \middle| r_m > 0\right), \text{ even though } \frac{1}{n}\sum_{i=1}^{n}\operatorname{var}\left(r_i \middle| r_m < 0\right) \approx \frac{1}{n}\sum_{i=1}^{n}\operatorname{var}\left(r_i \middle| r_m > 0\right).$$

The reduction in diversification when return is negative causes the unlevered market index to become more volatile during bad times even though an average unlevered firm's volatility remains the same. Covariance asymmetry is therefore related to our finding that index-level volatility asymmetry still exists after unlevering, while firm-level volatility asymmetry is eliminated after unlevering.

VII. Conclusion

Using an unlevering approach, this paper examines the source of volatility asymmetry in thousands of US firms. Our unlevering approach makes it possible to examine the impact of leverage on volatility asymmetry using a firm-level, as supposed to a portfolio-level, analysis. Using this approach, we document the key role of financial leverage in affecting volatility asymmetry at the firm level.

We have done extensive robustness checks to adjust for the effect of market leverage, including the use of the Merton-KMV model and the market price of debt with similar ratings. While we acknowledge that each method alone may not fully capture market leverage, consistency across different sets of results nonetheless suggests that financial leverage indeed accounts for most of the volatility asymmetry at the firm level.

While financial leverage explains most of the firm-level asymmetry in a large sample of US firms, it explains only a small portion of the index-level asymmetry. This is consistent with the general equilibrium model of Aydemir, Gallmeyer and Hollifield (2006), which shows that the determinants of firm-level and market-level volatility asymmetry are potentially different. We hope that our result will serve as a catalyst for more theoretical research that aims to understand the roles of leverage and risk premium in volatility asymmetry.

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Table 1
Summary Statistics

The data are from January 1986 to December 2003. Volatility is monthly standard deviation of the stocks computed based on daily returns. Returns are monthly returns of the stocks. Financial leverage is the ratio of equity to the total assets of the firm. Market capitalization is computed by multiplying monthly stock prices from CRSP by common shares outstanding. Beta is the beta of the stocks with respect to the CRSP market index. Book-to-market is the ratio of book value of equity to market value of equity. Operating leverage is the coefficient from a regression of the percentage change of EBIT (earnings before interest and tax) on the percentage change of sales revenue.

Variables	***Volatility***	***Returns***	***Financial Leverage***	***Market Capitalization***	***Beta***	***Book-to-market***	***Operating Leverage***
Number of Observations	767268	767268	767268	767268	767268	767268	474669
Mean	0.14	0.02	0.37	1535.33	0.70	0.68	1.84
Standard deviation	0.09	0.15	0.23	9408.92	1.24	0.52	1.72
Median	0.12	0.01	0.35	147.08	0.61	0.55	1.49

Table 2
Regressions of Change in Volatility on Returns
(Merton-KMV Unlevering)

Panel A shows results from the U-shape volatility asymmetry metric and is based on the following regression model:

$$\ln\frac{\sigma_{k,t}}{\sigma_{k,t-2}}=\sum_{i=1}^{10}\beta_i D_{i,t-1}+\varepsilon_t$$

where k = S or V. The raw volatility column shows the results when k=S, where the dependent variable is the log change in stock standard deviation from t-2 to t. The unlevered volatility column shows the results when k=V, where the dependent variable is the log change in standard deviation after the Merton-KMV unlevering in equation (5). $D_{i,t-1}$ is a dummy variable that equals one if returns r fall within a range at t-1, and zero otherwise. D_1 for r < –0.20; D_2 for –0.20 < r < –0.15; D_3 for –0.15 < r < –0.10; D_4 for –0.10 < r < –0.05; D_5 for –0.05 < r < 0; D_6 for 0 < r < 0.05; D_7 for 0.05 < r < 0.10; D_8 for 0.10 < r < 0.15; D_9 for 0.15 < r < 0.20; and D_{10} for r > 0.20. Robust t-statistics with firm-clustering are in parentheses. U-shape volatility asymmetry is the area between the two tails superposed with absolute returns on the x-axis (see Figure 1). The area will be negative (positive) if there is negative (positive) asymmetry. Statistical significance of the metric is established by deriving its distribution via Monte Carlo Integration. Percentage (%) reduction in asymmetry shows the extent to which volatility asymmetry is reduced after unlevering.

Panel B shows results from the V-shape volatility asymmetry metric and is based on the following regression model:

$$\ln\frac{\sigma_{k,t}}{\sigma_{k,t-2}}=\beta_- D_{-,t-1}\ln\frac{S_t}{S_{t-1}}+\beta_+ D_{+,t-1}\ln\frac{S_t}{S_{t-1}}+u_t$$

where D_- (D_+) is a dummy variable that takes on a value of 1 when t-1 returns are negative (positive), and 0 otherwise. This model fits a linear regression for negative returns and positive returns separately. V-shape volatility asymmetry is the area between the two lines superposed with absolute returns on the x-axis (see Figure 2). The number of firm-month observations is reported.

