Balance sheet explanations for asymmetric volatility

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ABSTRACT

Changes in firm value are likely to be accompanied by changes in the values of a firm's riskier assets (say, growth options) relative to its less risky assets (say, assets in place). These changes should in turn lead to changes in stock return volatility. This paper argues that such balance-sheet effects explain the positive contemporaneous relation between stock returns and volatility at the firm level. The theory of balance-sheet effects implies that cross-sectionally, betas and book/market ratios should predict the strength of the return-volatility relation. These implications are supported in the data. The results also indicate that the well-known pattern of higher correlations among stock returns in down markets is in large part driven by a positive relation between market returns and idiosyncratic volatility.

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1 Introduction

Stock returns are correlated with both contemporaneous and future stock return volatility, a pattern often termed asymmetric volatility. Theory offers many potential explanations for this well-known relation but the evidence stubbornly refuses to fit well with any of them. The earliest proposed explanation is the "leverage effect" formalized in Black (1976) and Christie (1982). It implies that stock returns are negatively associated with volatility because changes in stock prices affect firms' financial leverage. This implication is consistent with the return-volatility relation in aggregate stock returns. However, the limitations of this explanation are now well-known. In particular, Duffee (1995) notes one of the embarrassing facts for this hypothesis: at the firm level, stock returns and volatility are contemporaneously positively correlated.

Although this positive relation is hard to reconcile with the leverage effect, it is consistent with a generalization of the logic underlying the leverage effect. The leverage effect is a special case of what we can call "economic balance sheet" explanations for a link between returns and volatility. The composition of a firm's economic balance sheet changes when the value of the firm changes (although the accounting balance sheet may be unaltered). The leverage effect emphasizes the change in the relative values of debt and equity, but, as noted by Rubinstein (1983), the relative values of a firm's assets will also change. Consider, for example, a firm with multiple assets that differ in their volatilities. An increase in the value of the firm is, on average, associated with an increase in the value of riskier assets relative to less-risky assets, and thus overall volatility of the firm tends to rise. To complicate matters, if some of these assets are growth options, then the standard inverse relation between an option's moneyness and its return volatility can produce an ambiguous link between returns and volatility.

In this paper I test the empirical relevance of these balance sheet explanations. I emphasize two main implications. First, balance-sheet effects for a given firm should be the same regardless whether the change in firm value is the result of an idiosyncratic shock or a marketwide shock. Second, balance-sheet effects should differ across firms based on the relative importance of the firms' growth options. To partially control for business-cycle effects, I focus on the relation between stock returns and the volatility of the idiosyncratic portion of firms' stock returns. I follow Sagi and Seasholes (2001) and use firms' book-to-market ratios as proxies for the importance of growth options among the firms' assets.

The weight of evidence presented here, which is drawn from 40 years of data on U.S. firms, supports the view that balance-sheet effects drive a positive relation between returns and idiosyncratic volatility. A positive shock to a firm's stock return corresponds to an increase in idiosyncatic volatility; the strength of this relation does not depend on whether the shock is a marketwide or idiosyncratic shock. In addition, firms with high betas have a larger positive relation between aggregate stock returns and contemporaneous idiosyncratic return volatility than do firms with low betas. Finally, book-to-market ratios are very strong cross-sectional predictors of the strength of asymmetric volatility. Firms with lower book-to-market ratios (suggestive of growth options that are more in-the-money) have, on average, a less positive relation between returns and idiosyncratic volatility than do firms with higher book-to-market ratios.

An obvious limitation of this story is that it is incapable of explaining the negative relation between returns and volatility at the aggregate level. A complete explanation of the return-volatility relation needs more than balance-sheet effects, but I do not attempt to explore the potential sources of the aggregate-level relation. The only use I make of aggregate volatility here is to shed some light on the issue of "asymmetric correlations." Earlier research concluded that correlations among aggregate stock returns in different countries tend to be higher when markets fall than when markets rise, a pattern termed asymmetric correlations. Ang and Chen (2002) find the same pattern with portfolios of U.S. stocks. The usual interpretation is that marketwide shocks are larger in absolute value when stock prices are falling. The evidence here indicates another reason for asymmetric correlations–idiosyncratic volatility is higher on days when the market rises. I find that for correlations between individual stocks, close to half of the difference between up-market correlations and down-market correlations is attributable to the behavior of idiosyncratic volatility.

The results are not all supportive of balance-sheet effects. Changes in the structure of a firm's assets and liabilities owing to a change in firm value should persist until the firm alters its mix of assets and liabilities. But Figlewski and Wang (2000) point out that the return-volatility relation seems too short-lived to be consistent with persistent changes in balance sheets. Similarly, I find that the cross-sectional predictive power of beta and book-to-market ratios is short-lived. This pattern is a little hard to reconcile with balance-sheet effects, although I make some efforts to explain it away.

The outline of the remainder of this paper is as follows. Section 2 explains how this paper fits into the existing literature. Section 3 provides a theoretical framework that motivates the empirical tests that are described in Section 4. Results are reported in Section 5. Some concluding comments are contained in the final section.

2 What we know about asymmetric volatility

At the aggregate level, stock returns are negatively correlated with both contemporaneous volatility (i.e., returns are negatively skewed) and future volatility. Black (1976) emphasized the role of leverage in explaining this relation. The leverage hypothesis implies a negative return-volatility relation for individual firms, which was consistent with Black's view of the evidence. But, as discussed in Duffee (1995), the evidence was misinterpreted. Instead, firm-level returns and volatility are typically contemporaneously positively correlated (positive skewness). Simkowitz and Beedles (1978) first documented the positive skewness of firm-level returns, a pattern that is periodically rediscovered. Duffee (1995) and Braun, Nelson, and Sunier (1995) find no clear relation between firm-level returns and future volatility.

