THE VOLATILITY OF THE FIRM'S ASSETS

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Abstract:

This paper investigates the conditional volatility of the firm's assets in contrast to existing studies that focus primarily on equity volatility. Using a novel dataset that allows us to map out significant portions of the capital structure, we examine the volatility properties of asset returns as calculated by a weighted average of equity, bond and loan prices. The two fundamental findings in this paper are that asset volatility is time-varying and that financial leverage matters and has a large influence on equity volatility. Within this backdrop, several new results emerge. First, leverage plays a more important role than previously thought in explaining the well-documented asymmetric volatility effect. Second, equity volatility possesses both a transitory component due primarily to asset volatility and a more permanent component due to financial leverage. Third, in terms of a breakdown of the determinants of equity volatility, we relate implied equity volatility levels and changes to different components of estimated asset volatility (i.e., both idiosyncratic and market, including lagged volatility and asymmetric return shocks) and to leverage at the firm level.

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I. Introduction

Understanding why asset (i.e., firm value) volatility changes through time is a fundamental issue in finance. This is because asset volatility plays a key role both in determining capital structure valuation[1] and the standard return/risk tradeoff independent of financial leverage[2]. Surprisingly, very little, however, is known about the cross-sectional and time-series properties of asset volatility. Due to the lack of comprehensive data on public debt, the focus of the finance literature has been to analyze equity return volatility with occasional references to the "leverage effect".

This paper provides a detailed examination of asset volatility across a broad cross-section of publicly traded firms using a novel dataset that includes prices and other information on equities, publicly traded debt and syndicated loans. This dataset allows us to map out significant portions of the firm's capital structure. Viewing the firm's assets as a portfolio of the individual securities within the firm (a la Modigliani and Miller (1961)), we are able to estimate the return on the firm's assets from a weighted-average return on these individual components. Measurement error aside, this provides a distinct advantage to the existing literature.

Specifically, we can directly address questions relating to asset volatility whereas previously they were implied from a joint analysis of equity volatility using limited data on a firm's debt and overly simple models of a firm's capital structure. Because these models are most probably not accurate descriptions of reality, the link between equity and asset volatility is broken. As just one illustration, one of the implications of these models is that the individual securities may have nonstationary and complex, nonlinear forms for expected returns as risk gets shifted across security classes within the firm (as the probability of distress moves around). The underlying asset return (i.e., the portfolio of these securities), however, is more likely to be better behaved and more conducive for standard empirical analysis.

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[1] e.g., see Black and Scholes (1973), Merton (1974), and the proliferation in credit market research over the last decade, for example, Black and Cox(1976), Leland and Toft(1996), Longstaff and Schwartz(1995), Collin-Dufresne and Goldstein(2002)

[2] e.g., French, Schwert and Stambaugh (1987), Glosten, Jagannathan, and Runkle(1993), Whitelaw (1994), Lettau and Ludvigson(2003), Brandt and Kang(2004), Ghysels, Santa-Clara and Valkanov (2005), Bali and Peng (2004), and Guo and Whitelaw (2006)

As an application, we are able to provide new evidence on a heavily researched area, namely the stylized fact that stock return volatility rises after stock prices fall. There has been considerable debate about how much of this effect is due to financial leverage as a result of the stock price fall (i.e., "leverage effect") versus time-varying risk premia (i.e., "volatility feedback"). (See, for example, Black (1976), Christie (1982), French, Schwert, and Stambaugh (1987), Campbell and Hentschel (1992), Engle and Ng (1993), Duffee (1995), Bekaert and Wu (2000) and Wu (2001), among others). Moreover, now added to the fray are behavioral economists who argue that this stylized fact may be due to noise trading on the part of irrational agents. (For some recent discussion of this literature with application to idiosyncratic volatility, see, for example, Chen, Hong and Stein (2001), Goyal and Santa Clara (2003), and Hong and Stein (2003)). We provide an estimated breakdown of how much of a firm's equity volatility is due to the various components, such as financial leverage, risk premia, time-varying asset volatility, and so forth. The main conclusion is that the level of conditional equity volatility of a firm is mostly described by financial leverage, the lagged asset volatility of markets, and the lagged asset volatility of the firm. In contrast, changes in this equity volatility are explained by financial leverage, asymmetric shocks described by the current stock market return (i.e., risk premia effect) and the firm's asset return (i.e., idiosyncratic risk effect), and not mean-reversion in volatility.

This paper provides several additional contributions to our existing empirical knowledge of firm volatility. First, in terms of new stylized facts, we document a very strong negative relation between asset volatility and leverage. This is a potentially important finding because it suggests one may have to be careful of looking at equity volatility and leverage together. In other words, they are jointly determined by the volatility of the firm's assets as many corporate finance theories would ex ante suggest. Second, while there is clear evidence of the existence of a leverage effect, most of the explained variation of volatility can be attributed to time-variation in the underlying idiosyncratic assets of the firm. This evidence is confirmed both at the portfolio and individual firm level and poses some challenges for future research. Third, consistent with the literature that documents both transitory and permanent components to conditional equity volatility, we show that the transitory component is due primarily to asset volatility and the more permanent component is due to financial leverage.

This paper is organized as follows. Section 2 provides a detailed analysis of the data. In particular, we describe how each firm's capital structure is mapped out given the various data sources. Special attention is devoted to the staleness of the data. Some important and new stylized facts are provided. Section 3 presents the time-varying properties of volatility both at the individual, industry and individual firm level. As an application, in Section 4, we estimate the contribution of various proposed sources of volatility to a firm's equity volatility. Section 5 concludes.

II. Data Description

In order to map out the capital structure and construct the returns on a firm's assets, we need to utilize a number of datasets, including (i) CRSP for equity prices, (ii) the Bridge EJV database from Reuters for corporate bond prices and details, (iii) the FISD from Mergent for additional corporate bond details and checking of the EJV data, (iv) Dealscan and the mark-to-market pricing services from Loan pricing Corporation for loans, (v) Compustat for the face value of debt and other accounting information, and (vi) Bloomberg for fact checking discrepancies. The construction of the asset return series and the description of the data are provided in detail in Choi (2008). As a result, we summarize the less well-known data and the asset return construction briefly below, and then provide some stylized facts.

A. Data Sources

The most important data source in this paper are the corporate bond prices given in the EJV database of Reuters. Each day, the bid and ask prices are gathered from dealers in the marketplace and then aggregated to one set of bid and ask prices. As an indication of its importance in the corporate bond market, most participants use this database to mark their books each day. In terms of the sample period, the database covers the period from July 1991 to December 2007, although the data is quite spotty prior to the mid 1990s.

The bond data requires substantial cleaning. For example, a number of bonds are issued under rule 144a before later being exchanged to the public market. This creates numerous periods of double counting in the dataset. In addition, bonds are called, converted and tendered which also leads to errors. To the extent possible, the data is carefully matched against the Mergent Fixed Income Securities Database (FISD) and, when appropriate, hand checked against data provided in Bloomberg and 10-K filings (especially around firms showing a change in their outstanding debt). We selected bond issuers that have CRSP stock return and Compustat accounting information, and that were nonfinancial in nature (due to the degree of leverage and what that means for financial firms).[3]

The two most serious problems with the bond price data are the potential for staleness and matrix pricing. With respect to staleness, many of the bonds do not trade on a frequent basis, so the daily quotes reflect average bid prices of the dealers for untraded securities. Because these bids are only indicative in the marketplace, updating is perhaps less important than other security markets. This point aside, these updates may reflect "sloppy" matrix pricing, leading to excessive comovement within a firm's securities and possibly across similar types of firms. Section II.C below will provide descriptive statistics on some of these issues. Nevertheless, to alleviate the problem, we (i) use monthly data closest to the end of month as these prices tend to be more carefully updates (Warga (1991)), and (ii) only look at firms with at least $250mm of total assets. This latter restriction avoids levered firms with small bond issues that rarely trade.

Table 1 summarizes the coverage of our sample relative to the usual CRSP/Compustat universe. It also shows the effect of dropping financial firms and firms with a "low" amount of market value of their assets. The table reports several summary statistics.

Table 1A shows that the primary difference between the two samples is one of asset size. For example, restricting the comparison to firms with debt, the median size of the firm's market value of assets is $2.19 billion for our universe versus $0.31 billion for the CRSP universe. While this fact is marginally related to our restricting the sample to $0.25 billion size firms, the primary reason is that the bond data base does not include small firms with small amounts of debt. In particular, the median market value of assets/equity ratio (i.e., leverage ratio) is 1.5 versus 1.25 in the two samples. At first glance, this might suggest that our bond universe is small. This is not the case, however, as we overlap with over 90% of the bonds in the Mergent FISD. Of some note, Table 1B shows the leverage within our sample across ratings classes, namely with median leverage ratio of (1.05, 1.16, 1.31, 1.48, 1.65, 1.96, and 3.41) for (AAA, AA, A, BBB, BB, B and CCC), respectively.

[3] Firms with substantial financial operations, such as General Electric, General Motors and Ford, were also

More importantly, in terms of matching our firms to those in Compustat, the public bonds in our sample cover on average 56% of Compustat's long-term debt firm by firm. Table 1B looks at this calculation more closely by calculating the coverage across firms in different ratings classes. The table suggests the coverage is much higher for high-yield firms than for investment grade firms. For example, the AAA and AA firms' percentages are 24.8% and 43.7%, respectively whereas the B and CCC (and lower) firms have 73.2% and 68.6% coverage, respectively (For a more detailed description of the characteristics of the data, see Choi (2008).)

As shown in Table 1, only a portion of the debt of a company comes in the form of publicly traded bonds. A considerable portion can be explained by bank loans. The major sources for the bank loan data are Dealscan (going back to 1987), and, for the pricing and more detailed characteristics of the loans, the Loan Syndications and Trading Associations (LSTA) and Loan pricing Corporation (LPC). There have been some analyses of the quality of the pricing data, most notably Taylor and Sansone (2007). The main conclusion that, at least for cases where traded prices are available, the average dealer marks are representative. One drawback of the data is (i) that it is available over a much shorter time period, and (ii) that active volume, and thus reliable secondary prices, occur only for leveraged loans. Of course, bank loans of investment grade firms tend to trade around par if their coupon rates float. For the coincident period in which we have access to both bond and loan data, Table 1A shows that over 94% of the capital structure is covered.

B. Construction of Asset Returns

Assuming Modigliani and Miller (1961), the firm's assets and liabilities exactly offset, so that we can represent the return on a firm's assets by its weighted average return of its underlying financial claims. In order to calculate these returns, we therefore need to (i) map out the firm's entire capital structure (and its corresponding securities), and (ii) record prices and interim payments of each piece of the capital structure.

The capital structure for each firm is mapped out month by month using all the above datasets. Because of the dynamic nature of the firm's capital structure, in particular, the debt amount outstanding changes for a number of reasons, the datasets are not always

excluded.

aligned.[4] As mentioned in II.A. above, discrepancies in amounts outstanding or other differences in the data were generally refereed manually using Bloomberg's corporate actions item or 10-K filings. For the period which we have both bond and loan data, Table I shows that we can identify most of the capital structure of the firm. For periods in which we have only bond data, we feel comfortable therefore assuming the difference between long-term debt and the public debt are loans.

Given this mapping, how do we measure the returns on the assets of the firm? Appealing to Modigliani and Miller (1961), the value of the real assets can be represented by the value of the financial assets, so that two identical firms with quite different capital structures can have the same value of its underlying assets. This allows us to write the return on the assets of the firm as a weighted average of the return on each of the firm's financial assets, the weights being determined by the relative value of each of the financial assets.