Panel A				**Panel B**			
	Raw Volatility	***Unlevered Volatility***	***% Reduction in Asymmetry***		***Raw Volatility***	***Unlevered Volatility***	***% Reduction in Asymmetry***
U-shaped Volatility Asymmetry	-2.9373	-0.2309	92.14	V-shaped Volatility Asymmetry	-2.4123	-0.1932	91.99
t-Statistic	(-4.00)	(-0.31)		t-Statistic	(-8.65)	(-1.92)	
β_1	0.1874	0.0547		β_-	-0.5841	-0.1137	
	(67.82)	(53.53)			(-7.23)	(-3.64)	
β_2	0.1041	0.0108		β_+	-0.1878	0.0519	
	(36.70)	(12.60)			(-4.97)	(6.78)	
β_3	0.0608	0.0000					
	(29.64)	(0.01)					
β_4	0.0207	-0.0086					
	(13.99)	(-18.17)					
β_5	-0.0167	-0.0155					
	(-13.65)	(-38.62)					
β_6	-0.0404	-0.0154					
	(-36.93)	(-43.36)					
β_7	-0.0457	-0.0098					
	(-31.69)	(-20.91)					
β_8	-0.0483	-0.0023					
	(-25.61)	(-3.90)					
β_9	-0.0454	0.0015					
	(-17.75)	(1.82)					
β_{10}	-0.0514	0.0213					
	(-25.60)	(32.29)					
F-Stat	1100.33	962.58		F-Stat	4177.73	1587.92	
Number of Observations	767268	767268		Number of Observations	767268	767268	

Table 3
Regressions of Change in Volatility on Returns
(Simple Unlevering)

Panel A shows results from the U-shaped volatility asymmetry metric and is based on the following regression model:

$$\ln\frac{\sigma_{k,t}}{\sigma_{k,t-2}} = \sum_{i=1}^{10}\beta_i D_{i,t-1} + \varepsilon_t$$

where k = S or V. The raw volatility column shows the results when k=S, where the dependent variable is the log change in stock standard deviation from t-2 to t. The unlevered volatility column shows the results when k=V, where the dependent variable is the log change in standard deviation unlevered through the simple unlevering model in equation (6). $D_{i,t-1}$ is a dummy variable that equals one if returns r fall within a range at t-1, and zero otherwise. D_1 for $r < -0.20$; D_2 for $-0.20 < r < -0.15$; D_3 for $-0.15 < r < -0.10$; D_4 for $-0.10 < r < -0.05$; D_5 for $-0.05 < r < 0$; D_6 for $0 < r < 0.05$; D_7 for $0.05 < r < 0.10$; D_8 for $0.10 < r < 0.15$; D_9 for $0.15 < r < 0.20$; and D_{10} for $r > 0.20$. Robust t-statistics with firm-clustering are in parentheses. U-shaped volatility asymmetry is the area between the two tails superposed with absolute returns on the x-axis (see Figure 1). The area will be negative (positive) if there is negative (positive) asymmetry. Statistical significance of the metric is established by deriving its distribution via Monte Carlo Integration. Percentage (%) reduction in asymmetry shows the extent to which volatility asymmetry is reduced after unlevering.

Panel B shows results from the V-shaped volatility asymmetry metric and is based on the following regression model:

$$\ln\frac{\sigma_{k,t}}{\sigma_{k,t-2}} = \beta_- D_{-,t-1}\ln\frac{S_t}{S_{t-1}} + \beta_+ D_{+,t-1}\ln\frac{S_t}{S_{t-1}} + u_t$$

where D_- (D_+) is a dummy variable that takes on a value of 1 when t-1 returns are negative (positive), and 0 otherwise. This model fits a linear regression for negative returns and positive returns separately. The raw volatility column shows the results when k=S, where the dependent variable is the log change in stock standard deviation from t-2 to t. The unlevered volatility column shows the results when k=V, where the dependent variable is the log change in standard deviation unlevered through the simple unlevering model in equation (6). V-shaped volatility asymmetry is the area between the two lines superposed with absolute returns on the x-axis (see Figure 2). The number of firm-month observations is reported.

Panel A

	Raw Volatility	***Unlevered Volatility***	***% Reduction in Asymmetry***
U-shaped Volatility Asymmetry	-4.1545	-0.7152	82.79
t-Statistic	(-5.65)	(-0.96)	
β_1	0.2727	0.0831	
	(33.56)	(10.12)	
β_2	0.1461	0.0413	
	(18.05)	(5.10)	
β_3	0.0968	0.0263	
	(17.48)	(4.67)	
β_4	0.0410	0.0026	
	(11.61)	(0.73)	
β_5	-0.0049	-0.0190	
	(-1.96)	(-7.55)	
β_6	-0.0434	-0.0361	
	(-19.94)	(-16.49)	
β_7	-0.0456	-0.0182	
	(-14.53)	(-5.73)	
β_8	-0.0574	-0.0094	
	(-12.58)	(-2.05)	
β_9	-0.0529	0.0153	
	(-7.61)	(2.13)	
β_{10}	-0.0799	0.0397	
	(-11.52)	(5.43)	
F-Stat	236.96	74.02	
Number of Observations	113693	113693	

Panel B

	Raw Volatility	***Unlevered Volatility***	***% Reduction in Asymmetry***
V-shaped Volatility Asymmetry	-3.6398	-0.3975	89.08
t-Statistic	(-7.34)	(-0.81)	
β_-	-0.8097	-0.1606	
	(-6.07)	(-1.22)	
β_+	-0.3550	0.0334	
	(-4.13)	(0.39)	
F-Stat	1444.38	46.97	
Number of Observations	141714	141714	