Nonetheless, Black's work was followed by research to test further the implications of the leverage hypothesis. Christie (1982), Cheung and Ng (1992), and Duffee (1995) all found that firms with larger debt/equity ratios exhibited stronger negative relations between returns and volatility, consistent with the leverage hypothesis. Unfortunately, all of this evidence is statistically suspect. Christie does not report any formal statistical tests of the link between debt/equity ratios and the return-volatility relation. Cheung-Ng and Duffee's statistical tests rely on the (invalid) assumption that firms' stock returns can be treated as independent across firms. Moreover, Schwert (1989) finds that the aggregate debt/equity ratio explains only a small part of aggregate stock return volatility. Overall, it is fair to conclude that there is minimal evidence to support the leverage hypothesis.

The difference between aggregate and firm-level behavior tells us that multiple explanations are likely needed to explain the return-volatility relation. One effect operates at the market level and produces a negative relation; another operates at the firm level and produces a positive relation. Marketwide effects are easy to envision but hard to verify. It is possible that asset returns are simply more volatile in recessions. For example, inflation, commodity prices or interest rates may fluctuate more at those times, leading to higher asset volatility at precisely those times when asset values are low. We can think of this as a fundamental link between asset returns and asset return volatility. Although this fundamental link is plausible, Schwert (1989) finds only weak evidence that macroeconomic volatility explains aggregate stock return volatility.

An alternative explanation for the negative return-volatility relation at the aggregate level is "volatility feedback." This hypothesis takes changes in volatility as exogenous. Pindyck (1984) posits that investors' required risk premia change with changes in volatility. Thus investors bid up (down) stock prices when they perceive decreases (increases) in volatility. Although the hypothesis is intuitive, supporting evidence is weak. French, Schwert, and

Stambaugh (1987) and Campbell and Hentschel (1992) note that the leverage effect is not strong enough to produce the large inverse relation between aggregate returns and volatility in the data, leading them to conclude that the volatility feedback hypothesis is probably correct. But Poterba and Summers (1986) argue that changes in volatility appear to be too short-lived to lead to large changes in investors' valuations. In addition, a large body of research finds that changes in aggregate stock return volatility are unaccompanied by corresponding changes in expected future aggregate stock returns.[1] Finally, the volatility feedback hypothesis leaves unanswered the question of what causes volatility to change in the first place.

To summarize, the return-volatility relation at the aggregate level has received much attention, yet its determinants remain largely a mystery. By contrast, the positive return-volatility relation at the firm level has received comparatively little attention, but is perhaps easier to explain. One explanation uses the same logic that is employed in the leverage hypothesis: changes in firm value are typically accompanied by changes in the relative values of items on a firm's "economic" (i.e., true) balance sheet.

The displaced diffusion model of Rubinstein (1983) is the simplest framework that can generate a positive return-volatility relation through balance-sheet effects. The model allows for the leverage effect to be reversed if firms hold more riskless assets than they have issued as debt. The broader message of Rubinstein's model is that a mixture of assets induces a positive return-volatility relation. The formal model in the next section goes into this in more detail, but the basic idea is simple. Shocks to firm value are caused by shocks to asset values. Riskier assets have larger absolute shocks, thus a positive (negative) shock to firm value is typically accompanied by a increase (decrease) in the value of the firm's risky assets relative to the value of its less-risky assets. Sagi and Seasholes (2001) use a generalization of this idea to attempt to explain momentum in stock prices.

A more complicated relation between returns and volatility results if some of the assets held by a firm are growth options. The importance of growth options in the stock market is indicated by the analysis of Berk, Green, and Naik (1999). They conclude that a variety of stylized facts about the predictability of stock returns are explained by the presence of such options. The existence of growth options produces an ambiguous relation between returns and volatility. For firms with both low-volatility assets in place and high-volatility growth options, the mixture-of-assets effect leads to a positive relation. Offsetting this is negative relation between the moneyness of a call option and its instantaneous return volatility. For

[1] See Whitelaw (2000) for a discussion and references. Wu (2001) concludes that the volatility feedback hypothesis has merit, but his model assumes that aggregate risk premia are determined entirely by the level of aggregate volatility. Since risk premia are positive on average, the model essentially forces risk premia to vary positively with volatility.

example, if the option value increases, the firm will have a relatively larger share of high-volatility assets but the volatility of the growth option will fall.

Hong and Stein (1999) and Chen, Hong, and Stein (2001) offer another explanation for a firm-level relation between returns and volatility. They argue that changes in stock prices affect the identity of the marginal investor. The model relies on investor heterogeneity combined with short-sale constraints. As a stock's price declines, the marginal investor tends to shift to those who are more bearish. The information held by these bearish investors is then revealed, which can lead to further declines in the stock price. Because this effect induces negative skewness in stock returns, it cannot be the only reason why firm-level returns and volatility are related. One difference between their story and balance-sheet effects is persistence: Balance-sheet effects should generate a relation between returns and future volatility as well as contemporaneous volatility.

Aside from work on the leverage effect, there is scant empirical evidence on the determinants of the firm-level return-volatility relation. A notable recent effort is Chen et al. (2001), which finds some support for their model. They also document a pattern they did not anticipate: firms that experience increases in value over the past three years tend to have more negatively-skewed returns. They interpret the result in terms of stock-price bubbles. I argue later that the result can be interpreted as evidence of balance-sheet effects.

3 Models of balance-sheet effects

The goal of this paper is to investigate empirically the importance of balance-sheet effects, and in particular the role of growth options, in explaining the return-volatility relation at the firm level. This section sets up two models that provide the testable hypotheses. The model in Section 3.1 is basically Rubinstein's displaced diffusion model set in a dynamic framework. For tractability reasons, it does not include any growth options. Sagi and Seasholes (2001) and Berk et al. (1999) amply illustrate the difficulties involved in dynamic models with growth options. The model in Section 3.2 is a stripped-down framework that illustrates the effects of growth options.