In terms of each individual component, equity returns are calculated the usual way from month to month, as next period's price plus any dividends paid divided by the current price. Bond returns are calculated similarly each period from the quoted bond prices, coupon and accrued interest.[5] The more tricky calculation revolves around the returns of bank loans. On the positive side, because bank loans reside towards the top of the capital structure (or at least until quite recently), their price variation is not particularly large.[6] On the negative side, there are a number of difficulties in estimating loan returns. First, there are many types of bank loans, e.g., most notably amortizing versus revolving loans, with various features including floating versus fixed payments, built-in prepayment options, rate resets based on a change of credit risk of the borrowers, etc…Second, given these issues, we make the following assumptions, namely that term loans amortize linearly over their life, and, for revolvers, that 20% is drawn down during the year. For the sample period which the loan data are coincident with the bond data, returns are calculated using loan prices and the interest over the month. The third problem is that, prior to November 1999 or for a

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[4] For example, some problem areas are bonds being either called, converted, tendered, repurchased with sinking fund provisions, or exchanged in the case of Rule 144A securities, and so forth.
[5] For the case where a bond price is missing for the month, we interpolate the bond price assuming it changes in relative proportion to other bonds of the firm, the relative change being determined by its relative duration. Interpolation occurs in 0.91% of the sample.
[6] See, for example, Altman (2006) and Acharya, Bharath and Srinivasan (2007) who document very high recovery rates on bank loans and thus low losses given default.

number of firms not covered in the pricing dataset, we need to apply an alternative approach to generating loan returns. Specifically, since both the bonds and loans can be viewed as contingent claim's on the firm's assets, we run a panel regression, broken down by firm ratings, of the excess return on a firm's bank loans against excess returns on the firm's bond portfolio and treasuries (of similar duration to the bonds). These coefficients are then used to matrix price the loans of firms (and periods) which bank loan data are not available.[7]

Thus, the return on a firm's assets is calculated as

$$R_{t+1}^{Asset} = \frac{E_t}{E_T + B_t + L_t} R_{t+1}^{Equity} + \frac{B_t}{E_T + B_t + L_t} R_{t+1}^{Bond} + \frac{L_t}{E_T + B_t + L_t} R_{t+1}^{Loan}, \tag{1}$$

where E is the market value of equity, B is the market value of the bonds, and L is the estimated market value of the loans.

C. Stylized Facts

The most important, and novel, data in this paper are the bond price data. While bank loans affect the leverage within the firm, their dependency on changes in underlying asset values is much less due their being at the top of the capital structure. Table 2A provides a summary of the quality of the bond data that is used throughout the study and was alluded to in Section II.A. above. The table breaks down each firm into different ratings classes (from AAA to CCC and below). For each class, we calculate the number of represented firms, the number of monthly bond observations, the frequency by which the bond prices do not change from month to month, the frequency by which at least one bond within a firm does not change from month to month and this frequency weighted by the amount outstanding and the firm size. While a zero bond price change is suggestive of staleness, it is by no means generally true. For example, if expectations of the probability of default and/or interest rates do not materially change, then one might expect a zero change.

Nevertheless, that said, across all bonds, this incidence occurs only 3.62% of the time. As the ratings decrease across firms, the probability tends to rise, reaching a peak of 14.62% with B-rated firms. At the firm level, it is more likely that at least one bond not change price, e.g., 10.25% overall, with high yield firms of BB, B and CCC having respectively

[7] The results are robust to various specifications, most probably due to the relatively low volatility of bank loans in the first place.

17.86%, 15.63% and 22.58% incidences.[8] When these results are weighted by both the amount of bonds outstanding and the firm size, these incidences drop dramatically to 6.33%, 5.27% and 7.24%, respectively. Thus, it can be correctly inferred it tends to be an issue with much smaller firms.

Another way to gauge the quality of the data is to look at the contemporaneous and lead-lag autocorrelation properties of the firm's bond, equity and asset returns. For the entire sample and across each ratings class, Table 2B reports these statistics. For example, the autocorrelations of each firm's bond portfolio return are quite small albeit positive. Depending on the number of bonds within each firm, the positive number can be consistent with some degree of nontrading as described by Scholes and Williams (1978). Interestingly, the firm's asset returns first pickup the autocorrelation properties of the equity for the more highly rated firms and move to those of the bond returns for the lower rated firms. This is quite consistent with the Black and Scholes (1971) and Merton (1974) view of the firm's capital structure. In fact, the contemporaneous correlation between equity and bond returns of the firm is in the mid teens percentage wise for AAA through A, and then is 0.19, 0.39, 0.46 and 0.43 for BBB, BB, B and CCC, respectively. Thus, the implication that debt looks more like equity as the assets decrease in value (here represented by firm rating) holds true.

As a final check on the data, Table 2B also reports various lead-lag relations between equity and bonds. There is some evidence of a lead-lag relation between equity and bonds for the lower rated firms. While essentially zero up to BBB-rated firms, BB, B and C have 0.09, 0.10 and 0.15 correlation at the first lag respectively. While this could be slow response to information across different markets, it could also represent some degree of staleness. One way to differentiate staleness versus the market segmentation hypothesis is to check whether bonds also lead stocks. The table shows similar cross-correlation patterns albeit at lower magnitudes, e.g., BB, B and C have 0.03, 0.04 and 0.05 at the first lag respectively. For either lead-lag relation, the correlation drops to zero at the second lag. Coupled with Table 2A and 2B, it is reasonable to conclude that there exists a small, but not major, degree of staleness at the monthly level.

Given the comfort level with the data, in this paper, we look at the properties of two different series: (i) quintile portfolios formed on leverage, and (ii) individual firms.

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[8] As an aside, the fact that the occurrences are much higher at the firm level suggests blanket matrix pricing

i. Portfolios

With respect to the portfolio formation method, consider the leverage portfolios. The sample period covers March 1991 to October 2007. For a firm to be included in the portfolio, it must be a non-financial firm and have market value of the assets to be at least 250mm in December of the previous year. In each December, firms are sorted according to their leverage ratios and then held throughout the year. We form quintile portfolios with the first portfolio being firms with zero leverage. After each year, portfolios are reformulated.

Table 3A provides summary statistics for the equity and asset returns on these two sets of portfolio series, in particular, their mean, volatility and asset/equity ratio. Consider first the leverage portfolios. The zero leverage portfolio aside, the mean asset/equity ratio over the sample period is 112%, 135%, 168% and 285% respectively for the levered portfolios. Monthly expected returns on equity increase similarly from 0.46%, 0.63%, 0.65% and 0.82%, with volatility at 3.8%, 3.7%, 3.7% and 4.5%, respectively.[9] At first glance, one might be surprised by the relatively flat pattern of the volatility of equity returns across levered portfolios. Ceteris paribus, standard theory would imply that equity volatility should be increasing across leverage.

Of course, the amount of leverage is an endogenous choice by the managers of the firm. Faced with a given business uncertainty (i.e., the firm's asset volatility), and if there are costs to financial distress, then one might expect the managers to choose leverage accordingly. As a first pass, Table 3A shows that this is indeed the case. Across the levered portfolios, monthly asset volatility drops from 3.4% to 2.8% to 2.3% to 1.7%. It may be that leverage is optimally chosen to target a specific level of equity volatility, perhaps proxying for a default probability. While this deserves future research, this result is important because it suggests one needs to be careful when investigating the risk/return relation in the cross-section if portfolio sorting or additional factors correlate to leverage.

ii. Individual Firms

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probably does not occur.

[9] The zero leverage portfolio is a little anomalous here with monthly expected returns of 0.91% and volatility of 7.8%. This period includes the so-called internet bubble and thus the zero levered firms have a significant technology tilt.

Table 3B summarizes the mean and volatility of the equity and asset return of individual firms by presenting their mean and median in the overall sample and in the cross-section of the 4 leverage portfolios. The results are similar in spirit to III.C.i above. For example, across these portfolios, the average firm equity volatility on a monthly level is 13.2%, 12.3%, 12.2% and 15.8%, respectively. Again, without seeing the portfolio results above, the finding may be surprising given that the average market leverage ratio for each firm is respectively 1.19, 1.39, 1.75 and 3.66. The above explanation is that leverage is a choice variable, and due to the impact of asset volatility on the costs of financial distress, the tradeoff theory of capital structure would suggest a negative relation between leverage and firm level volatility, i.e., 11.4%, 9.2%, 7.5% and 6.3% as leverage increases.

III. The Conditional Volatility of Asset Returns

There is overwhelming evidence that the volatility of equity returns is time varying and persistent. This is true at the market index, portfolio and individual firm level. Some of the earlier literature in support of these findings include Engle (1982), Bollerslev (1986), Bollerslev, Chou and Kroner (1992), and Bollerslev, Engle and Nelson (1994), among many others. An addition, there is equally strong support for asymmetry in the relation between volatility and return shocks. In particular, volatility increases with negative returns. Again, this result is robust to index, portfolio and individual firm data (e.g., Nelson (1991), Cheung and Ng (1992), Glosten, Jagannathan and Runkle (1993), and Braun, Nelson and Sunier (1995), among others). While researchers have employed various models to capture this asymmetric volatility relation, the workhorse has often been the EGARCH(1,1) model of Nelson (1991) given by

$$\begin{aligned} R_{t+1} &= h_{t+1}\varepsilon_{t+1} \\ \log h_{t+1}^2 &= \varpi + \theta\varepsilon_t + \gamma\left(\left|\varepsilon_t\right| - E\left|\varepsilon_t\right|\right) + \lambda \log h_t^2 \end{aligned} \tag{2}$$

For our sample, Table 4A reports the estimation results of an EGARCH(1,1) for each of the five levered portfolios. The four less levered portfolios show considerable persistence in volatility with the GARCH coefficient ranging from 0.90 to 0.98. Interestingly, the most levered portfolio has a considerably smaller coefficient, namely 0.77. At first glance, this result is surprising. Since equity prices approximately follow a random walk, one might expect that the debt/equity ratio, $\frac{B_t+L_t}{E_T}$, is highly persistent, therefore, leading to the most levered portfolio having the greater persistence. However, leverage is a choice variable. It might be the case that, as equity prices fall, firms actually delever, thus causing a quicker reversion in volatility.

The most important parameter for our purposes is the coefficient on the asymmetric term. Several observations are in order. First, while the coefficient is negative for the four levered portfolios, it is actually positive for the zero leverage portfolio. This suggests leverage plays an important role in the determination of the well-documented asymmetric volatility result. Second, though negative, the statistical significance of the less levered portfolios is less than the usual levels for two of the three portfolios. Finally, and most crucially, the most levered portfolio has a much larger coefficient than the other portfolios, both in magnitude (e.g., 66% higher than the next largest coefficient) and in statistical significance (e.g., a t-statistic of 3.57).

The evidence above is consistent with the stylized fact that stock return volatility rises after stock prices fall. Our new finding is the importance of leverage within the EGARCH(1,1) analysis of stock return portfolios. Of course, there has been considerable debate and empirical evidence generated about how much of the asymmetric volatility effect is due to financial leverage as a result of the stock price fall (i.e., "leverage effect") versus time-varying risk premia (i.e., "volatility feedback"). Among the papers that have analyzed this question are Black (1976), Christie (1982), French, Schwert, and Stambaugh (1987), Campbell and Hentschel (1992), Duffee (1995), Bekaert and Wu (2000) and Yu (2005).

Because we measure the actual returns on the assets, we can additional evidence to this debate. Specifically, Table 4B presents EGARCH(1,1) estimates for the returns on the assets of the same five levered portfolios. The unique aspect of this analysis is that the portfolios are in terms of the underlying assets (i.e., delevered), so, by construction, leverage cannot be a factor. First, volatility persistence now appears similar across the five portfolios with coefficients ranging from 0.89 to 0.98. This is consistent with the deleveraging hypothesis discussed above for the most levered portfolio. Second, and of particular interest to the debate on leverage versus volatility feedback, the coefficients on the asymmetric volatility part drop for every levered portfolio. For example, the coefficient on the most levered portfolio drops from -0.35 to -0.09 after deleveraging. Third, while the

asymmetric volatility coefficients are not statistically significant, the coefficients are of all four levered portfolios are still negative, ranging from -0.03 to
-0.19.

This final finding suggests that, although leverage is a key factor in explaining the asymmetry, there is some residual asymmetry remaining. As a way to breakdown the leverage and volatility feedback hypotheses more closely, we repeat the EGARCH(1,1) analysis of Table 4 at the individual firm level.

A. Individual Firms

For the individual firm by firm EGARCH(1,1) estimation, due the amount of noise in individual equity and asset returns, we require the firm have (i) "reasonable" (i.e, stationary) ARCH and GARCH parameter estimates[10], and (ii) at least 60 months of continuous data. We also allow for non-Gaussian error distributions by including t-distributions as a possibility due to the kurtotic data at the individual firm level. Of the initial 1711 firms, 853 remain that satisfy all these criteria.