Table 4
Regression of Change in Volatility on Returns (One-month Lag)

Panel A shows results from the U-shaped volatility asymmetry metric and is based on the following regression model:

$$\ln\frac{\sigma_{k,t}}{\sigma_{k,t-1}} = \sum_{i=1}^{10}\beta_i D_{i,t-1} + \varepsilon_t$$

where k = S or V. The raw volatility column shows the results when k=S, where the dependent variable is the log change in stock standard deviation from t-1 to t. The unlevered volatility column shows the results when k=V, where the dependent variable is the log change in standard deviation unlevered through the Merton-KMV model in equation (5). $D_{i,t-1}$ is a dummy variable that equals one if returns r fall within a range at t-1 and zero otherwise. D_1 for r < –0.20; D_2 for –0.20 < r < –0.15; D_3 for –0.15 < r < –0.10; D_4 for –0.10 < r < –0.05; D_5 for –0.05 < r < 0; D_6 for 0 < r < 0.05; D_7 for 0.05 < r < 0.10; D_8 for 0.10 < r < 0.15; D_9 for 0.15 < r < 0.20; and D_{10} for r > 0.20. Robust t-statistics with firm-clustering are in parentheses. U-shape volatility asymmetry is the area between the two tails superposed with absolute returns on the x-axis (see Figure 1). The area will be negative (positive) if there is negative (positive) asymmetry. Statistical significance of the metric is established by deriving its distribution via Monte Carlo Integration. Percentage (%) reduction in asymmetry shows the extent to which volatility asymmetry is reduced after unlevering.

Panel B shows results from the V-shaped volatility asymmetry metric and is based on the following regression model:

$$\ln\frac{\sigma_{k,t}}{\sigma_{k,t-1}} = \beta_- D_{-,t-1}\ln\frac{S_t}{S_{t-1}} + \beta_+ D_{+,t-1}\ln\frac{S_t}{S_{t-1}} + u_t$$

where D_- (D_+) is a dummy variable that takes on a value of 1 when t-1 returns are negative (positive), and 0 otherwise. This model fits a linear regression for negative returns and positive returns separately. V-shaped volatility asymmetry is the area between the two lines superposed with absolute returns on the x-axis (see Figure 2). The number of firm-month observations is reported.

Panel A

	Raw Volatility	*Unlevered Volatility*	*% Reduction in Asymmetry*
U-shaped Volatility Asymmetry	-3.1594	-0.1211	96.17
t-Statistic	(-4.30)	(-0.16)	
β_1	-0.0857	0.0124	
	(-29.11)	(23.01)	
β_2	0.0305	0.0035	
	(10.98)	(6.28)	
β_3	0.0523	0.0015	
	(26.91)	(3.59)	
β_4	0.0687	-0.0016	
	(48.10)	(-4.85)	
β_5	0.0816	-0.0045	
	(65.27)	(-16.35)	
β_6	0.0499	-0.0055	
	(47.24)	(-22.41)	
β_7	-0.0292	-0.0042	
	(-21.55)	(-12.90)	
β_8	-0.0892	-0.0025	
	(-50.29)	(-6.04)	
β_9	-0.1425	-0.0022	
	(-57.64)	(-3.90)	
β_{10}	-0.2734	0.0014	
	(-115.87)	(3.54)	
F-Stat	2151.09	236.33	
Number of Observations	767268	767268	

Panel B

	Raw Volatility	*Unlevered Volatility*	*% Reduction in Asymmetry*
V-shaped Volatility Asymmetry	-2.3171	-0.0835	96.40
t-Statistic	(-6.65)	(-2.26)	
β_-	-0.0478	-0.0287	
	(-0.46)	(-2.64)	
β_+	-0.6937	0.0020	
	(-16.66)	(0.42)	
F-Stat	3775.78	210.01	
Number of Observations	768340	768340	

Table 5
Volatility Asymmetry based on Different Financial Leverage, Beta, Book-to-market, and Operating Leverage Quintiles

We compute each firm's financial leverage, beta, book-to-market, and operating leverage based on its time-series data. Stocks are then sorted into quintiles based on the cross-section of these firm factors. This table reports the average volatility asymmetry for stocks in each quintile of firm factors. Panel A presents the average volatility asymmetry when firms are sorted by financial leverage (the ratio of total market debt to total firm value). Panel B shows the average volatility asymmetry when firms are sorted by beta. Beta is calculated from regression of individual firm returns on market index returns. Panel C shows the average volatility asymmetry when firms are sorted by book-to-market ratio (book equity divided by market capitalization). Panel D shows the average volatility asymmetry when firms are sorted by operating leverage, i.e. the percentage change in EBIT (earnings before interest and taxes) for a given percentage change in sales revenue. Each firm's volatility asymmetry is computed using V-shaped volatility asymmetry as illustrated in Figure 2. Robust t-statistics corrected for firm-level clustering are in the parentheses.