3.1 A dynamic displaced-diffusion model

3.1.1 Asset dynamics

Firms are indexed by $i = 1, \ldots, N$. The value of firm i is the sum of the assets held by the firm. Firms invest in riskless and risky assets. The notation is

$$V_i(t) = A_i(t) + B_i(t)$$

where $V_i(t)$ is the value of the firm, $B_i(t)$ is the amount of riskfree bonds it holds, and $A_i(t)$ is the value of its risky assets. The dynamics of the bonds held by firms satisfy

$$\frac{dB_i}{B_i} = rdt$$

where for simplicity the instantaneous interest rate is assumed to be constant. The risky asset has dynamics that depend on both market-wide and idiosyncratic shocks. I assume asset return dynamics of the form

$$\frac{dA_i}{A_i} = \mu_{iA}(t)dt + \begin{pmatrix} \beta_i^* \sigma_{mA}(t) \\ \sigma_{iA}^I(t) \end{pmatrix} \begin{pmatrix} dZ_m(t) \\ dZ_i(t) \end{pmatrix}. \quad (1)$$

Because our interest is in the volatility of asset returns, the drift function $\mu_{iA}(t)$ is not given any structure. There are both marketwide (dZ_m) and idiosyncratic (dZ_i) shocks to asset values. The effects of these shocks depend on the firm's asset beta β_i^* and the volatility functions $\sigma_{mA}(t)$ and $\sigma_{iA}^I(t)$. The asterisk on beta is used to differentiate the asset beta from the stock return beta. The subscripts on $\sigma_{mA}(t)$ indicate that this is the volatility of marketwide asset shocks. The superscript and subscripts on $\sigma_{iA}^I(t)$ indicate that this is the volatility of idiosyncratic (I) shocks to firm i's asset value.

The aggregate value of risky assets is the sum of all N firms' asset values:

$$A(t) \equiv \sum_{i=1}^{N} A_i(t).$$

To determine the dynamics of $A(t)$, sum the dynamics of the individual firm asset values and assume that N is sufficiently large that the idiosyncratic terms can be ignored. The result is

$$\frac{dA}{A} = \mu_A(t)dt + \frac{\sum_{i=1}^{N} \beta_i^* A_i(t)}{\sum_{i=1}^{N} A_i(t)} \sigma_{mA}(t) dZ_m(t).$$

Again, the drift term is left unspecified. The dynamics of marketwide volatility $\sigma_{mA}(t)$ are assumed to take the form

$$\frac{d\sigma_{mA}}{\sigma_{mA}} = \alpha_{mA}(t)dt + \gamma_m \sigma_{mA}(t)dZ_m(t).$$

This functional form was chosen to allow for a "fundamental" contemporaneous correlation between aggregate asset returns and volatility. The key parameter is γ_m, which determines the sign of this correlation. I will assume it is negative because its role is to capture a marketwide force that produces a negative relation between aggregate asset returns and aggregate asset return volatility. Since research to date has been unsuccessful at explaining the nature of the aggregate-level relation, γ_m is taken as exogenous. I include $\sigma_{mA}(t)$ in the diffusion component because it simplifies the math that follows; nothing important is lost if it is removed. Because aggregate asset return volatility depends only on dZ_m, it is instantaneously perfectly correlated with aggregate asset returns. This assumption is not important either, but adding an independent source of variation in $\sigma_{mA}(t)$ adds nothing to the intuition of the model.

Volatility dynamics for firm-specific shocks differ in two ways from the volatility dynamics for aggregate shocks. First, I do not include any fundamental correlation between idiosyncratic volatility and asset-return shocks. Second, I allow idiosyncratic volatility to vary independently of asset returns. The dynamics are

$$\frac{d\sigma_{iA}^I}{\sigma_{iA}^I} = \alpha_i(t)dt + \gamma_i^I dZ_{iV}(t) \tag{2}$$

where the $dZ_{iV}(t)$ is independent $dZ_i(t)$ and $dZ_m(t)$. I do not require that $dZ_{iV}(t)$ be independent of dZ_{jV}. In other words, shocks to firms' idiosyncratic asset volatilities can be contemporaneously correlated. These dynamics are an oversimplification of reality (as we will see in the empirical results that follow), but the setup is sufficient to illustrate balance-sheet effects.

3.1.2 Stock value dynamics

The value of a firm $V_i(t)$ is the sum of the claims on the firm's assets. Claims on firms' assets are held by stockholders and bondholders, or

$$V_i(t) = S_i(t) + L_i(t)$$

Debt issued by the firm is denoted $L_i(t)$ and is assumed to be default-free. (Firms go out of business before their asset values fall below the value of their debt.) The value of stock is

$S_i(t)$. The dynamics of the bonds issued by firms are

$$\frac{dL_i}{L_i} = rdt.$$

The dynamics of the firm's stock value $S_i(t)$ are denoted

$$\frac{dS_i}{S_i} = \mu_{is}(t)dt + \begin{pmatrix} \sigma_{iS}^m(t) \\ \sigma_{iS}^I(t) \end{pmatrix} \begin{pmatrix} dZ_m(t) \\ dZ_i(t) \end{pmatrix}. \tag{3}$$

Substitution of (1) into (3) allows us to express the volatility functions in (3) in terms of the underlying asset volatilities and the firm's risky asset value relative to its stock value:

$$\sigma_{iS}^m(t) = \frac{A_i(t)}{S_i(t)}\beta_i^* \sigma_{mA}(t),$$

$$\sigma_{iS}^I(t) = \frac{A_i(t)}{S_i(t)}\sigma_{iA}^I(t). \tag{4}$$

The return to the aggregate stock market is

$$\frac{dS}{S} = \mu_{mS}(t)dt + \sigma_{mS}(t)dZ_m(t)$$

where

$$\sigma_{mS}(t) = \frac{\sum \beta_i^* A_i(t)}{S(t)}\sigma_{mA}(t)$$

and $S(t)$ denotes the sum of individual firm stock values. The instantaneous beta of a firm's stock return is (using somewhat informal notation)

$$\beta_i(t) \equiv \frac{\text{Cov}_t\left(dS/S, dS_i/S_i\right)}{\text{Var}_t(dS/S)} = \frac{A_i(t)\beta_i^* / \sum(A_i(t)\beta_i^*)}{S_i(t)/S(t)}.$$