Table 5A reports the mean and median estimates of the ARCH, GARCH and asymmetric coefficient for the EGARCH(1,1) firm by firm estimation in the overall sample, as well as across the five groupings based on leverage. The results are similar in spirit to the portfolio results provided in Table 4 in a number of ways. First, the mean GARCH parameter is around 0.9 across the various groupings for both the equity and asset return estimations. Second, the asymmetric coefficients are negative across every portfolio grouping, confirming the well-known result. Third, for the less levered portfolios, there is not much difference in the mean estimates between equity and asset returns (e.g., for the least levered portfolio, -0.14 versus -0.10, and for the next, less levered portfolio, -0.17 versus -0.11). In contrast, for the more levered portfolios, the differences are magnified (e.g., -0.11 versus -0.04 for the second highest levered portfolio, and -0.17 versus -0.08 for the most levered portfolio).

As a final comment on these individual estimates, to get around dropping almost half the firms, we also perform a stacked regression which puts all the firm observations together. To adjust for differences in volatility levels, the volatilities are standardized across

[10] Specifically, we require the GARCH coefficients to be between 0.1 and 1, and positive ARCH coefficients.

firms. Table 5A reports the set of parameters from these EGARCH(1,1) estimates for both equity and asset returns. Consistent with the mean and median estimates, the stacked estimates show (i) a high level of persistence for both the equity and asset returns, (ii) negative coefficients on asymmetry, and (iii) a decline across the board in asymmetry moving from equity to the assets, with the greatest drops occurring for the most levered portfolios (e.g., -0.096 to -0.026 and -0.123 to -0.053, respectively).

Part of the motivation for looking at individual firms was to be able to separate the volatility feedback effect from the leverage hypothesis. Specifically, the volatility feedback story argues that, if market volatility is priced and increases, then the risk premium will also increase, leading to a stock price decline. Thus, the causality between increasing volatility and negative returns is opposite to that of the leverage effect. In order to separate the effects, we run a one-factor model with an idiosyncratic EGARCH(1,1) volatility:

$$\begin{aligned} R_{t+1}^{equity} &= \beta\left(\frac{A_t \partial E_t}{E_t \partial A_t}\right) R_{mt+1} + h_{t+1}\varepsilon_{t+1} \\ R_{t+1}^{asset} &= \beta R_{mt+1} + h_{t+1}\varepsilon_{t+1} \end{aligned} \tag{3}$$

where the market value of the assets $A=B+L+E$, and R_m is the return on the unlevered market from our sample (albeit including zero levered firms and financial firms).[11] Note that equation (3) removes the market factor and therefore the volatility feedback effect as a possible explanation. If volatility feedback were a primary explanation of the asymmetry, then the coefficients on idiosyncratic volatility should fall dramatically.

Table 5B reports the results for the analysis of the idiosyncratic volatility. The results are generally not good news for the volatility feedback effect. In particular, the mean estimates at the idiosyncratic, firm level are only marginally lower than before, e.g., for equity, across the five portfolios respectively, from (-0.13, -0.13, -0.16, 0-.12 and -0.19) to (-0.10, -0.08, -0.13, -0.11, and -0.18). Similar results hold at the asset return level. In general, there is a uniform drop of around 0.03 across all the portfolios. These results are also confirmed at the EGARCH(1,1) stacked estimation of idiosyncractic volatility for both equity and asset returns. On the positive side, removing the market portfolio causes a

[11] The partial derivative in (3) is calculated from the Black-Scholes formula and given as $\frac{\partial E_t}{\partial A_t} = \frac{\ln(A/K) + (r + .5\sigma_A^2)T}{\sigma_A \sqrt{T}}$ where A/K is ratio of asset value to face value of long-term debt, r is 1-year treasury constant maturity yield, σ_A is asset volatility using the full sample and T is face-value-weighted time-to-maturity.

uniform drop in all the asymmetric coefficient estimates. On the negative side, the drop is quite small. Coupled with the previous results at the portfolio level in Tables 4A and 4B, and with the individual results of Table 5A, the findings here in Table 5B suggest the factors in order of importance for explaining asymmetric volatility is leverage, then an unspecified residual, and finally the volatility feedback (i.e., time-varying risk premium).

IV. The Conditional Volatility of Asset Returns: A Structural Approach

The evidence given above suggests that leverage is an important component for explaining time-variation in volatility, especially with respect to the stylized fact that volatility increases when the underlying stock price falls. The unresolved question from the analysis in Section III is just how important is leverage?

Suppose the assumptions underlying Black and Scholes (1971) and Merton (1974) hold so that asset returns follow a geometric Brownian motion, interest rates are constant, there are no impediments to arbitrage, and that the firm's capital structure can be collapsed into equity plus one issue of zero coupon debt (with a maturity that matches the duration of the actual data). Then, for any firm i, we can start with the basic result from Black-Scholes-Merton that $R_E^i = \frac{A^i}{E^i}\frac{\partial E^i}{\partial A^i} R_A^i$. Aggregating to the portfolio level, it is possible to show that

$$\sum w_E^i R_E^i = \frac{\sum A^i}{\sum E^i} \cdot \sum w_A^i \frac{\partial E^i}{\partial A^i} R_A^i \,, \tag{4}$$

where w represents the market value weights of the equity and asset portfolio, respectively.[12]

[12] To see this, note that

Using equation (4), we can then model the conditional volatility or log conditional volatility of portfolio returns on equity in terms of two factors: (i) the portfolio's leverage, or specifically total assets to equity, and (ii) the conditional volatility of the portfolio's adjusted asset returns:

$$vol_t\left(\sum\left(w_E^i R_{E:t+1}^i\right)\right) = \left(\frac{\sum A^i}{\sum E^i}\right) \times vol_t \sum\left(w_A^i \tilde{R}_{A:t+1}^i \right), \tag{5}$$

where the adjusted asset return $\tilde{R}_A^i = \frac{\partial E^i}{\partial A^i} R_A^i$. We can look at changes such as

$$\Delta \log\left(\sigma_E^2\right) = \Delta \log\left(\frac{\sum A}{\sum E}\right)^2 + \Delta \log\left(\tilde{\sigma}_A^2\right) \tag{6}$$

to better understand the volatility properties of equity portfolios.

As a first pass, Figure 1 graphs side by side the EGARCH(1,1) estimated volatility of the four levered portfolios and their market ratio of assets/equity over the entire sample period. Several features of these graphs capture the more detailed analysis to follow. First, given that the asset volatility and leverage ratio enter into equation (5) in equal proportion, the graphs show immediately that asset volatility is the more important factor. Across all the portfolios, even the most levered one, asset volatility varies by a multiple more than leverage. While this is partly due to construction (i.e., the portfolios are rebalanced yearly in terms of leverage), it nevertheless shows that equity volatility's time-varying properties are for the most part due to the underlying assets. (Note that the rebalancing issue is addressed in the subsection below when we look at individual firms.) Second, leverage ratios are much

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$$R_E^i = \frac{A^i}{E^i}\frac{\partial E^i}{\partial A^i} R_A^i$$

$$E^i R_E^i = A^i \frac{\partial E^i}{\partial A^i} R_A^i$$

$$\sum\left(E^i R_E^i\right) = \sum\left(A^i \frac{\partial E^i}{\partial A^i} R_A^i \right)$$

$$\frac{\sum\left(E^i R_E^i\right)}{\sum E^i} \cdot \sum E^i = \frac{\sum\left(A^i \frac{\partial E^i}{\partial A^i} R_A^i \right)}{\sum A^i} \cdot \sum A^i$$

$$\frac{\sum\left(E^i R_E^i\right)}{\sum E^i} = \frac{\sum A^i}{\sum E^i} \cdot \frac{\sum\left(A^i \frac{\partial E^i}{\partial A^i} R_A^i \right)}{\sum A^i}$$

more persistent than asset volatility through time. This implies that, even though asset volatility is the predominant source of time-varying equity volatility, leverage has long-term effects. Thus, a shock in asset values that increases both the leverage and the underlying asset volatility will have long- and short-term impact, respectively. Finally, although these results hold across the four levered portfolios, it is clear that the most levered portfolio has more interesting properties, such as its leverage ratio is more variable and asset volatility appears less persistent.

In three separate panels, Table 6 presents summary statistics for the four levered portfolios in terms of the breakdown between leverage volatility and adjusted asset return volatility. Using equations (5) and (6), Panel A directly compares the variability of asset volatility and leverage in both levels and changes across the four portfolios. Panel B presents the autocorrelation properties of asset volatility, leverage and equity volatility implied by the structural model at monthly lags 1-3, 6 and 12. Using the structural models in equations (5) and (6), Panel C directly calculates the proportion of time-varying equity volatility that can be explained by asset volatility and leverage, respectively.

With respect to Panel A, both in levels and differences, the volatility of asset volatility is much greater than the volatility of market leverage ratios. Of course, part of this explanation may be due to measurement error in our asset volatility estimates. Nevertheless, in levels, the volatility of asset volatility versus financial leverage is (0.27, 0.25, 0.19 and 0.24) versus (0.03, 0.05, 0.09 and 0.16) respectively across the four leverage portfolios. From the structural point of view, in terms of the ability to explain the time-varying properties of equity volatility, asset volatility is therefore necessarily the more important factor.

Panel B shows that, in general, leverage is more persistent than asset volatility. At a first look, the most levered portfolio aside, the first order autocorrelation suggests similar properties, e.g, for the four levered portfolios respectively, the autocorrelations are (0.95, 0.97, 0.97 and 0.96) for their leverage component and (0.93, 0.88, 0.97, and 0.51) for their asset volatilities. When the autocorrelations, however, are extended to 6 and 12 lags respectively, the results look quite different. For example, at the 12th lag, the autocorrelations are (0.82, 0.75, 0.74 and 0.63) for their leverage component while only

(0.57, 0.38, 0.68, and 0.05) for their asset volatilities. This necessarily means that shocks to asset prices affect volatility both in the short- and long-term albeit through different mechanisms, namely the transitory properties of asset volatility and more permanent shocks of financial leverage.

This is quite noticeable when we use the structural model of equation (5) to estimate the autocorrelation of equity volatility. The autocorrelation will be a function of the individual autocovariances as well as the variances of the leverage component and asset volatility. Since the variance of asset volatility is much higher, the initial autocorrelation properties of equity volatility take on the underlying asset volatility, only to eventually take on primarily the properties of leverage. For example, consider the most levered portfolio. The autocorrelations of equity volatility implied by the structural model over lags 1, 2, 3, 6 and 12 are respectively 0.68, 0.47, 0.39, 0.40, and 0.28. A similar pattern holds across the other portfolios. This result may help explain the well-known stylized fact that volatility has both a mean-reverting standard GARCH-like representation with a long memory component (e.g., see Bollerslev and Mikkelsen (1996), Engle and Lee (1999), Adrian and Rosenberg (2008) and Engle and Rangel (2008)).

This long-term dependence aside, Panel C directly calculates the proportion of conditional equity volatility explained by the leverage component versus the underlying volatility of the assets. These calculations are performed in both levels and changes in volatility using equations (5) and (6). In levels, perhaps not surprisingly, the relative importance of leverage for explaining equity volatility increases with leverage. For example, from the low to high levered portfolios, the contribution goes from -0.4% to 10.0% to 23.4% and to 34.7%, respectively.

We noted above that, by rebalancing the portfolio every year into one of five quintile portfolios, we might be removing some interesting dynamics of leverage at the individual firm level. Moreover, it would be nice to be able to further breakdown the relative proportion of explained equity volatility. For example, along with the aforementioned leverage versus time-varying risk premia debate, how much of time-varying equity volatility is explained by market versus idiosyncratic movements?