	Panel A: Financial Leverage		**Panel B: Beta**		**Panel C: Book-to-market**		**Panel D: Operating Leverage**	
Portfolio	***Mean Financial Leverage***	***Volatility Asymmetry***	***Mean Beta***	***Volatility Asymmetry***	***Mean Book-to-Market***	***Volatility Asymmetry***	***Mean Operating Leverage***	***Volatility Asymmetry***
P1	0.2274	-2.7767	0.3153	-3.3159	0.2526	-3.3742	0.5672	-3.2386
		(-15.52)		(-18.50)		(-18.86)		(-18.98)
P2	0.3946	-3.0724	0.5762	-3.3930	0.4525	-3.0172	1.1386	-3.3815
		(-17.18)		(-18.94)		(-16.87)		(-19.82)
P3	0.5119	-3.2512	0.7725	-3.2442	0.6297	-3.1179	1.5383	-3.4117
		(-18.18)		(-18.10)		(-17.43)		(-20.00)
P4	0.6235	-3.3867	0.9845	-3.3096	0.8412	-2.8955	2.1231	-3.0957
		(-18.93)		(-18.47)		(-16.19)		(-18.15)
P5	0.7850	-3.6238	1.5153	-2.8481	1.4873	-3.7060	3.5176	-3.1753
		(-20.26)		(-15.89)		(-20.72)		(-18.61)
P1-P5		0.8470		-0.4678		0.3319		-0.0633
P-value (P1=P5)		0.001		0.065		0.190		0.793
Number of Obs		1970		1970		1970		1695

Table 6

Regression of Firm Volatility Asymmetry on Financial Leverage, Beta, Book-to-market and Operating Leverage

This table presents coefficients from cross-sectional regressions of volatility asymmetry on various factors and characteristics. To calculate individual firm volatility asymmetry, we first fit a linear regression for negative returns and positive returns separately. The difference in slopes between the "negative" segment and the "positive" segment is a measure of V-shaped volatility asymmetry for each firm, as illustrated in Figure 2. Individual firm volatility asymmetry is regressed upon time-series averages of the individual firm's financial leverage, beta, book-to-market and operating leverage. Financial leverage refers to the ratio of total market debt to total firm value. Beta is calculated from regression of individual firm returns on market index returns. Book-to-market ratio is book value divided by market capitalization of the firm. Operating leverage is defined as the percentage change in EBIT (earnings before interest and taxes) for a given percentage change in sales revenue. Robust t-statistics corrected for firm-level clustering are in parentheses.

	Volatility Asymmetry	***Volatility Asymmetry***	***Volatility Asymmetry***	***Volatility Asymmetry***	***Volatility Asymmetry***	***Volatility Asymmetry***	***Volatility Asymmetry***	***Volatility Asymmetry***
Constant	-2.4850	-3.5755	-2.9603	-3.3708	-2.7641	-2.4888	-2.7616	-3.0524
	(-12.53)	(-18.29)	(-18.54)	(-20.58)	(-7.72)	(-12.72)	(-12.19)	(-8.41)
Financial Leverage	-1.4497				-1.2717	-1.3397	-1.2592	-1.0988
	(-3.75)				(-2.90)	(-2.85)	(-3.24)	(-2.08)
Beta		0.4243			0.2264			0.2513
		(2.43)			(1.15)			(1.33)
Book-to-market			-0.3574			-0.0711		0.0236
			(-1.82)			(-0.30)		(0.09)
Operating Leverage				0.0621			0.0793	0.0740
				(0.84)			(1.07)	(1.00)
F-value	F(1, 1969) = 14.06	F(1, 1969) = 5.91	F(2, 1969) = 3.32	F(1, 1969) = 0.7	F(2, 1969) = 8.57	F(1, 1969) = 7.21	F(3, 1969) = 10.53	F(1, 1969) = 4.96
P-value	0.0002	0.0152	0.0688	0.4019	0.0002	0.0008	0.0012	0.0020
Number of Observations	1970	1970	1970	1695	1970	1970	1695	1695

Table 7
Index vs Component Stock Volatility Asymmetry

We construct an equal-weighted market index based upon stocks in the Standard and Poor's (S&P) mid-cap 400, small-cap 600 indices and the S&P 500 index. This table shows the regression and volatility asymmetry results on the index and on the component stocks based on the following model:

$$\ln\frac{\sigma_{k,t}}{\sigma_{k,t-2}} = \beta_{-} D_{-,t-1} \ln\frac{S_t}{S_{t-1}} + \beta_{+} D_{+,t-1} \ln\frac{S_t}{S_{t-1}} + u_t.$$

where k = S or V, and D_- (D_+) is a dummy variable that takes on a value of 1 when t-1 returns are negative (positive), and 0 otherwise. This model fits a linear regression for negative returns and positive returns separately. The V-shaped volatility asymmetry reported is illustrated in Figure 2. Panel A shows the results for the index. Panel B shows the relation for the panel of individual stocks that compose the index. The raw volatility column shows the results when k=S, where the dependent variable is the log change in stock standard deviation from t-2 to t. The unlevered volatility column shows the results when k=V, where the dependent variable is the log change in unlevered standard deviation. To unlever index returns, the daily returns of each stock are first unlevered based on equation (6). The unlevered market return and volatility are then computed based on the unlevered returns of the component stocks. To unlever the component stock returns, we use the simple unlevering model in equation (6).