Our primary interest here is in the dynamics of idiosyncratic stock return volatility. From (4), these dynamics can be expressed as

$$\frac{d\sigma_{iS}^I}{\sigma_{iS}^I} = \alpha_{iS}(t)dt + \frac{B_i(t) - D_i(t)}{S_i(t)} \begin{pmatrix} \beta_i^* \sigma_{mA}(t) \\ \sigma_{iA}^I(t) \end{pmatrix} \begin{pmatrix} dZ_m(t) \\ dZ_i(t) \end{pmatrix} + \gamma_i^I dZ_{iV}(t). \tag{5}$$

Equation (5) says there are two reasons why idiosyncratic stock return volatility varies unexpectedly over time. The first is a balance-sheet effect. If $B(t) > D(t)$, an unexpected increase in the firm's stock price corresponds to higher stock return volatility because the value of the firm's riskier assets rises relative to the value of its less risky assets. If the inequality is reversed, this effect is dominated by the leverage effect; the firm is effectively less leveraged, and its stock return volatility falls. Second, idiosyncratic volatility can vary independently over time.

3.1.3 Testable implications

Consider the theoretical population regression coefficient from a regression of (log) instantaneous idiosyncratic stock return volatility on either the idiosyncratic return to firm i's stock or the return to the aggregate stock market. The former regression coefficient is (after some algebra)

$$\lambda_{iI} \equiv \frac{\mathrm{Cov}_t\left(\sigma_{iS}^I dZ_i, d\sigma_{iS}^I/\sigma_{iS}^I\right)}{\mathrm{Var}_t(\sigma_{iS}^I dZ_i)} = \frac{B_i(t) - D_i(t)}{A_i(t)}. \tag{6}$$

This coefficient can be thought of as a measure of the asymmetric volatility induced by balance-sheet effects. The coefficient from a population regression of idiosyncratic volatility on market returns is

$$\lambda_{im} \equiv \frac{\mathrm{Cov}_t\left(dS/S, d\sigma_{iS}^I/\sigma_{iS}^I\right)}{\mathrm{Var}_t(dS/S)} = \frac{B_i(t) - D_i(t)}{A_i(t)}\beta_i(t). \tag{7}$$

The logic of (7) is straightforward, given (6). The stock's beta converts the market return into its effect on the firm's return. If, say, this beta is zero, the change in the value of the market has no effect on the value of the firm, and thus does not alter the firm's capital structure.

Equations (7) and (6) provide the first two testable implications of the model.

Hypothesis 1. The cross-sectional mean of λ_{im} should equal the cross-sectional mean of λ_{iI} plus the cross-sectional covariance between λ_{iI} and β:

$$\overline{\lambda_{im}} = \overline{\lambda_{iI}} + Cov(\lambda_{iI}, \beta_i)$$

To see this, take the cross-sectional mean of (7), then set the mean beta to one and substitute in (6).

Hypothesis 2. Holding all else constant, firms with larger betas should have more extreme values of λ_{im}.

In other words, holding constant the measure of balance-sheet-induced volatility asymmetry, firms with higher betas should have larger responses of volatility to market returns. The caveat that all else is held constant is important because of potential cross-correlation between $\beta_i(t)$ and $(B_i(t) - D_i(t))/A_i(t)$.

Another potentially testable implication of the model is the leverage effect. Holding all else constant, firms with a higher debt/asset ratio should have more negative coefficients λ_{im} and λ_{iI}. But the requirement "all else constant" is almost impossible to impose in such a test. Because of the tax advantage of debt, firms have an incentive to increase their leverage until the marginal risk of financial distress exceeds the marginal tax benefit. A firm with a relatively high proportion of low-risk assets is able to increase its leverage more than a firm with a low proportion of low-risk assets. In the context of the model, this means that cross-sectionally there should be a positive correlation between $B_i(t)$ and $D_i(t)$. Thus the unconditional cross-sectional relation between $D_i(t)/A_i(t)$ and either λ_{im} or λ_{iI} is unclear.

Although this paper does not focus on the behavior of aggregate volatility, it is useful to express the population regression coefficient from a regression of aggregate stock return volatility on aggregate stock returns. The formula for the coefficient is more complicated than the above formulas because there are two other effects that operate at the market level. The first is the fundamental link between returns and volatility captured by γ_m. The second is an additional balance-sheet effect. At the firm level, there is a mixture of assets ($A_i(t)$ and $B_i(t)$) with different levels of risk; this induces a positive relation between returns and volatility. At the aggregate level, there is not only this breakdown between aggregate risky assets $A(t)$ and aggregate riskfree assets $B(t)$, but also between low-beta stocks and high-beta stocks. Thus even if firms had no riskfree assets, the mixture-of-assets effect would show up at the aggregate level. The regression coefficient is

$$\begin{aligned}\frac{\mathrm{Cov}_t\left(dS/S, d\sigma_{mS}/\sigma_{mS}\right)}{\mathrm{Var}_t(dS/S)} &= [B(t)-D(t)]\frac{\sum(\beta_i^*)^2 A_i(t)}{(\sum\beta_i^* A_i(t))^2} + \frac{\gamma_m}{\frac{\sum(\beta_i^* A_i(t))}{S(t)}} \\ &+ \frac{\mathrm{Var}_t(\beta_i^* A_i(t)) - \mathrm{Cov}_t(A_i(t),(\beta_i^*)^2 A_i(t))}{E_t(\beta_i^* A_i(t))^2} \end{aligned} \tag{8}$$

In (8), the covariances and means are cross-sectional. In the special case of no cross-sectional variation in asset betas, the first term on the right reduces to $(B(t)-D(t))/A(t)$ and the third term on the right disappears.[2]

This model implies that balance-sheet-induced volatility asymmetries are measured by the ratio $(B_i(t)-D_i(t))/A_i(t)$. This ratio should not be taken too seriously, because it is simply the easiest way to illustrate balance-sheet effects in a model. In reality, firms have a variety of assets that differ in riskiness, including assets that have nonlinear payoffs. This leads to a key question: Is there any information on firm's (accounting) balance sheets that can be used to determine the importance of (economic) balance-sheet-induced volatility

[2] Note that the numerator in the third term on the right hand side can be written as $E(x/y)E(xy)-[E(x)]^2$, where $x=\beta_i^* A_i(t)$ and $y=\beta_i^*$.

asymmetries? The approach I take here is to use a firm's book-to-market ratio as a crude proxy for the relative importance of growth options among the firm's assets. I motivate this choice in the next subsection.