A. Individual Firms: Structural Estimates

The derivations of the structural model at the individual firm level follows similarly to that at the portfolio level described at the beginning of this section. Assuming the Black-Scholes-Merton type assumptions, it is possible to show that

$$\sigma_E^2 = \left(\frac{A}{E} N(d_1)\right)^2 \sigma_A^2, \tag{7}$$

where $N(d_1) = \frac{\ln\left(A/K\right) + \left(r + .5\sigma_A^2\right)T}{\sigma_A \sqrt{T}}$, T is the maturity of the debt, r is the riskless rate and K is the face value of the zero coupon debt. Following along the lines of the above analysis, we can either model the volatility or log volatility using the above time series methods, and evaluate the properties of the pricing errors, such as unbiasedness, mean-squared error (i.e., r-squareds). We can also look at changes:

$$\Delta \log\left(\sigma_E^2\right) = \Delta \log\left(\frac{A}{E} N(d_1)\right)^2 + \Delta \log\left(\sigma_A^2\right). \tag{8}$$

Table 7 presents summary statistics for individual firms in the overall sample and across the different leverage groupings. As in Table 6, we focus on three panels covering the relative variation of the leverage and asset volatility components, the persistence properties of these components, and their estimated contribution to equity volatility. From Panel A, the variation of the firm's leverage component versus its asset volatility is quite large relative to the aforementioned results for portfolios. This is true across all leverage groupings although clearly is most prevalent for the higher levered firms. In levels, average volatility of financial leverage versus asset volatility for individual firms is (0.08, 0.14, 0.20, 0.39) versus (0.26, 0.26, 0.26, 0.28) respectively across the four leverage groups, whereas its portfolio level counterpart is (0.03, 0.05, 0.09, 0.16) versus (0.27, 0.25, 0.19, 0.24). The basic premise here is that, in terms of the structural model, the data suggests that leverage plays an important role in determining the time-variation of equity volatility. The most likely explanation for the contrast with the portfolio results is that the rebalancing of the portfolios reduces the effect of within-firm changes in leverage as these firms move from one levered portfolio to the next.

Table 7, Panel B shows that, similar to the portfolio results, the persistence of the leverage piece is much greater than that of the firm's asset volatility. For example, at the

12th lag, the mean autocorrelations for leverage are (0.42, 0.39, 0.40, 0.40) whereas their asset volatility counterparts are (0.37, 0.32, 0.35, 0.24). Thus, equity volatility at the firm level has two components, a transitory one driven by the variation in the underlying assets, and a more permanent one driven by financial leverage. Given the well-documented asymmetry in volatility, the most likely source for both these components is the same factor, namely negative shocks to the underlying assets.

Panel C presents estimates of the relative contribution of the leverage component and asset volatility to variation in the firm's equity volatility. The results are presented for the mean and median estimates for both levels and changes in volatility, using either the individually estimated EGARCH(1,1) coefficients or the stacked estimation.[13] As the leverage of the grouping increases, the contribution of leverage towards the time-variation in equity volatility also increases, e.g., in levels, from 11.8% to 22.2% to 32.1% to 44.4%, and, in changes, from 11.2% to 22.8% to 34.1% to 55.8%. This basic finding is robust to whether we use medians or the stacked EGARCH(1,1).

i. Implied Equity Volatility and Its Determinants

In the analysis so far, we have looked at equity volatility implied by the model structure given by equations (7) and (8). Ideally, it would be nice to relax the structure and relate how much of the "true" time-varying equity volatility could be explained by asset volatility (and its individual components) and financial leverage. This is important because a number of assumptions went into the derivations of (7) and (8). The problem, of course, is that our estimates of time-varying equity and asset volatility use some of the same underlying data (e.g., equity returns) and the EGARCH framework. Thus, regressing estimates of asset volatility on equity volatility will involve considerable common measurement error. As a way around this problem, we collected 1-month implied volatilities from at-the-money options on the equity for as many of the firms in our sample as possible from Optionmetrics. This reduces our sample size from 647 firms (1920 if stacked) to 554 firms (1322 if stacked); in other words, the coincident sample of implied equity volatilities and monthly asset volatility estimates is about 86% as large. The nice feature of this approach is

[13] Recall the motivation for using the stacked EGARCH was that it allowed us to use the full sample of firms, while about one-half the sample of individual estimations had to be dropped due to nonstationary estimates of EGARCH.

that the data sources are quite different, namely options data on the firm versus the return on the firm's assets (derived from equity, bond and loan data).[14]

As a first look at the data, we run the following regression:

$$\begin{aligned}
\log\left(\sigma_E^2\right)_t &= \phi \log\left(\frac{A}{E} N(d_1)\right)_t^2 + \gamma \log\left(\sigma_A^2\right) + \varepsilon_t \\
\Delta \log\left(\sigma_E^2\right)_t &= \theta \Delta \log\left(\frac{A}{E} N(d_1)\right)_t^2 + \lambda \Delta \log\left(\sigma_A^2\right) + \eta_t
\end{aligned}, \qquad (9)$$

where equity volatility, σ_E^2, is the monthly implied volatility from option markets, asset volatility, σ_A^2, is estimated from an EGARCH(1,1) using asset returns, and *A/E* is the market leverage of the firm.

The initial results are reported in Table 8 for both the mean and medians of the regressions, as well as the stacked regression where we estimate one set of coefficients. While the structural theory of equations (7) and (8) imply coefficients of 1 and R-squareds of 100% if there were no measurement error, Table 8A provides impressive results nonetheless. The regression estimates of (9) are biased downward, hovering around 0.5 for leverage and 0.7 for asset volatility with R-squareds of approximately 55%. These results are robust across the different leverage cross-sections. Moreover, if we use the stacked regression estimates, the coefficients are much closer to the theoretical value of 1, especially for asset volatility. This is consistent with measurement error in the EGARCH estimation of asset volatility. Perhaps, not surprisingly, the results of the difference regressions are weaker though similar in spirit. The R-squareds drop precipitously to between 10%-15% with a corresponding fall in the coefficient of asset volatility.

What do these results mean in terms of what drives time-varying equity volatility? Table 8B reports the variance decomposition of equity volatility in terms of its explained portion. Similar to previous results, asset volatility is the dominant factor for firms with low leverage. This is true for both levels and differences of volatility, and whether we measure the mean or median within the sample, or run a stacked regression. For example, its mean percentage contribution for equity volatility levels is on average 81%, 70%, 69% and 57%, respectively as leverage increases. Moreover, for the stacked regression, the results are

[14] For the EGARCH parameter estimates of asset volatility at any given point in time, we use the entire sample except for the period immediately surrounding the implied volatility.

similar albeit weaker, 70%, 67%, 55% and 50%, respectively. Financial leverage is therefore still an important determinant, especially when firms have high leverage.

Equation (3) of this paper separated asset volatility into two components, namely market-wide and idiosyncratic asset volatility. We can rewrite this equation in terms of equity volatility by levering up using the adjusted leverage ratio, that is,

$$\sigma^2_{E_i,t} = L^2_{i,t}\beta^2_i\sigma^2_{M_A,t} + L^2_{it}\sigma^2_{A_i,t} \tag{10}$$

where the β_i is the asset beta of firm i, $\sigma^2_{M_A}$ is the EGARCH estimated variance of the asset return on the market, $\sigma^2_{A_i}$ is the EGARCH estimate of the idiosyncratic volatility of the assets, and $L_i = \frac{A_i}{E_i}\frac{\partial E_i}{\partial A_i}$ is the adjusted leverage ratio of asset i.

The above equation (10) can be log-linearized and rewriiten in the following terms:

$$\log(\sigma_{E,t}) \approx \log(L_t) + \frac{1}{1+e^{\bar{x}}}\log(\sigma_{M_A t}) + \frac{e^{\bar{x}}}{1+e^{\bar{x}}}\log(\sigma_{A,t}) + k \tag{11}$$

where we have suppressed the firm subscripts, *k* is a constant, and *x* is assumed to be stationary and given by the formula $x = \log\left(\frac{\sigma^2_A}{\beta^2\sigma^2_{M_A}}\right)$.[15]

There are several implications of equation (11). The coefficient on the log of adjusted financial leverage is one, while the other two coefficients on the asset volatility of the market and idiosyncratic asset volatility sum up to one (and therefore both coefficients are less than one). Of course, the quantity x_t differs across firms, so these coefficients will vary across firms as well, the beta of the assets being an important determinant of this.

[15] To see this, note that by taking logs of equation (10), we get $2\log(\sigma_{E,t}) = 2\log(L_t) + \log\left(\beta^2\sigma^2_{M_A}\right) + \log\left(1 + \frac{\sigma^2_A}{\beta^2\sigma^2_{M_A}}\right)$. Now expand the last term around the mean of $x_t = \log\left(\frac{\sigma^2_{At}}{\beta^2\sigma^2_{M_t}}\right)$. Thus, $2\log(\sigma_{E,t}) = 2\log(L_t) + \log\left(\beta^2\right) + 2\log\left(\sigma_{M_At}\right) + \log\left(1 + e^{x}\right)$ can be written as approximately $2\log(\sigma_{E,t}) \approx 2\log(L_t) + \log\left(\beta^2\right) + 2\log\left(\sigma_{M_At}\right) + \log\left(1 + e^{\bar{x}}\right) + \frac{e^{\bar{x}}}{1+e^{\bar{x}}}\left(x_t - \bar{x}\right))$. Substituting in for x, rearranging terms, dividing both sides by 2, and collapsing the non time-varying terms into the constant k, we get the desired result in equation (11).

The top rows of Table 9A provides the results for the regression of time-varying asset volatility of the market, idiosyncratic volatility of the firm's assets, and the firm's market leverage on the implied volatility of the firm's equity. In levels, the variables capture quite well the variation in implied equity volatility. The R-squareds across the four leverage groupings are all in the 60+% range. The average coefficients on market and idiosyncratic asset volatility do not quite sum to 1, but are in the range of 0.79 to 0.96. Interestingly, the coefficients are of similar magnitude. As with previous tables, leverage also plays an important role, albeit in the 0.37 to 0.48 range, somewhat far from its theoretical value of 1. The top panel of Table 9B provides the decomposition results. For the low leverage groupings, leverage has only a small impact, e.g., 8%, but grows steadily with leverage, from 18% to 34%.[16] The remaining components are somewhat split between market and idiosyncratic asset volatility. The results in implied volatility differences are also shown in Tables 9A and 9B. The R-squareds are in the 15% range. The coefficients are similar in magnitude to the results in levels, with perhaps a strengthening of the effect of changes in leverage and a weakening effect of the changes in market and idiosyncratic volatility.

As mentioned in section III, there is considerable interest in trying to better understand the asymmetric volatility relation, and, in particular, the importance of leverage versus risk premia versus idiosyncratic (possible "behavioral") effects. Currently, our approach and others is to test for how big these effects are within a GARCH-like framework. An alternative approach would be to see whether these estimated effects actually explain the implied volatility levels or changes through time. Note that equation (11) can be rewritten in terms of the individual components of the EGARCH(1,1) estimates of market and idiosyncratic asset volatility. That is,

$$\log \sigma_t^E = a \log l_t + b \log \sigma_{t-1}^{Mkt} + c\varepsilon_{t-1}^{mkt} + d|\varepsilon_{t-1}^{mkt}| + f \log \sigma_{t-1}^{idio} + g\varepsilon_{t-1}^{idio} + h|\varepsilon_{t-1}^{idio}| \tag{12}$$

where the coefficients a-h are not imposed by the model in (11) and are allowed to be unconstrained. We can also calculate equation (12) in changes, specifically taking the difference,

[16] The stacked regression results support an even stronger leverage component to a firm's implied equity volatility. Moreover, across the groupings from low to high leverage, the sum of the volatility coefficients are quite close to 1, equaling respectively 0.98, 0.90, 0.93 and 0.92. These results are presented in Tables 9C and 9D.

$$\Delta \log \sigma_t^{equity} = a\Delta \log l_t + b(\log \sigma_t^{Mkt} - \log \sigma_{t-1}^{Mkt}) + c(\log \sigma_t^{idio} - \log \sigma_{t-1}^{Mkt})$$, and plugging in the EGARCH(1,1) estimates for market and idiosyncratic asset volatility, we obtain the following :

$$\Delta \log \sigma_t^E = a\Delta \log l_t + b \log \sigma_{t-1}^{Mkt} + c\varepsilon_{t-1}^{mkt} + d|\varepsilon_{t-1}^{mkt}| + f \log \sigma_{t-1}^{idio} + g\varepsilon_{t-1}^{idio} + h|\varepsilon_{t-1}^{idio}| \quad . \qquad (13)$$

The terms in equations (12) and (13) have a clear interpretation in terms of the impact of the theories underlying asymmetric volatility. ε_{t-1}^{Mkt} and ε_{t-1}^{idio} represent the shock to the market return of the assets and to the idiosyncratic return of the firm's assets. The former represents the time-varying risk premia effect commonly termed the feedback effect, while the latter is a more puzzling idiosyncratic component that some researchers might denote behavioral. In terms of other major components, l_t represents the leverage effect, and the lagged volatilities, σ_{t-1}^{Mkt} and σ_{t-1}^{idio}, are the persistent effect of market and idiosyncratic asset volatility. For example, in equation (13), the lagged volatility terms represent the decay effect given that volatility is in fact mean reverting.