	Panel A				**Panel B**		
	Raw Volatility	***Unlevered Volatility***	***% Reduction in Asymmetry***		***Raw Volatility***	***Unlevered Volatility***	***% Reduction in Asymmetry***
Index Volatility Asymmetry	-14.4872	-12.8928	11.01	Component Stock Volatility Asymmetry	-3.7657	-0.8542	77.32
t-Statistic	(-4.09)	(-3.05)		t-Statistic	(23.63)	(-1.58)	
β_-	-2.8503	-2.2885		β_-	-0.8256	-0.2423	
	(-3.52)	(-2.86)			(-40.97)	(-11.98)	
β_+	-1.7856	-1.8372		β_+	-0.3794	-0.0310	
	(-2.64)	(-2.74)			(-23.23)	(-1.89)	
Number of Observations	212	212		Number of Observations	90315	90315	

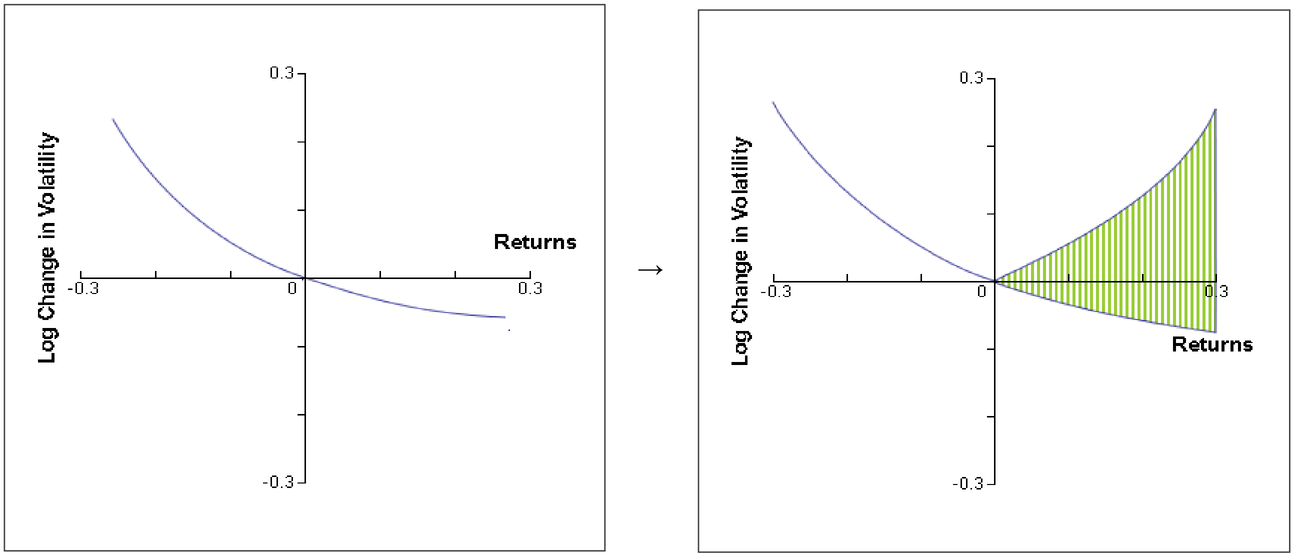

Figure 1. A graphical illustration of the U-shaped volatility asymmetry metric. U-shaped volatility asymmetry is the (signed) area between the two curves on the positive side of the x-axis (shaded area). The area will be negative (positive) if there is negative (positive) asymmetry.

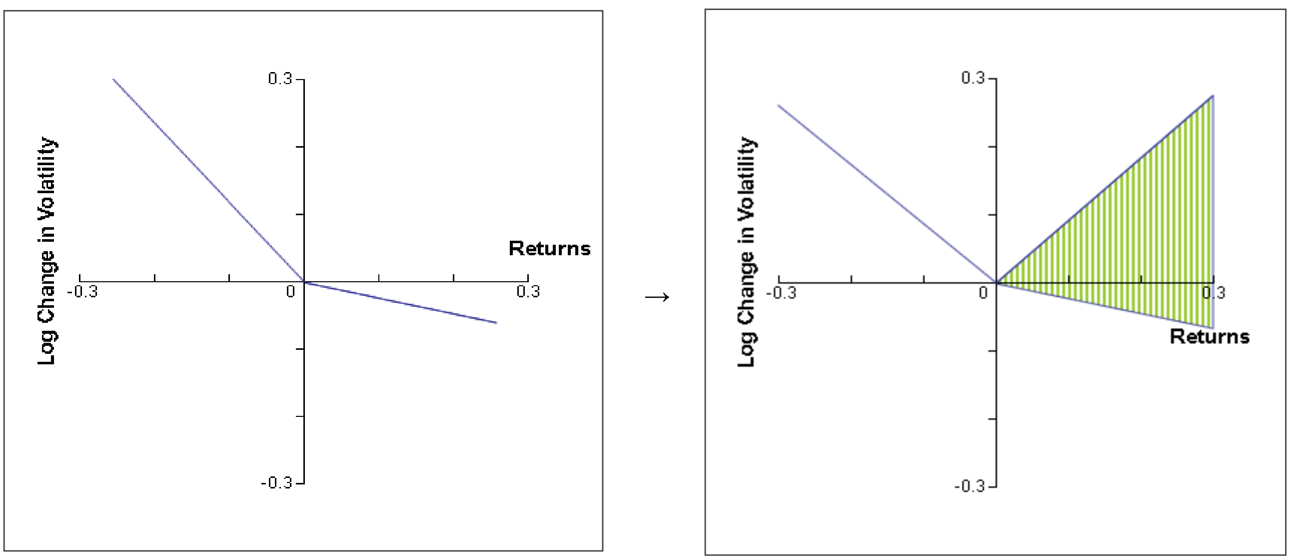

Figure 2. A graphical illustration of the firm V-shaped volatility asymmetry metric. V-shaped volatility asymmetry is the (signed) area between the two curves on the positive side of the x-axis (shaded area up until returns of 0.3). The area will be negative (positive) if there is negative (positive) asymmetry.