3.2 Growth options

An important kind of asset for many firms is the option to grow. More precisely, a firm may have the option to spend money to aquire an asset that generates cash flows. The presence of growth options among a firm's assets has two competing effects on the return-volatility relation. The first is the same that operates in the model of Section 3.1. A mixture of assets with different levels of risk induces a positive relation. An opposite effect is the negative relation between a call option's value and its return volatility. The net effect is ambiguous, as this simple model illustrates. (A more complicated model would not eliminate the ambiguity.)

I examine a single firm with two assets. The first is a real asset with value $A(t)$. The instantaneous standard deviation of returns to the asset is σ_A. Again for simplicity, assume that the firm just purchased the asset, so its book value is also $A(t)$. The asset will pay no dividends through some fixed time T. The second asset is a growth option. The firm has the option to spend K to double the size of its real assets. In other words, the firm can spend K to acquire another asset worth $A(t)$. To make it easy to value this option, it expires at time T. The interest rate is fixed at zero. In a diffusion world, the option can be valued by the Black-Scholes formula. Denote its value by $C(A, t; K, T)$. The derivative of the call price with respect to the underlying asset's value is denoted $\delta(A, t; K, T)$.

The market value of the firm is

$$V(t) = A(t) + C(A, t; K, T).$$

Assume the firm is entirely equity financed. Then the instantaneous standard deviation of the firm's stock return is

$$\sigma_S(t) = (1 + \delta(A, t; K, T)) \frac{A(t)}{V(t)} \sigma_A.$$

We are interested in how this standard deviation varies with the stock price. Some algebra reveals (suppressing the arguments of V, A, C, and δ)

$$\frac{\partial \log \sigma_S}{\partial \log V} = \frac{V/A}{(1+\delta)^2} \left[\frac{\partial \delta}{\partial A} A + (1+\delta) \left(\frac{C}{V} - \delta \frac{A}{V} \right.\right. \qquad (9)$$

The sign of (9) is ambiguous. When the option deep out of the money, the mixture of high and low risk assets dominates the pure call option relation. Thus the sign is positive. When the option is deep in the money, volatilities of the two assets converge and the only effect is the call option relation. As the option value rises, $\delta(A, t; K, T)$ approaches one and (9) approaches $-K/(A+C+K)$. This ratio is the same implied by the displaced diffusion model when a firm has assets of $2A(t)$ and debt of K.

The market-to-book ratio for the firm is

$$V(t)/A(t) = \frac{A(t) + C(A, t; K, r, T)}{A(t)}.$$

The relation between this ratio and the derivative in (9) is also ambiguous. Figure 1 illustrates the relation for a given set of parameters. For low market-to-book, the return-volatility relation is positive and decreasing. For very high market-to-book, the relation is negative and increasing because $-K/(A + C - K)$ goes to zero as A and C increase.

This setup implied that a firm's book-to-market ratio was determined by the moneyness of its option. In the empirical work that follows we will examine cross-sectional variation in book-to-market ratios, which can vary not only because of cross-sectional variation in moneyness but in cross-sectional variation in the amount of options held by firms. This second source of cross-sectional variation adds to the ambiguity of the relation between the derivative in (9) and book-to-market. Without going into details, the effects of more options (say, the option to triple the size of the firm for a strike price of $2K$) are to increase the market-to-book ratio and magnify the derivative in (9). Since the sign of this derivative is ambiguous, so is the cross-sectional variation with book-to-market.

The only clear conclusion we can draw from this analysis of growth options is that the presence of growth options should affect the return-volatility relation. We cannot sign this relation, except to note that it is unlikely that the various effects at work will exactly cancel each other out. The model implies that book-to-market measures the importance of growth options, which is in line with the logic of Berk et al. (1999) and Sagi and Seasholes (2001). This leads to

Hypothesis 3a. (growth option version) The cross-sectional relation between firms' book-to-market ratios and the sensitivity of stock return volatility to stock returns should be nonzero.

A popular alternative interpretation of book-to-market, due to Fama and French (1995), is that the ratio measures financial distress. Financially-distressed firms are likely to have greater operating leverage than less-distressed firms. For example, financially-distressed firms are likely to have less cash flow relative to their operating expenses. Operating leverage works like financial leverage from the perspective of the return-volatility relation. High financial leverage (higher book-to-market) should therefore correspond to a more negative relation between stock returns and stock return volatility. This leads to an alternate version of the hypothesis:

Hypothesis 3b. (financial distress version) The cross-sectional relation between firms' book-to-market ratios and the sensitivity of stock return volatility to stock returns should negative.

If hypothesis 3b is confirmed in the data, we cannot distinguish between these two views of book-to-market. Conveniently, however, the data firmly reject this latter hypothesis. I turn to the data next.

4 The econometric methodology

4.1 The data

Stock return data are from the 2001 version of the Center for Research in Security Prices (CRSP) NYSE/Amex/Nasdaq daily file. The analysis is restricted to common stocks of domestic firms. (These are securities with CRSP sharecodes of 10 or 11 over their entire sample.) I follow Chen et al. (2001) by dropping stocks with market capitalizations below the 20th percentile of NYSE-listed stocks. The method used to eliminate these securities is discussed below. I use the return to the CRSP value-weighted index as a measure of aggregate stock returns.