The bottom rows of Table 9A-9D provide the results for the regressions in equation (12) and (13). The level regressions all produce signs and, to some extent, coefficients in the direction of our intuition. Financial leverage, the most recent market volatility and idiosyncratic volatility all come in positive and large in magnitude. These are the major effects in terms of explaining time-varying equity volatility. As an illustration, consider the most levered grouping of firms; the variance decomposition shows that leverage, lagged market asset volatility and lagged idiosyncratic asset volatility explain 34%, 29% and 29%, respectively of the explained variation with an R-squared of 68%. This is not to imply that the lagged return (asymmetric shock) or lagged absolute return (volatility shock) are not important. In fact, their signs, i.e., a negative asymmetric shock and positive volatility shock, across all groupings, mean versus median, and stacked regressions are generally consistent with their "hypothesis". However, the results clearly show that they are not crucial for understanding the level of volatility.

These results, however, are completely reversed for changes in equity volatility. Though mean reversion in current volatility has the potential to be an important determinant of volatility changes, the effect is close to zero. All the variation is now due to the asymmetric shocks, i.e., lagged return components, or to changes in financial leverage. For example, for the most levered grouping (which is typical of the other groupings as well), the relative contribution to equity volatility changes is 16%, 17%, 10%, 39% and 12% respectively for changes in financial leverage, lagged market returns, lagged market absolute returns, lagged idiosyncratic returns, and lagged absolute idiosyncratic returns. Thus, idiosyncratic shocks to asset returns have a large impact on conditional volatility changes. This result presents a stylized fact that needs to be explained. Given that these shocks are, for the most part, diversifiable, it is not clear why the conditional volatility of equity responds. This point aside, a common feature of both the level and change regressions for implied volatility, however, is the continued importance of financial leverage.

V. Conclusion

Using a unique dataset of equity, bond and loan returns at the firm level, we are able to measure a firm's asset returns and estimate the volatility of a firm's assets. This allows us to more directly investigate the impact of financial leverage on the equity volatility of the firm. An overall conclusion from this study is that financial leverage is important for explaining movements in equity volatility. This is true at the individual firm and portfolio levels, and is robust to numerous specifications. The results from this paper also show, however, that asset volatility itself time-varies and, except for the most levered firms, is the dominant factor.

Some of the results in this paper suggest valuable areas of future research. First, the time-variation of both financial leverage and asset volatility argues for perhaps a more fundamental approach to analyzing asset pricing theories relating equity returns to market factors. That is, the literature should take a more serious look at unlevered returns. Second, another finding, namely that leverage has more a permanent impact on equity volatility than the transitory (albeit large) effect of asset volatility, implies interesting dynamics at short and long horizons that should further be explored. Third, we document important idiosyncratic effects at the asset level on equity volatility levels and changes. A reasonable question is what type of model can produce these effects. Lastly, the stylized fact that leverage is inversely related to asset volatility has important implications for corporate finance, and, in particular, the tradeoff theory of capital structure. While this fact was not explored in the paper, we feel it is a potentially important result that deserves future attention.

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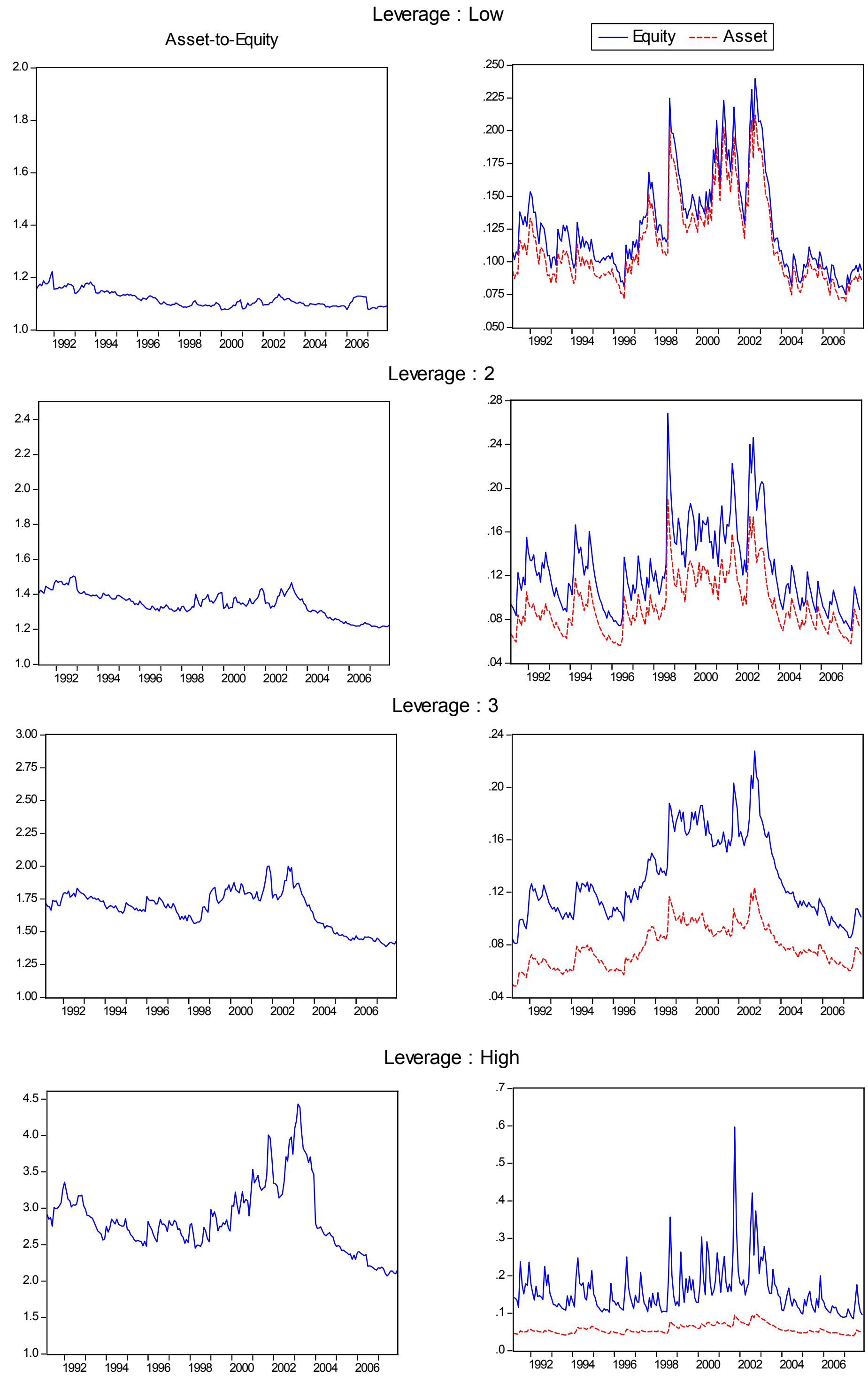
Figure 1: Leverage and Equity and Asset Volatility



For each leverage portfolio, asset-to-equity ratios and equity and asset volatilities estimated from EGARCH(1,1,1) model are plotted. Portfolios are formed in every January with firms whose asset size is greater than $250MM at the time of portfolio formation. Leverage is calculated as market asset-to-market equity ratios.

Table 1. Sample Coverage

Panel A: Coverage of the sample relative to the CRSP/Compustat Universe

	CRSP Universe			Our Sample	
	Overall	With Debt	No Debt	With Debt	Size 250
Num. Obs.	861516	734369	127147	175352	155416
Avg Asset	2281.1	2520.0	901.0	8948.5	9983.3
Median Asset	177.6	200.3	103.0	2195.7	2692.0
Median Book Lev	1.32	1.47	1.00	1.87	1.83
Median Mkt Lev	1.18	1.26	1.00	1.50	1.48
% Covered by Bonds				56.3%	54.9%
% Covered by Bonds and Loans				94.0%	95.0%

Panel B: Sample Coverage By Ratings

Rating	AAA	AA	A	BBB	BB	B	CCC	NR
Num. Obs.	1618	6702	30219	41931	37087	29338	3412	25045
Avg Asset	131918.4	34777.1	16627.8	9050.9	3493.9	2272.2	1906.3	1512.2
Median Asset	68291.3	16339.7	6893.3	4189.8	1530.9	783.8	394.7	692.2
Median Book Lev	1.23	1.54	1.69	1.80	2.07	2.51	2.98	1.93
Median Mkt Lev	1.05	1.16	1.31	1.48	1.65	1.96	3.41	1.48
% Covered by Bonds	24.8%	43.7%	46.3%	53.2%	57.0%	73.2%	68.6%	63.6%

Coverage statistics for the following five sets of samples. (a) all firms , (b) firms with non-zero debt outstanding and (c) firms with zero debt from CRSP/Compustat universe and (d) firms from our sample and (e) firms with more than $250MM asset size from our sample. Asset sizes are in million dollars using market values of debt for our sample and book values of debt for the CRSP/Compustat universe. Book leverage is book asset value to book equity value and market leverage is market asset value to market equity value. For the CRSP/Compustat universe, market asset is the sum of market equity and book debt. (% Covered by Bond) and (% Covered by Bond + Loan) are the median value of the fraction of long-term debt and current portion of long-term debt covered by the bond data and bond and loan data combined, respectively.

Table 2. Bond Quality Statistics

Panel A: Frequency of Bond Observations with No Price Change

	ALL	AAA	AA	A	BBB	BB	B	CCC~	UNRATED
# of Total Firms	1566	16	98	352	558	645	535	148	266
# of Total Obs.	776935	5188	42217	187392	275206	143593	78990	10896	33453
Bond Obs.	3.62%	1.48%	0.76%	0.83%	1.43%	5.61%	14.62%	8.96%	4.86%
Firm Obs.	10.25%	4.86%	4.28%	3.83%	6.72%	17.86%	15.63%	22.58%	8.85%
Weighted Bond Obs.	1.48%	0.50%	1.08%	0.57%	1.05%	6.33%	5.27%	7.24%	3.43%

Panel B: Autocorrelations and Cross-correlations

	Portfolio Level Autocorrelations							
	AAA	AA	A	BBB	BB	B	CCC~	UNRATED
# of Firms	7.0	32.7	144.7	200.7	166.1	120.0	14.8	77.1
Bond	-0.06	0.13	0.11	0.11	0.10	0.09	0.16	0.29
Equity	-0.07	-0.09	-0.07	0.01	0.08	0.11	0.06	0.07
Firm	-0.08	-0.09	-0.05	0.00	0.06	0.10	0.10	0.10

	Firm Level Autocorrelations							
	AAA	AA	A	BBB	BB	B	CCC~	UNRATED
# of Obs.	1565	6973	30705	41328	33475	24176	2599	15733
Bond	0.02	0.10	0.06	0.04	0.03	0.02	0.08	0.02
Equity	-0.07	-0.06	-0.04	-0.01	0.00	0.01	0.03	-0.03
Firm	-0.08	-0.07	-0.04	-0.01	0.02	0.04	0.08	-0.01

	Cross-correlations							
	AAA	AA	A	BBB	BB	B	CCC~	UNRATED
Bond, Equity	0.17	0.13	0.14	0.19	0.39	0.46	0.43	0.46
Bond, Equity (-1)	0.02	0.01	0.01	0.03	0.09	0.10	0.15	0.05
Bond, Equity (-2)	0.00	-0.01	-0.01	0.00	0.01	0.01	0.02	0.01
Bond, Equity (-3)	-0.02	0.00	0.00	0.02	0.00	-0.01	0.00	-0.01
Equity, Bond(-1)	-0.02	0.02	0.02	0.02	0.03	0.04	0.05	0.01
Equity, Bond(-2)	0.01	0.02	0.02	0.01	0.00	0.00	-0.01	-0.01
Equity, Bond(-3)	-0.01	0.00	0.01	0.01	0.00	0.00	-0.01	-0.02

Panel A reports the frequency by which prices do not change from month to month. The numbers of firms are the counts of firms that are in each rating portfolio for at least one month. Bond Obs. reports the frequency of bond level observations with no price change month to month and Firm Obs. reports the frequency by which at least one bond within a firm does not change month to month. Weighted Bond Obs. reports the frequency of bond level observations weighted by the amount outstanding. Panel B reports autocorrelations and cross-correlations at the portfolio and individual firm levels. Portfolios are formed every month based on issuer-ratings from S&P and the autocorrelations are estimated from value-weighted bond, equity and firm returns. # of Firms is the average number of firms in each portfolio. For firm level autocorrelations and cross-correlations in each rating group, the individual firm level estimates are first calculated and assigned to each corresponding firm-month observation. Then the average of the autocorrelations and cross-correlations are calculated for each rating group.