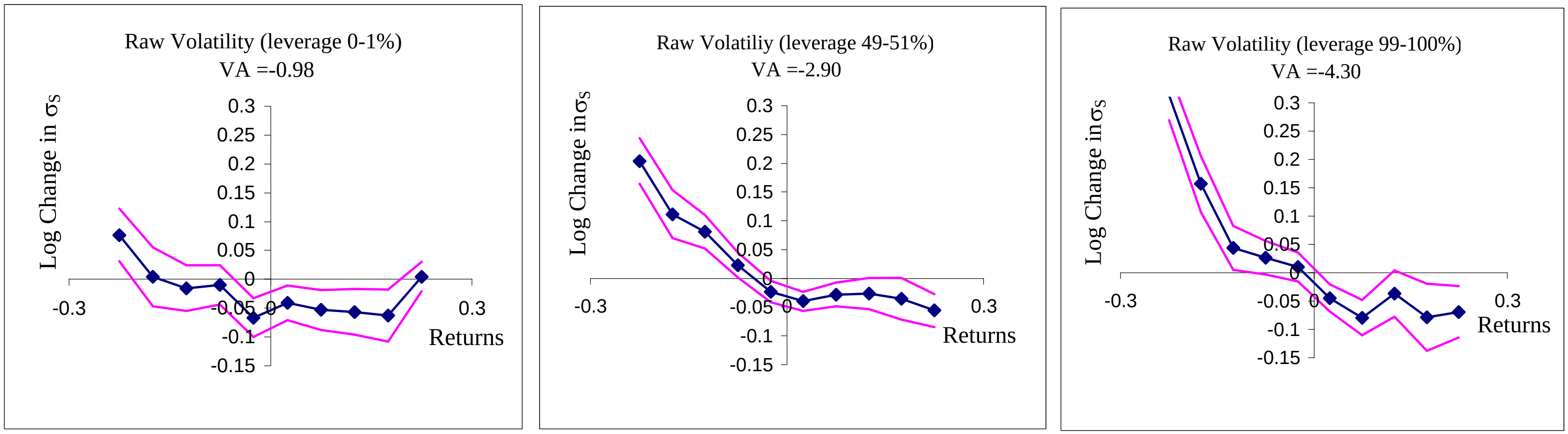

Figure 3. The response of volatility changes from time t-2 to t to returns at t-1 for firms at different financial leverage levels. For all panels, the dependent variable is the percentage change in stock standard deviation (σ_S). The independent variables are dummy variables $D_{i,t-1}$ that represent a range of returns at t-1. Panel A shows the results for firms in the lowest 1 percentile of financial leverage level. Panel B shows the results for firms in the median (i.e. 49-51 percentile) of financial leverage level. Panel C shows the results for firms in the highest 1 percentile of financial leverage level. Volatility Asymmetry (VA) refers to the level of U-shaped asymmetry metric, as illustrated in Figure 1. The band around the curves is a two standard error confidence interval (robust standard errors with firm clustering).