Year-end market value of equity is from CRSP. Accounting information is from Compustat annual files. Book value of equity is constructed using the definition in Table I of Fama and French (1995). Book value of debt is the sum of short-term liabilities, long-term liabilities, and preferred stock. I do not require that firms have December fiscal year-ends, therefore the numerators and denominator in BE/ME and D/ME are sometimes not measured simultaneously. Because the extremely high debt/equity ratios of financial firms might skew the results, I drop such firms from any analysis that uses Compustat data.

4.2 The effects of using discretely-measured returns

The model describes the behavior of instantaneous stock returns, while in practice we observe returns over discrete horizons. This discrepancy drives a wedge between the implications of the model and the behavior of observed returns. To fix ideas, assume that we observe continuously-compounded returns at equally spaced intervals $1, \ldots, K$. The idiosyncratic component of the return to firm i's stock from the end of period $k-1$ to the end of period k is denoted $\ _i(k)$ and the standard deviation of this discretely-measured return is $DEV_i(k)$. (In practice, the idiosyncratic component and its standard deviation must be estimated, as discussed below.) The relation between $\ _i(k)$ and $DEV_i(k)$ is a noisy estimate of the instantaneous relation between returns and volatility because the model implies that volatility is persistent. For example, a return shock in the first day of a month will affect volatility throughout the month, while a return shock in the last day of the month will not.

An obvious alternative is to examine the relation between $\ _i(k)$ and future volatility $DEV_i(k+j), j > 0$. But this relation depends on the amount of persistence in volatility. Shocks to volatility that are the result of balance-sheet effects are probably long-lived. They should die out only as firms' capital structures change. One caveat is that if firms' growth options have short tenors, balance-sheet effects owing to such options will be short-lived.

The relation between $\ _i(k)$ and $DEV_i(k+j)$ may also affected by fundamental shocks to asset return volatility that are correlated with idiosyncratic return shocks. Such shocks are ruled out in the model (there is no $dZ_i(t)$ term in (2)) but that is largely for convenience. Thus if the predictive power of $\ _i(k)$ for $DEV_i(k+j)$ dies off quickly, we cannot necessarily conclude that balance-sheet effects are non-existent or short-lived; it may simply reflect low persistence of unmodeled fundamental shocks.

4.3 Estimation of idiosyncratic returns

I estimate idiosyncratic daily stock returns for security i with rolling regressions used out-of-sample. Days are indexed by d. The regression equation is

$$r_i(d) = b_{i0} + b_{i1} r_m(d) + b_{i2} r_i(d-1) + b_{i3} r_m(d-1) + \ _i(d). \tag{10}$$

I estimate this equation using the first 500 daily non-missing observations of log returns for security i, then use the resulting parameter estimates to produce out-of-sample residuals $\ _i(d)$ for the next 60 valid observations (501 through 560). The procedure is repeated by estimating the equation over observations 61 through 560, using the estimated parameters to produce residuals for observations 561 though 620, and so on. The return $r_i(d)$ is set to a missing value if it is missing in the CRSP data or if either of the prices on days $d-1$ or d are bid-ask averages instead of transaction prices. Although CRSP data begin with July 1962, programming considerations led me to ignore all returns prior to January 1963.

Throughout this paper I refer to the shocks $\ _i(d)$ as idiosyncratic shocks. This is a bit of a stretch since only a single common factor was removed from firm-level stock returns. I experimented with including industry stock returns along the lines of Campbell, Lettau, Malkiel, and Xu (2001), but the results were almost identical.

The model of balance-sheet effects implies that (10) is misspecified because a firm's stock return beta should vary with stock prices. If a firm exhibits a positive relation between returns and volatility, it should also exhibit a positive relation between idiosyncratic returns and conditional beta. Although models that allow betas to vary with returns can be estimated (see, e.g., Braun et al. (1995)), the broad cross-section of firms used in this paper makes such an approach too time-consuming. The misspecification will show up in both higher average variances of idiosyncratic returns and noisy estimates of beta. The important issue for the purposes of this paper is whether the misspecification will bias the observed relation between returns and idiosyncratic return volatility. Because the bias in beta (and therefore in the idiosyncratic variance) is symmetric in shocks to returns, it should not affect the main results here.

The standard deviation of idiosyncratic daily returns is (crudely) estimated with the absolute value of the day's idiosyncratic return. The use of absolute values instead of squares follows Duffee (1995) and is motivated by the evidence in Davidian and Carroll (1987) that absolute values are more robust to outliers.

I also examine monthly idiosyncratic returns. These returns, which are indexed by t, are the sum of daily returns. I estimate the standard deviation of month t's idiosyncratic return with the square root of the sum of squared daily idiosyncratic returns in the month.

$$ {}_i(t) = \sum_{j=d_1}^{d_{N_t}} {}_i(j), \quad DEV_i(t) = \sqrt{\sum_{j=d_1}^{d_{N_t}} [\, {}_i(j)]^2} $$

where the days in month t are indexed $d_1, \ldots, d_{N_t}$. Monthly returns and standard deviations are set to a missing value if there are fewer than 15 days in the month with valid observations. The aggregate return to the stock market in month t is the sum of daily log returns to the CRSP value-weighted index. The standard deviation of this monthly return is estimated with the square root of the sum of squared demeaned daily returns in the month, where the mean is calculated over the entire sample period (not just over the days in the the month).

4.4 The regression equations

The starting points of the empirical analysis are the hypothetical regressions of instantaneous idiosyncratic return volatility on market returns (7) and idiosyncratic returns (6). Because these returns are uncorrelated by construction, I combine the regressions and estimate at the daily frequency

$$\frac{|\ _i(d)|}{\overline{|\ _i|}} = c_{i,j} + \lambda_{i,m,j} r_m(d-j) + \lambda_{i,I,j}\ \ _i(d-j) + v_{i,j}(d), \quad j = 0, \ldots, 3 \tag{11}$$

In (11), $r_m(d)$ is the daily market return. In the hypothetical regressions changes in volatility are expressed in relative (i.e., log) terms. Because the log transformation is susceptible to inliers, I follow Duffee (1995) by normalizing absolute residuals by the mean absolute residual instead of taking logs. Lags from $j = 0$ to $j = 3$ are considered to examine the persistence of the return-volatility relation, as discussed in Section 4.2. The coefficients $\lambda_{i,m,j}$ are the counterpart to λ_{im} in (7) and the coefficients $\lambda_{i,I,j}$ are the counterpart to λ_{iI} in (6).