Table 3A : Summary Statistics for Leverage-sorted Portfolios and Individual Firms

Panel A: Summary Statistics for Leverage-Sorted Portolios

	Equity Portfolio Returns				
	Leverage Quintile				
	No Debt	1	2	3	High
Mean	0.91%	0.46%	0.63%	0.65%	0.83%
Std. Dev.	7.75%	3.79%	3.72%	3.75%	4.46%
Asset/Equity	1.00	1.12	1.35	1.68	2.85

	Asset Portfolio Returns				
	No Debt	1	2	3	High
Mean	0.91%	0.42%	0.50%	0.43%	0.32%
Std. Dev.	7.75%	3.42%	2.80%	2.31%	1.71%

Panel B:Summary Statistics for Individual Securities

	Equity Return Statistics : Mean					
	Leverage Quintile					
	All	No Debt	1	2	3	High
Mean	0.20%	0.21%	-0.01%	0.60%	0.74%	0.40%
Std. Dev.	14.8%	16.5%	13.2%	12.3%	12.2%	15.8%
Asset/Equity	1.77	1.00	1.19	1.39	1.75	3.66
	Equity Return Statistics : Median					
Mean	0.77%	0.63%	0.62%	0.80%	0.85%	1.06%
Std. Dev.	12.6%	14.2%	10.7%	10.3%	10.5%	13.3%
Asset/Equity	1.23	1.00	1.16	1.33	1.64	2.42

	Asset Return Statistics : Mean					
	All	No Debt	1	2	3	High
Mean	0.18%	0.22%	-0.08%	0.47%	0.47%	0.18%
Std. Dev.	11.5%	16.5%	11.4%	9.2%	7.5%	6.3%
	Asset Return Statistics : Median					
Mean	0.51%	0.63%	0.53%	0.56%	0.52%	0.43%
Std. Dev.	9.02%	14.14%	9.19%	7.65%	6.45%	5.32%

Panel A reports summary statistics for the five leverage-sorted portfolios. In every January, no-debt firms are all allocated in the No-Debt portfolio. Rest of the firms are sorted into leverage quartile portfolios. To be included in the portfolios, firms' asset size should be greater than $250MM at the time of portfolio formation. Once the portfolios are formed, averages and standard deviations of value-weighted returns and averages of value-weighted asset-to-equity ratios are reported. Asset-to-equity ratios are weighted by market equity value. Panel B reports summary statistics for individual firms in each leverage group. Firms are assigned to leverage groups by their median values of leverage ratios. Averages and standard deviations of individual firms' equity and asset returns and averages of asset-to-equity ratio are calculated and, then, cross-sectional mean and median are reported for each leverage group.

Table 4. EGARCH Estimation Results for Leverage-Sorted Portfolios

Panel A: Equity Portfolio

	Leverage Quintile				
	Zero	1	2	3	High
ARCH	0.22	0.28	0.18	0.20	0.47
	(0.12)	(0.14)	(0.14)	(0.11)	(0.15)
ASYM	0.06	-0.10	-0.21	-0.05	-0.35
	(0.06)	(0.08)	(0.1)	(0.07)	(0.1)
GARCH	0.98	0.90	0.90	0.95	0.77
	(0.02)	(0.08)	(0.06)	(0.04)	(0.09)

Panel B: Asset Portfolio

	Leverage Quintile				
	Zero	1	2	3	High
ARCH	0.22	0.27	0.17	0.15	0.14
	(0.12)	(0.14)	(0.14)	(0.1)	(0.11)
ASYM	0.06	-0.08	-0.19	-0.03	-0.09
	(0.06)	(0.08)	(0.1)	(0.07)	(0.08)
GARCH	0.98	0.92	0.89	0.95	0.93
	(0.02)	(0.07)	(0.07)	(0.05)	(0.06)

Panel A reports EGARCH(1,1,1) estimation results for the leverage-sorted quintile equity portfolios. Firms with no debt outstanding are allocated to Zero quintile portfolio. The rest of firms are sorted into quintile portfolios based on January leverage ratios. The sample period is from March 1991 to October 2007. The numbers in parentheses are the standard errors. Panel B reports the same EGARCH(1,1,1) model estimation results for the returns of the leverage-sorted asset portfolios.

Table 5A: EGARCH Estimation Results at the Individual Firm Level

Mean							
			Equity			Firm	
Leverage	# of Firms	ARCH	GARCH	ASYM	ARCH	GARCH	ASYM
Zero	206	0.21	0.88	-0.13	0.21	0.88	-0.13
1	161	0.17	0.92	-0.13	0.17	0.91	-0.11
2	162	0.17	0.89	-0.16	0.18	0.88	-0.11
3	162	0.20	0.91	-0.12	0.19	0.90	-0.05
High	162	0.21	0.88	-0.19	0.22	0.86	-0.10
Overall	853	0.19	0.89	-0.14	0.19	0.89	-0.10
Median							
Zero	206	0.16	0.94	-0.10	0.16	0.94	-0.10
1	161	0.16	0.95	-0.14	0.17	0.95	-0.10
2	162	0.16	0.94	-0.17	0.17	0.94	-0.11
3	162	0.18	0.95	-0.11	0.17	0.95	-0.04
High	162	0.19	0.92	-0.17	0.20	0.93	-0.08
Overall	853	0.17	0.94	-0.14	0.17	0.94	-0.08
Stacked Estimation							
Leverage	# of Obs.	ARCH	GARCH	ASYM	ARCH	GARCH	ASYM
Zero	88713	0.19	0.87	-0.09	0.20	0.88	-0.07
1	42861	0.19	0.91	-0.09	0.19	0.91	-0.06
2	41600	0.18	0.92	-0.10	0.18	0.91	-0.05
3	43880	0.19	0.94	-0.10	0.18	0.91	-0.03
High	36434	0.16	0.92	-0.12	0.20	0.86	-0.05

This table reports EGARCH(1,1,1) estimation results at the individual firm level. Top and middle panels have the mean and the median of EGARCH estimates for individual firms for each leverage group. Firms are categorized into five leverage groups by their median leverage ratios. To be included in the sample, firms have to have more than 60 months of observations. Firms with bad EGARCH estimates are filtered out if they do not have (ii) positive ARCH and asymmetric coefficient or (iii) GARCH coefficient between 0.1 and 1. The bottom panel reports EGARCH results based on stacked estimation. For each leverage group, we stack firms with more than 12 months of data to obtain one long time-series and estimate EGARCH(1,1,1). # of Obs. is length of the stacked time-series for each leverage group.

Table 5B. Idiosyncratic Volatility EGARCH Estimation Results at the Individual Firm Level

		Mean					
		Equity			Firm		
Leverage	# of Obs.	ARCH	GARCH	ASYM	ARCH	GARCH	ASYM
Zero	139	0.21	0.89	-0.10	0.21	0.89	-0.10
1	123	0.16	0.93	-0.08	0.17	0.93	-0.06
2	122	0.18	0.92	-0.13	0.21	0.90	-0.09
3	131	0.22	0.92	-0.11	0.21	0.92	-0.04
High	136	0.25	0.90	-0.18	0.23	0.88	-0.07
Overall	651	0.21	0.91	-0.12	0.21	0.91	-0.07
		Median					
Zero	139	0.16	0.94	-0.07	0.16	0.94	-0.07
1	123	0.15	0.96	-0.09	0.16	0.96	-0.07
2	122	0.17	0.95	-0.12	0.19	0.94	-0.08
3	131	0.20	0.95	-0.11	0.20	0.95	-0.03
High	136	0.22	0.95	-0.15	0.20	0.94	-0.06
Overall	651	0.19	0.95	-0.12	0.19	0.95	-0.06
		Stacked Estimation					
Leverage	# of Obs.	ARCH	GARCH	ASYM	ARCH	GARCH	ASYM
Zero	88713	0.18	0.89	-0.06	0.19	0.89	-0.04
1	42861	0.17	0.93	-0.06	0.17	0.92	-0.04
2	41600	0.18	0.93	-0.08	0.17	0.93	-0.03
3	43880	0.19	0.94	-0.08	0.18	0.92	-0.02
High	36434	0.17	0.92	-0.11	0.20	0.88	-0.04

This table reports EGARCH(1,1,1) estimation results for idiosyncratic volatility at the individual firm level. For equity and asset returns, the following models,

$$R_{t+1}^{equity} = \beta\left(\frac{A_t \partial E_t}{E_t \partial A_t}\right) R_{mt+1} + h_{t+1}\varepsilon_{t+1}$$

$$R_{t+1}^{asset} = \beta R_{mt+1} + h_{t+1}\varepsilon_{t+1}$$

are estimated with EGARCH(1,1,1) for the residual term ε_{t+1}. Top and middle panels have the mean and the median of EGARCH estimates for individual firms for each leverage group. Firms are categorized into five leverage groups by their median leverage ratios. To be included in the sample, firms have to have more than 60 months of observations. Firms with bad EGARCH estimates are filtered out if they do not have (ii) positive ARCH and asymmetric coefficient or (iii) GARCH coefficient between 0.1 and 1. The bottom panel reports EGARCH results based on stacked estimation. For each firm with more than 12 months of data, simple OLS is estimated using the models above without imposing EGARCH assumption. Then, for each leverage group, we stack the residuals from the OLS regressions to obtain one long time-series and estimate EGARCH(1,1,1). # of Obs. is the length of the stacked time-series for each leverage group.

Table 6: Summary Statistics for Leverage-Sorted Portfolios

Panel A: Standard Deviations of Leverage and Asset Volatility

	In Log Levels				
Leverage	Zero	1	2	3	High
Asset/Equity	0	0.03	0.05	0.09	0.16
Asset Volatility	0.43	0.27	0.25	0.19	0.24
	In Log Differences				
Asset/Equity	0	0.01	0.01	0.02	0.04
Asset Volatility	0.07	0.10	0.12	0.05	0.24

Panel B: Autocorrelogram

	Log Asset-to-Equity Ratio				
Leverage	Lags				
Quartile	1	2	3	6	12
Low	0.95	0.90	0.87	0.80	0.82
2	0.97	0.94	0.91	0.86	0.75
3	0.97	0.94	0.91	0.85	0.74
High	0.96	0.93	0.89	0.82	0.63
	Log Adjusted Asset Volatility				
	1	2	3	6	12
Low	0.93	0.89	0.84	0.72	0.56
2	0.88	0.78	0.69	0.55	0.38
3	0.97	0.94	0.91	0.84	0.68
High	0.51	0.17	0.08	0.09	0.05

Panel C: Variance Decomposition

	In Log Levels			
	Leverage Quartile			
	Low	2	3	High
$Cov(\sigma_E, A/E)/Var(\sigma_E)$	-0.4%	10.0%	23.4%	34.7%
$Cov(\sigma_E, \sigma_A)/Var(\sigma_E)$	100.4%	90.0%	76.6%	65.3%
	In Log Differences			
	Low	2	3	High
$Cov(\Delta\sigma_E, \Delta A/E)/Var(\Delta\sigma_E)$	2.9%	6.9%	22.5%	9.2%
$Cov(\Delta\sigma_E, \Delta\sigma_A)/Var(\Delta\sigma_E)$	97.1%	93.1%	77.5%	90.8%

Panel A provides standard deviations of log leverage and log adjusted asset returns both in levels and in differences for five the leverage-sorted portfolios. Adjusted asset returns are calculated using

$$\widetilde{R}_A^i = \frac{\partial E^i}{\partial A^i} R_A^i$$

, where the partial derivative is obtained from the Black-Scholes formula. Panel B reports autocorrelogram of leverage and volatility on adjusted asset returns. Panel C reports variance decomposition of equity volatility obtained based on the structural model:

$$\log\left(vol_t\left(\sum\left(w_E^i R_{E:t+1}^i\right)\right)\right) = \log\left(\left(\frac{\sum A^i}{\sum E^i}\right)\right) + \log\left(vol_t \sum\left(w_A^i \tilde{R}_{A:t+1}^i\right)\right)$$

Then the fraction of variance of equity volatility coming from covariance with leverage and covariance with adjusted asset return volatility are reported. The bottom two rows of Panel C report the variance decomposition of changes in equity volatility into covariance with change in leverage and change in adjusted asset volatility.