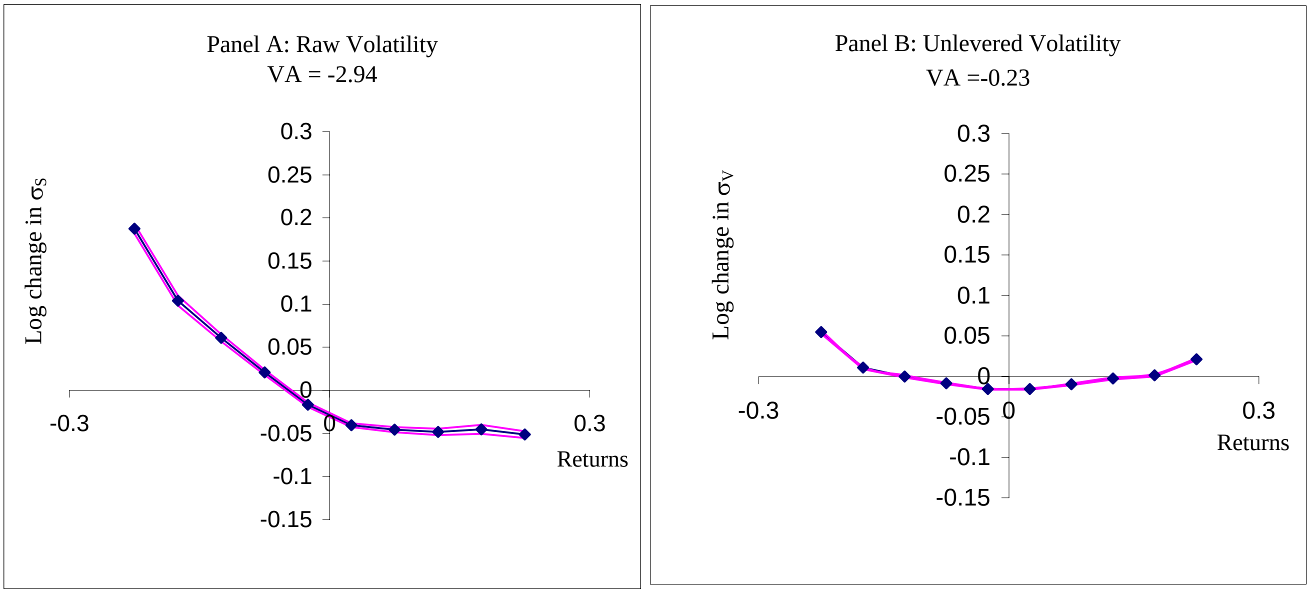

Figure 4. The response of volatility changes from time t-2 to t to returns at t-1. This is a plot of the results from table 2, based on Merton-KMV unlevering. In the left panel, the dependent variable is the log change in stock standard deviation (σ_S). In the right panel, the dependent variable is the percent change in stock standard deviation that was transformed by equation (5) to account for financial leverage using Merton-KMV method (σ_V). Volatility Asymmetry (VA) refers to the level of U-shaped asymmetry metric as illustrated in Figure 1. The band around the curves is a two standard error confidence interval (robust t-statistics wtih firm clustering).

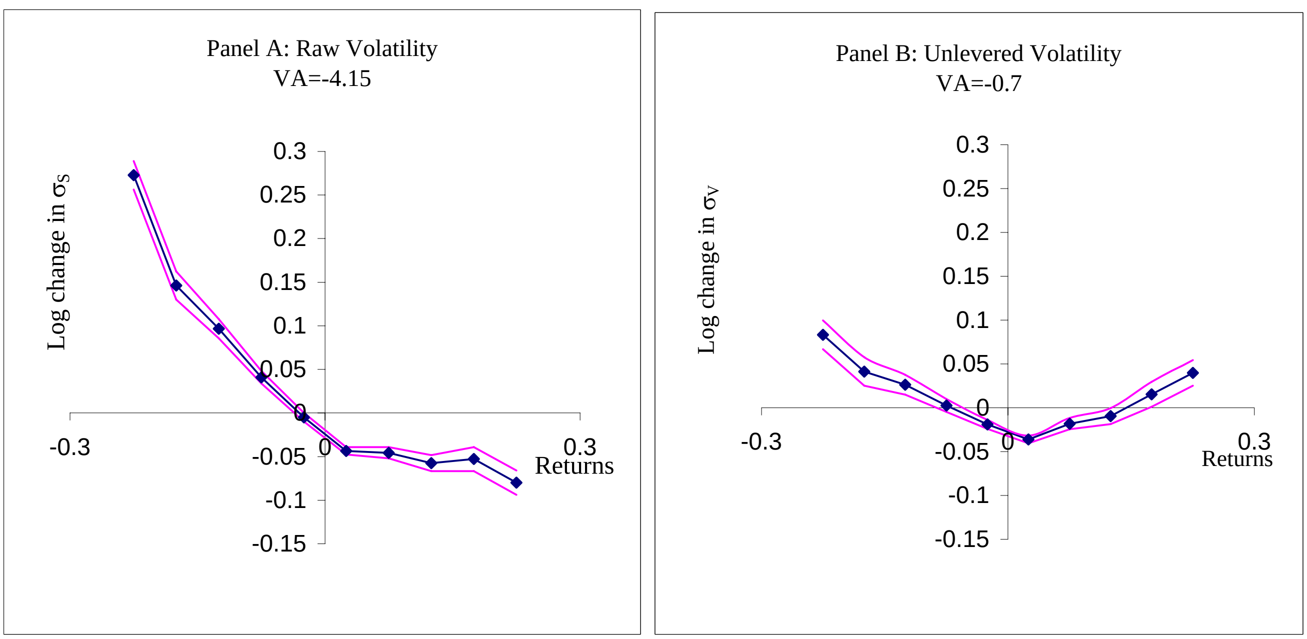

Figure 5. The response of volatility changes from time t-2 to t to returns at t-1. This is a plot of the results from table 3, based on simple unlevering. In the left panel, the dependent variable is the percent change in stock standard deviation (σ_S). In the right panel, the dependent variable is the percent change in stock standard deviation that was transformed by the simple unlevering model in equation (6) to account for financial leverage (σ_V). Volatility Asymmetry (VA) refers to the level of U-shaped asymmetry metric as illustrated in Figure 1. The band around the curves is a two standard error confidence interval (robust t-statistics wtih firm clustering).