At the monthly frequency the regression is

$$\log DEV_i(t) = c_{i,j} + \lambda_{i,m,j} r_m(t-j) + \lambda_{i,I,j}\ \ _i(t-j) + v_{i,j}(t), \quad j = 0, \ldots, 3 \tag{12}$$

where $r_m(t)$ is the monthly market return. I use the log transformation in (12) because inliers are not a problem with monthly volatility estimates.

4.5 Estimation procedure

The trickiest problem to address in estimating (11) and (12) is the contemporaneous correlation in the residuals across firms. Formally, the shocks to idiosyncratic asset volatility $dZ_{iV}(t)$ in (2) may be correlated across i. One way to address the problem is to assume that correlations among residuals can be picked up with calendar dummies, as in Chen et al. (2001). That method is unappealing here because a primary focus of this paper is in how the estimated coefficients $\lambda_{i,m,j}$ and $\lambda_{i,I,j}$ vary across firms with different betas, debt/equity, and book/market. Calendar dummies pick up shocks that are common across all firms, but it is likely that firms with, say, similar book/market ratios have residuals that are more closely correlated than firms with dissimilar book/market ratios.

This problem is similar to the problem of estimating asset-pricing models with a panel data set that has more firms than time periods. Thus I adopt an estimation technique inspired by Fama and MacBeth (1973). For each firm i, I estimate (11) and (12) over each calendar year from 1965 through 2001, depending on data availability. (Because daily stock return residuals are constructed out-of-sample, no residuals are available for earlier years.) For example, if a stock has been continuously listed over the entire sample period, it will have 37 estimates of (11), corresponding to calendar years 1965 through 2001. Then cross-sectional regressions (e.g., $\hat{\lambda}_{i,m,j}$ on firm i's beta) are estimated separately for each year. Finally, the means of the yearly cross-sectional results are used as cross-sectional parameter estimates for the entire 37 years. Their standard errors are based on the sample standard deviations of the 37 sets of parameter estimates.

This cross-sectional approach will require year-by-year estimates of firm i's stock return beta. These estimates are produced with the regression (10) used in constructing daily idiosyncratic returns. Recall that this regression was estimated using an out-of-sample rolling procedure. The beta that I use for firm i in a given year is the sum

$$\hat{\beta}_i \equiv \hat{b}_{i1} + \hat{b}_{i3}$$

where the right-hand-side estimates are taken from the regression (10) used in constructing the idiosyncratic return on the first day of the year. Because this idiosyncratic return is estimated out-of-sample, the beta is uncorrelated with any shocks realized in that year.

The cross-sectional regressions will use the level of firm i's idiosyncratic return volatility as a control variable. I measure this volatility using the same regression used to construct the yearly beta estimates. The volatility measure is the in-sample standard deviation of the residuals, which I denote D_DEV_i (daily deviation).

5 Results

5.1 Time-series results

To put the firm-level results in context, I first look at the return-volatility relation at the market level. The market-level analogues to (11) and (12) are

$$\frac{|\tilde{r}_m(d)|}{\overline{|\tilde{r}_m|}} = c_j + \lambda_j r_m(d-j) + v_j(d)$$

where $r_m(d)$ is the demeaned daily market return, and

$$\log \sigma_m(t) = c_j + \lambda_j r_m(t-j) + v_j(t).$$

where $\sigma_m(t)$ is the square root of the sum of squared demeaned daily returns in month t. For comparability with the firm-level results, the regressions are estimated separately for each year from 1965 to 2001. Table 1 reports the mean estimated coefficients and the standard errors of the estimates. The results are consistent with the large literature that documents an inverse relation between aggregate stock returns and aggregate stock return volatility. A negative stock return corresponds to higher contemporaneous volatility (negative skewness) as well as higher volatility over the next month. The higher volatility then dies out.

I now turn to the results of estimating the firm-level regressions (11) and (12). The sample of firms used in these regressions requires some additional explanation. As discussed in Section 4.4, the regressions are estimated separately for each calendar year. Consider, say, 1975. Firms that have year-end 1974 market capitalizations less than the 20th percentile of the distribution of the NYSE-listed firms at year-end 1974 are dropped. For a remaining firm i, the daily regression is estimated if there are at least 200 valid observations in 1975. An observation is valid if, for day d in 1975, $_i(d)$ and $_i(d-j)$ are non-missing. Day $d-j$ does not need to be in 1975. I drop all of firm i's daily results from 1975 if any of the four daily regressions cannot be estimated. The remaining year-1975 sample consists of 1090 firms. The resulting 1090 sets of parameter estimates from (11) are then averaged, producing a single set of mean parameter estimates for 1975. This average is computed using both equal weights and year-end 1974 market capitalization weights. The same procedure is followed for the monthly regressions, for which a minimum of nine observations is required. The year-1975 sample size for the monthly regressions is 1100 firms.

After 37 sets of mean parameter estimates are calculated for the years 1965 through 2001, a grand mean of parameter estimates is computed by averaging across the years (using equal weights). These means are reported in Table 2. Standard errors are in parentheses. One and two asterisks denote significance at the 5% and 1% levels of significance, respectively. The column labeled 'mean number of firms' reports the mean, across years, of the number of firms for which regressions were estimated.

There are two broad conclusions to draw from Table 2. First, there is a strong, positive, short-lived relation between returns and idiosyncratic return volatility. Consider the results of the daily regressions. Regardless of whether the return is the market return or the firm's idiosyncratic return, volatility is substantially higher both on the day of the return and the next day. The point estimates imply that the level of volatility on a day when the return shock is one percent is about 1.06 times the corresponding level on a day when the return shock is minus one percent. (This conclusion holds whether equal weights or market capitalization weights are used.) The next day, volatility is about 1.02 times higher. This positive relation dies off by the third day. The results of the monthly regressions confirm this result. The month-level contemporaneous relation is positive for both market returns and idiosyncratic returns, although the standard errors on the market return coefficients are too large to pin down the relationship very precisely.