Table 7 Summary Statistics for Individual Firms

Panel A: Standard Deviation of Leverage and Asset Volatility

Mean					
	Log Levels				
Leverage Quintile	Zero	1	2	3	High
Asset/Equity	0	0.08	0.14	0.20	0.39
Asset Volatility	0.00	0.26	0.26	0.26	0.28
	Log Differences				
Asset/Equity	0	0.02	0.05	0.06	0.12
Asset Volatility	0.00	0.11	0.12	0.11	0.13
Median					
	Log Levels				
Asset/Equity	0	0.07	0.12	0.18	0.35
Asset Volatility	0.00	0.25	0.24	0.24	0.26
	Log Differences				
Asset/Equity	0	0.02	0.04	0.06	0.11
Asset Volatility	0.00	0.09	0.10	0.09	0.12

Panel B: Autocorrelogram

Mean					
	Log Asset-to-Equity				
Leverage			Lags		
Quartile	1	2	3	6	12
Low	0.92	0.85	0.80	0.65	0.42
2	0.90	0.83	0.77	0.61	0.39
3	0.91	0.83	0.77	0.62	0.40
High	0.91	0.85	0.79	0.64	0.40
	Log Asset Volatility				
Low	0.88	0.79	0.72	0.57	0.37
2	0.85	0.74	0.67	0.53	0.32
3	0.88	0.79	0.72	0.57	0.35
High	0.85	0.73	0.64	0.46	0.24
Median					
	Log Asset-to-Equity				
Low	0.94	0.89	0.84	0.69	0.44
2	0.92	0.86	0.80	0.65	0.44
3	0.92	0.87	0.81	0.67	0.42
High	0.94	0.88	0.83	0.69	0.41
	Log Asset Volatility				
Low	0.93	0.86	0.81	0.65	0.41
2	0.91	0.83	0.75	0.58	0.34
3	0.92	0.85	0.79	0.63	0.38
High	0.91	0.81	0.73	0.50	0.27

Panel A provides mean and median of standard deviations of log leverage and log asset returns both in levels and in differences for five the leverage-sorted groups. Panel B reports mean and median autocorrelations of leverage and asset volatility for individual firms. Leverage groups are based on median values of leverage.

Table 7C: Equity Volatility Variance Decomposition

Panel C: Variance Decomposition

Leverage Quartile	# Firms	Mean Asset/Equity	Mean Asset Vol.	Median Asset/Equity	Median Asset Vol.
		In Levels			
Low	161	11%	89%	8%	92%
2	162	23%	77%	21%	79%
3	162	34%	66%	32%	68%
High	162	56%	45%	57%	43%
All	647	31%	69%	27%	73%
		In Differences			
Low	161	11%	89%	8%	92%
2	162	22%	78%	19%	81%
3	162	32%	68%	30%	70%
High	162	44%	56%	44%	56%
All	647	27%	73%	22%	78%
		In Levels (Stacked Estimation)			
Low	480	24%	76%	18%	82%
2	480	43%	57%	41%	59%
3	480	61%	39%	63%	37%
High	480	81%	19%	84%	16%
All	1920	52%	48%	54%	46%
		In Differences (Stacked Estimation)			
Low	480	18%	82%	14%	86%
2	480	37%	63%	33%	67%
3	480	50%	50%	50%	50%
High	480	67%	34%	68%	32%
All	1920	43%	57%	41%	59%

Table 7C provides the variance decomposition of equity volatility obtained based on the following structural model:

$$\sigma_E^2 = \left(\frac{A}{E}N(d_1)\right)\sigma_A^2$$

Then the fraction of variance of log equity volatility contributed to by its covariance with log leverage and it covariance with log adjusted asset return volatility are reported using the following decomposition:

$$Var(\log(\sigma_E)) = Cov\left(\log\left(\frac{A}{E}N(d_1)\right), \log(\sigma_E)\right) + Cov(\log(\sigma_A), \log(\sigma_E))$$

The decompositions are done both in log levels and log differences at the individual firm level and the mean and median values reported for each leverage group. The bottom two sets of results in Panel C are based on stacked volatility estimates.

Table 8A. Regression of Implied Volatility

Leverage Quartile	# of Firms	Mean Asset/Equity	Mean Asset Vol.	Mean R^2	Median Asset/Equity	Median Asset Vol.	Median R^2
		In Log Levels					
Low	152	0.50	0.79	0.57	0.35	0.79	0.59
2	150	0.58	0.67	0.52	0.56	0.66	0.55
3	137	0.52	0.70	0.51	0.51	0.71	0.52
High	115	0.55	0.71	0.57	0.52	0.65	0.58
All	554	0.54	0.72	0.54	0.50	0.71	0.57
		In Log Differences					
Low	152	1.35	0.37	0.14	0.97	0.35	0.11
2	150	0.63	0.37	0.13	0.39	0.35	0.12
3	137	0.62	0.34	0.12	0.53	0.30	0.10
High	115	0.53	0.43	0.16	0.49	0.38	0.15
All	554	0.80	0.37	0.14	0.54	0.35	0.12
		In Log Levels (Stacked Estimation)					
Low	404	0.50	0.98	0.51	0.33	1.09	0.56
2	378	0.52	0.87	0.46	0.48	0.94	0.50
3	331	0.75	0.86	0.49	0.66	0.95	0.51
High	209	0.60	0.88	0.52	0.51	0.99	0.53
All	1322	0.58	0.90	0.50	0.52	0.99	0.53
		In Log Differences (Stacked Estimation)					
Low	404	1.68	0.53	0.15	1.14	0.58	0.13
2	378	0.89	0.48	0.14	0.64	0.51	0.11
3	331	0.84	0.41	0.16	0.64	0.47	0.12
High	209	0.44	0.55	0.18	0.42	0.59	0.15
All	1322	1.05	0.49	0.15	0.65	0.54	0.13

Table 8A provides the regression results of implied volatility based on the following model:

$$\log\left(\sigma_E^2\right)_t = \phi \log\left(\frac{A}{E}N(d_1)\right)_t^2 + \gamma \log\left(\sigma_A^2\right) + \varepsilon_t$$

$$\Delta \log\left(\sigma_E^2\right)_t = \theta \Delta \log\left(\frac{A}{E}N(d_1)\right)_t^2 + \lambda \Delta \log\left(\sigma_A^2\right) + \eta_t$$

Log implied volatilities of individual firms are regressed on log leverage and log adjusted asset volatilities, both in levels and changes. Median and mean values of regression coefficients and R^2 are reported for each leverage group. Coefficients are winsorized at the bottom and top 3% levels to calculate the mean values. The bottom two sets of results are using adjusted volatilities obtained from stacked estimation. Implied volatilities are from one month ahead at-the-money call options. Firms must have at least 12 months of observations to be included in the regressions.

Table 8B: Variance Decomposition of Implied Volatility

Leveraqe Quartile	# of Firms	Mean Asset/Equity	Mean Asset Vol.	Median Asset/Equity	Median Asset Vol.
		In Log Levels			
Low	152	19%	81%	6%	94%
2	150	30%	70%	15%	85%
3	137	31%	69%	24%	76%
High	115	43%	57%	41%	59%
All	554	30%	70%	20%	80%
		In Log Differences			
Low	152	30%	70%	26%	74%
2	150	36%	64%	30%	70%
3	137	44%	56%	46%	54%
High	115	44%	56%	52%	48%
All	554	38%	62%	36%	64%
		In Log Levels (Stacked Estimation)			
Low	404	30%	70%	18%	82%
2	378	33%	67%	22%	78%
3	331	45%	55%	41%	59%
High	209	50%	50%	49%	51%
All	1322	38%	62%	30%	70%
		In Log Differences (Stacked Estimation)			
Low	404	40%	60%	35%	65%
2	378	47%	53%	39%	61%
3	331	55%	45%	55%	45%
High	209	47%	53%	41%	59%
All	1322	47%	53%	41%	59%

Using the regression coefficients in Table 8A, the proportions of the equity implied volatilities explained by leverage and asset volatilities are reported. The decomposition is based on the following:

$$Var(\log(\sigma_E)) = \phi \cdot Cov\left(\log\left(\frac{A}{E}N(d_1)\right), \log(\sigma_E)\right) + \gamma \cdot Cov(\log(\sigma_A), \log(\sigma_E))$$

$$Var(\Delta\log(\sigma_E)) = \theta \cdot Cov\left(\Delta\log\left(\frac{A}{E}N(d_1)\right), \Delta\log(\sigma_E)\right) + \lambda \cdot Cov(\Delta\log(\sigma_A), \Delta\log(\sigma_E))$$

where ϕ, γ, θ and λ are the regression coefficients from Table 8A. For each firm, the fraction of variance of equity volatility due to leverage and asset volatility is calculated both in levels and in changes and their mean and median values are reported for each leverage group. All values are winsorized at the bottom and top 3% levels before the means are calculated. The bottom two sets of results in Panel C are based on stacked asset volatility estimates.

Table 9A: Regression of Implied Volatility on Market and Idiosyncratic Volatility

Leverage Quartile	# of Firms	Asset/Equity	σ_t^{Mkt}	σ_{t-1}^{Mkt}	ε_{t-1}^{mkt}	$\lvert \varepsilon_{t-1}^{mkt} \rvert$	σ_t^{idio}	σ_{t-1}^{idio}	ε_{t-1}^{idio}	$h \lvert \varepsilon_{t-1}^{idio} \rvert$	R^2
		Mean Levels									
1	116	0.41	0.48				0.48				0.69
2	113	0.48	0.33				0.43				0.61
3	115	0.37	0.37				0.42				0.60
4	98	0.47	0.38				0.46				0.64
1	116	0.37		0.44	-0.06	0.09		0.49	-0.08	0.11	0.72
2	113	0.43		0.34	-0.04	0.06		0.40	-0.06	0.09	0.66
3	115	0.34		0.39	-0.04	0.07		0.39	-0.06	0.11	0.66
4	98	0.44		0.35	-0.03	0.07		0.45	-0.07	0.10	0.68
		Mean Diff									
1	116	1.51	0.30				0.24				0.14
2	113	0.77	0.25				0.29				0.14
3	115	0.66	0.24				0.30				0.14
4	98	0.57	0.28				0.36				0.18
1	116	0.57		-0.02	-0.08	0.02		-0.01	-0.08	0.05	0.24
2	113	0.30		-0.01	-0.05	0.03		-0.02	-0.08	0.04	0.23
3	115	0.32		-0.01	-0.05	0.03		-0.03	-0.07	0.06	0.22
4	98	0.18		-0.03	-0.05	0.04		-0.02	-0.10	0.07	0.26
		Median Level									
	# of Firms	Asset/Equity	σ_t^{Mkt}	σ_{t-1}^{Mkt}	ε_{t-1}^{mkt}	$\lvert \varepsilon_{t-1}^{mkt} \rvert$	σ_t^{idio}	σ_{t-1}^{idio}	ε_{t-1}^{idio}	$h \lvert \varepsilon_{t-1}^{idio} \rvert$	R^2
1	116	0.39	0.47				0.43				0.73
2	113	0.49	0.36				0.43				0.63
3	115	0.39	0.39				0.40				0.63
4	98	0.49	0.38				0.47				0.67
1	116	0.35		0.45	-0.05	0.09		0.45	-0.07	0.11	0.75
2	113	0.45		0.35	-0.04	0.06		0.39	-0.05	0.09	0.67
3	115	0.38		0.38	-0.04	0.07		0.35	-0.06	0.10	0.66
4	98	0.47		0.34	-0.03	0.08		0.43	-0.07	0.10	0.72
		Median Diffs									
1	116	1.17	0.29				0.22				0.13
2	113	0.54	0.25				0.23				0.12
3	115	0.54	0.22				0.30				0.12
4	98	0.51	0.29				0.26				0.17
1	116	0.54		-0.02	-0.07	0.02		-0.01	-0.08	0.04	0.22
2	113	0.15		-0.01	-0.05	0.04		-0.03	-0.08	0.05	0.21
3	115	0.25		-0.01	-0.05	0.02		-0.03	-0.06	0.06	0.20
4	98	0.11		-0.01	-0.04	0.04		-0.02	-0.10	0.07	0.26