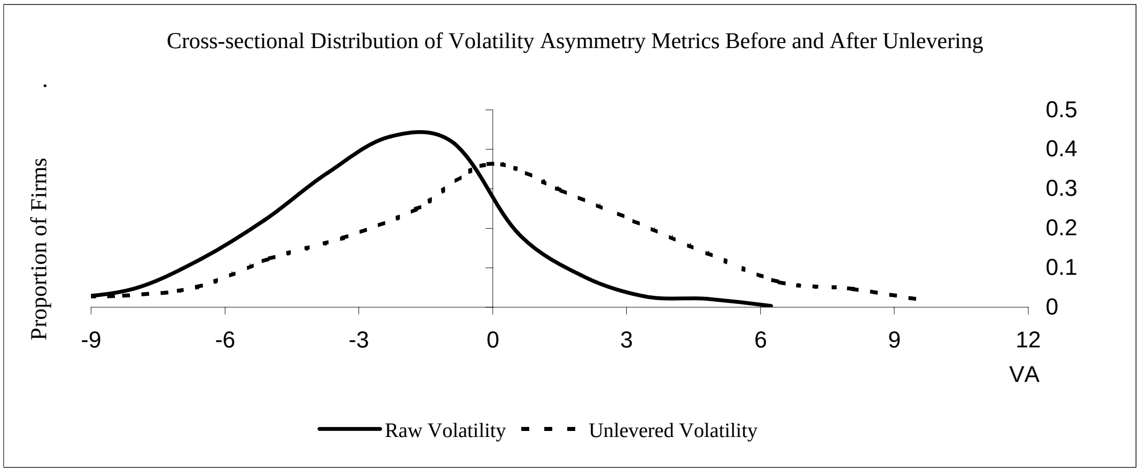

Figure 6. The figure plots the distribution of the firm V-shaped volatility asymmetry metric for all of our firms. The firm V-shape volatility asymmetry metric is computed using the following equation:

$$\ln\frac{\sigma_{k,t}}{\sigma_{k,t-2}} = \beta_- D_{-,t-1} \ln\frac{S_t}{S_{t-1}} + \beta_+ D_{+,t-1} \ln\frac{S_t}{S_{t-1}} + \varepsilon_t.$$

where k=S or V, and D_- (D_+) is a dummy variable that takes on a value of 1 when t-1 returns are negative (positive), and 0 otherwise. This model fits a linear regression for negative returns and positive returns separately. The difference in slopes between the "negative" segment and the "positive" segment is the volatility asymmetry metric (see Figure 2). Raw volatility uses as the dependent variable the log change in stock standard deviation, σ_S. Unlevered volatility uses as the dependent variable the log change in unlevered volatility $\sigma_{V,}$ i.e. stock standard deviation that is transformed by equation (5) to account for financial leverage using Merton-KMV method.

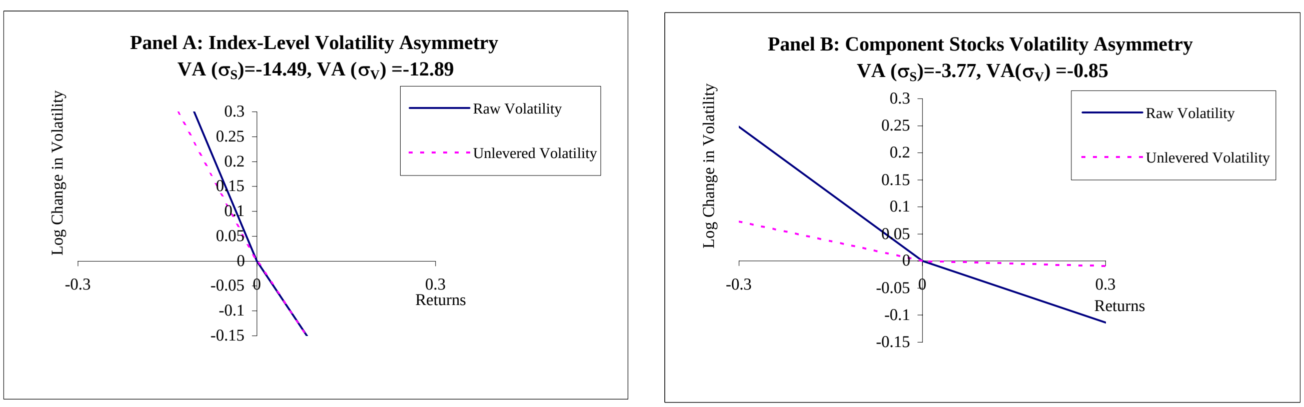

Figure 7. The response of volatility changes from time t-2 to t to returns at t-1 using the following equation:

$$\ln\frac{\sigma_{k,t}}{\sigma_{k,t-2}} = \beta_- D_{-,t-1} \ln\frac{S_t}{S_{t-1}} + \beta_+ D_{+,t-1} \ln\frac{S_t}{S_{t-1}} + \varepsilon_t$$

where k=S or V, and D_- (D_+) is a dummy variable that takes on a value of 1 when t-1 returns are negative (positive), and 0 otherwise. This model fits a linear regression for negative returns and positive returns separately. The difference in slopes between the "negative" segment and the "positive" segment is the volatility asymmetry (VA) metric (see Figure 2). Panel A shows the relation for the index. Panel B shows the relation for the panel of individual stocks that compose the index. For raw volatility, the dependent variable is the log change in σ_S. For unlevered volatility, the dependent variable is the log change in σ_V, i.e. stock standard deviation that was transformed by equation (6) to account for financial leverage.

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