Table 9A reports regression results of implied volatility as below:

$$\log \sigma_t^{E} = a \log l_t + b \log \sigma_t^{Mkt} + f \log \sigma_t^{idio}$$

$$\log \sigma_t^{E} = a \log l_t + b \log \sigma_{t-1}^{Mkt} + c\varepsilon_{t-1}^{mkt} + d \mid \varepsilon_{t-1}^{mkt} \mid + f \log \sigma_{t-1}^{idio} + g\varepsilon_{t-1}^{idio} + h \mid \varepsilon_{t-1}^{idio} \mid$$

Regressions in differences are based on simple differences for the first model and on equation (13) for the second model. Median and mean values of regression coefficients and R^2 are reported for each leverage group. Coefficients are winsorized at the bottom and top 3% levels to calculate the mean values. The bottom two sets of results are using adjusted asset volatilities obtained from stacked estimation. Implied volatilities are from one month ahead at-the-money call options. Firms must have at least 12 months of observations to be included in the regressions.

Table 9B: Variance Decompositions

Mean of the Variance Decompositions

Leverage Quartile	# of Firms	Asset/Equity	σ_t^{Mkt}	σ_{t-1}^{Mkt}	ε_{t-1}^{mkt}	$\lvert \varepsilon_{t-1}^{mkt} \rvert$	σ_t^{idio}	σ_{t-1}^{idio}	ε_{t-1}^{idio}	$h \lvert \varepsilon_{t-1}^{idio} \rvert$
		Mean Levels								
1	116	8%	54%				38%			
2	113	18%	44%				37%			
3	115	18%	43%				39%			
4	98	34%	34%				32%			
1	116	8%		46%	3%	3%		35%	2%	3%
2	113	17%		41%	3%	2%		30%	3%	4%
3	115	17%		38%	2%	3%		33%	4%	3%
4	98	31%		30%	2%	3%		28%	4%	3%
		Mean Differences								
1	116	33%	29%				38%			
2	113	34%	22%				44%			
3	115	40%	24%				37%			
4	98	42%	23%				35%			
1	116	10%		2%	34%	7%		3%	35%	10%
2	113	14%		2%	23%	7%		4%	38%	13%
3	115	17%		3%	24%	8%		4%	28%	16%
4	98	16%		2%	17%	10%		4%	39%	12%
		Median Levels								
Leverage	N	Asset/Equity	σ_t^{Mkt}	σ_{t-1}^{Mkt}	ε_{t-1}^{mkt}	$\lvert \varepsilon_{t-1}^{mkt} \rvert$	σ_t^{idio}	σ_{t-1}^{idio}	ε_{t-1}^{idio}	$h \lvert \varepsilon_{t-1}^{idio} \rvert$
1	116	2%	60%				38%			
2	113	12%	48%				41%			
3	115	8%	50%				42%			
4	98	37%	32%				31%			
1	116	2%		54%	2%	3%		34%	2%	3%
2	113	13%		45%	2%	2%		32%	2%	3%
3	115	9%		44%	2%	2%		38%	3%	2%
4	98	34%		29%	1%	2%		29%	3%	2%
		Median Differences								
1	116	33%	31%				36%			
2	113	30%	23%				47%			
3	115	42%	20%				38%			
4	98	49%	26%				25%			
1	116	6%		2%	44%	4%		1%	40%	4%
2	113	6%		1%	26%	7%		3%	47%	11%
3	115	18%		1%	19%	6%		2%	37%	17%
4	98	11%		1%	15%	8%		2%	54%	9%

Using the regression coefficients in Table 9A, the proportions of variance of equity implied volatilities explained by covariances with each regressors are reported. Equity implied volatility variances are decomposed into the covariances with each regressor by the following equation:.

$$Var(\log \sigma_t^E) = Cov(a \log l_t, \log \sigma_t^E) + Cov(b \log \sigma_t^{Mkt}, \log \sigma_t^E) + Cov(f \log \sigma_t^{idio}, \log \sigma_t^E)$$

and similarly for other specifications, too. Once the decompositions are done at the firm level, mean and median values are reported for each leverage group. All values are winsorized at the bottom and top 3% levels before the means are calculated.

Table 9C. Regression Coefficients with Stacked Estimation

Leverage Quartile	# of Firms	Asset/Equity	σ_t^{Mkt}	σ_{t-1}^{Mkt}	ε_{t-1}^{mkt}	$\|\varepsilon_{t-1}^{mkt}\|$	σ_t^{idio}	σ_{t-1}^{idio}	ε_{t-1}^{idio}	$h\,\|\varepsilon_{t-1}^{idio}\|$	R^2
		Mean Levels									
1	404	0.76	0.43				0.55				0.59
2	378	0.55	0.39				0.51				0.53
3	331	0.67	0.36				0.57				0.56
4	209	0.55	0.31				0.61				0.58
1	404	0.66		0.43	-0.05	0.10		0.48	-0.07	0.10	0.67
2	378	0.43		0.37	-0.03	0.07		0.46	-0.06	0.09	0.62
3	331	0.62		0.37	-0.02	0.07		0.52	-0.05	0.11	0.64
4	209	0.50		0.37	-0.02	0.07		0.53	-0.05	0.11	0.65
		Mean Differences									
1	404	2.00	0.24				0.30				0.15
2	378	1.02	0.23				0.31				0.15
3	331	0.85	0.22				0.27				0.18
4	209	0.48	0.25				0.41				0.20
1	404	0.34		-0.01	-0.08	0.03		-0.11	-0.09	0.03	0.30
2	378	0.09		-0.01	-0.06	0.03		-0.12	-0.09	0.03	0.28
3	331	0.11		-0.01	-0.05	0.03		-0.11	-0.11	0.04	0.30
4	209	-0.04		-0.05	-0.05	0.03		-0.09	-0.13	0.06	0.33

Leverage Quartile	# of Firms	Asset/Equity	σ_t^{Mkt}	σ_{t-1}^{Mkt}	ε_{t-1}^{mkt}	$\|\varepsilon_{t-1}^{mkt}\|$	σ_t^{idio}	σ_{t-1}^{idio}	ε_{t-1}^{idio}	$h\,\|\varepsilon_{t-1}^{idio}\|$	R^2
		Median Levels									
1	404	0.54	0.43				0.63				0.64
2	378	0.46	0.35				0.56				0.58
3	331	0.57	0.31				0.67				0.59
4	209	0.44	0.31				0.70				0.59
1	404	0.45		0.44	-0.05	0.11		0.56	-0.07	0.10	0.70
2	378	0.41		0.33	-0.03	0.07		0.50	-0.06	0.09	0.65
3	331	0.53		0.31	-0.03	0.07		0.62	-0.06	0.11	0.66
4	209	0.44		0.32	-0.02	0.08		0.68	-0.06	0.11	0.68
		Median Differences									
1	404	1.40	0.34				0.26				0.12
2	378	0.73	0.35				0.23				0.12
3	331	0.67	0.30				0.20				0.14
4	209	0.44	0.43				0.29				0.16
1	404	0.24		-0.01	-0.08	0.03		-0.08	-0.09	0.04	0.26
2	378	0.08		0.00	-0.06	0.03		-0.07	-0.08	0.04	0.24
3	331	0.19		-0.01	-0.06	0.03		-0.07	-0.09	0.05	0.25
4	209	0.06		-0.02	-0.05	0.04		-0.07	-0.11	0.07	0.28

Table 9C reports regression results of implied volatility as below:

$$\log \sigma_t^{E} = a \log l_t + b \log \sigma_t^{Mkt} + f \log \sigma_t^{idio}$$

$$\log \sigma_t^{E} = a \log l_t + b \log \sigma_{t-1}^{Mkt} + c\varepsilon_{t-1}^{mkt} + d\,|\varepsilon_{t-1}^{mkt}| + f \log \sigma_{t-1}^{idio} + g\varepsilon_{t-1}^{idio} + h\,|\varepsilon_{t-1}^{idio}|$$

Regressions in differences are based on simple differences for the first model and on equation (13) for the second model. Median and mean values of regression coefficients and R^2 are reported for each leverage group. Coefficients are winsorized at the bottom and top 3% levels to calculate the mean values. The bottom two sets of results are using adjusted asset volatilities obtained from stacked estimation. Implied volatilities are from one month ahead at-the-money call options. Firms must have at least 12 months of observations to be included in the regressions. Market and firm volatilities are obtained from EGARCH(1,1,1) using stacked estimation.

Table 9D: Variance Decomposition from Stacked Estimation

Panel D:

Leverage Quartile	# of Firms	Asset/Equity	σ_t^{Mkt}	σ_{t-1}^{Mkt}	ε_{t-1}^{mkt}	$\lvert\varepsilon_{t-1}^{mkt}\rvert$	σ_t^{idio}	σ_{t-1}^{idio}	ε_{t-1}^{idio}	$h\lvert\varepsilon_{t-1}^{idio}\rvert$
		Mean Levels								
1	404	18%	51%				31%			
2	378	23%	45%				32%			
3	331	34%	35%				31%			
4	209	40%	29%				30%			
1	404	17%		43%	4%	4%		23%	4%	5%
2	378	19%		37%	4%	4%		26%	6%	5%
3	331	30%		30%	3%	4%		24%	5%	5%
4	209	34%		26%	3%	3%		23%	5%	6%
		Mean Differences								
1	404	47%	23%				30%			
2	378	48%	21%				31%			
3	331	50%	21%				29%			
4	209	46%	20%				34%			
1	404	9%		2%	28%	9%		5%	35%	11%
2	378	12%		3%	23%	10%		5%	34%	13%
3	331	13%		3%	21%	10%		4%	36%	13%
4	209	12%		3%	18%	11%		6%	38%	14%

Leverage Quartile	# of Firms	Asset/Equity	σ_t^{Mkt}	σ_{t-1}^{Mkt}	ε_{t-1}^{mkt}	$\lvert\varepsilon_{t-1}^{mkt}\rvert$	σ_t^{idio}	σ_{t-1}^{idio}	ε_{t-1}^{idio}	$h\lvert\varepsilon_{t-1}^{idio}\rvert$
		Median Levels								
1	404	8%	60%				28%			
2	378	13%	53%				34%			
3	331	33%	34%				26%			
4	209	42%	25%				36%			
1	404	9%		53%	3%	4%		24%	2%	5%
2	378	12%		47%	3%	3%		26%	4%	5%
3	331	29%		32%	1%	3%		27%	3%	4%
4	209	42%		23%	1%	2%		24%	3%	4%
		Median Differences								
1	404	52%	20%				28%			
2	378	47%	19%				34%			
3	331	57%	17%				26%			
4	209	44%	20%				36%			
1	404	5%		1%	38%	6%		2%	41%	7%
2	378	8%		1%	26%	7%		3%	43%	11%
3	331	10%		1%	21%	7%		2%	47%	13%
4	209	8%		1%	18%	10%		3%	50%	11%

Table 10D reports the variance decomposition similar to Table 10B. The coefficients from Table 10C (stacked estimation results) are used to decompose variance of implied volatility. Firms' idiosyncratic volatilities are obtained from stacked estimations. Mean and median of decompositions are reported for each leverage group. All values are winsorized at the bottom and top 3%.