This positive relation is not a surprise, given earlier research. We know firm-level stock returns are positively skewed, which (given that market stock returns are negatively skewed) implies that idiosyncratic returns are positively skewed. The positive relation between market returns and idiosyncratic volatility is consistent with the comment by Stivers (2000) that firm-level return dispersion is higher on days when the market goes up.

The second broad conclusion is that this positive return-volatility relation is reversed within a month. High returns (either market or idiosyncratic) in month t are followed by low idiosyncratic volatility in months $t+1$ through $t+3$. Standard errors on the market returns are too high to reject the hypothesis that they are zero, but the statistical evidence for idiosyncratic returns is overwhelming.

How should we interpret this curious dynamic pattern? The model of balance-sheet effects presented earlier cannot, by itself, fit these dynamics. A positive contemporaneous return-volatility relation is easily explained by changing relative asset values. But this positive relation should persist until the firm's economic balance sheet is altered. There is nothing in the model that gives us a reversal of the original positive relation.

One ad-hoc way to explain this pattern is to add another kind of fundamental shock to the model of balance-sheet effects. Assume that firm-level asset returns and future asset-return volatility are negatively correlated. If, say, investors receive news that future cash flows are likely to be lower than usual, they also learn that these future cash flows are likely to be more volatile than usual. This fundamental shock produces a negative relation between current returns (a revision in my expectation of future cash flows) and future volatility (when the cash flows are realized). If this negative relation is sufficiently strong it will dominate a positive return-volatility relation induced by balance-sheet effects.

If this (after-the-fact) explanation is correct, it has a testable implication. Balance-sheet effects are present for more than a couple of days; they are simply obscured by another effect after that time. Therefore cross-sectional regressions that test for balance-sheet effects should indicate their presence in the days and months after the positive return-volatility relation has disappeared in the time series. I now turn to these cross-sectional tests.

5.2 Cross-sectional results

The first cross-sectional test is taken from Hypothesis 1 in Section 3.1.3. Intuitively, the hypothesis says that the effect of a market return on idiosyncratic volatility is the same as the effect of an idiosyncratic return, once the market return is scaled by the firm's beta. For each regression, I construct the difference between the cross-sectional mean of the coefficient on the market return and its value implied by Hypothesis 1:

$$h_{i,j} \equiv \overline{\lambda_{i,m,j}} - \overline{\lambda_{i,I,j}} - Cov(\lambda_{i,I,j}, \hat{\beta}_i), \quad j = 1, \ldots, 3.$$

The hypothesis implies $h_{i,j} = 0$.

As noted in Section 4.5, cross-sectional tests are performed separately for each calendar year from 1965 through 2001. To illustrate the procedure, consider the results for a single year. In 1975 the equal-weighted mean of $\lambda_{i,m,0}$ in daily data is 7.19. The corresponding mean of $\lambda_{i,I,0}$ is 3.59 and the covariance between $\lambda_{i,I,0}$ and $\hat{\beta}_i$ is -0.53. The result is $h_{i,j} = 4.13$. I also construct $h_{i,j}$ using market capitalization weights for the means and covariance. This weighted $h_{i,j}$ is 4.92. I follow this procedure for each calendar year and then compute grand means and standard deviations.

The results are not reported in any table because they are easy to summarize. In no case can the hypothesis that $h_{i,j} = 0$ be rejected. Across eight different regressions (four each for daily and monthly returns) and two weighting methods, no t-statistic exceeds 1.2 in absolute value. Overall, there is no evidence that market returns (scaled by beta) have a different effect on idiosyncratic volatility than do idiosyncratic returns.

Hypothesis 2 in Section 3.1.3 and Hypotheses 3a and 3b in Section 3.2 suggest tests using cross-sectional regressions. Hypothesis 2 implies that if the market-return coefficient $\lambda_{i,m,j}$ is regressed on firm i's beta, then holding all else constant, the sign of the coefficient should be the sign of the average balance-sheet effect. Hypotheses 3a and 3b imply that if either the market-return coefficient $\lambda_{i,m,j}$ or the idiosyncratic-return coefficient $\lambda_{i,I,j}$ is regressed on firm i's book/market ratio, the coefficient should be nonzero (although only Hypothesis 3b says what the sign should be).

Although this paper focuses on the role of beta and book/market, earlier literature justifies including other variables. One is the debt/equity ratio, motivated by the leverage hypothesis. Two others are motivated by the results of Chen et al. (2001). They show that the amount of skewness in firms' returns is related to market capitalization and volatility. Therefore I use five explanatory variables in the cross-sectional regressions: Beta, book/market, debt/equity, log of market cap, and log of the standard deviation of daily idiosyncratic returns.

Because the cross-sectional regressions are estimated for each calendar year, I need yearly values of these explanatory variables. Section 4.5 discusses the construction of the yearly estimates of beta $\hat{\beta}_i$ and the standard deviation of daily idiosyncratic returns D_DEV_i. Balance-sheet variables are taken from the previous year-end. These cross-sectional variables are all realized by the beginning of the year for which the cross-sectional regression is estimated.

The sample of stocks used in these cross-sectional regressions is smaller than the sample used in the time-series regressions reported earlier. As mentioned in Section 4.1, I drop nonfinancial firms. In addition, to reduce the importance of outliers, I drop those firms with book-to-market or debt-to-equity ratios in the top or bottom two percent of their respective distributions. (This is done year-by-year.) Because of these restrictions, and because a number of firms in the CRSP dataset do not have balance sheet information in Compustat, the sample sizes for the cross-sectional regressions are about one-third smaller than those for the time-series regressions.

Summary statistics for the variables used in the cross-sectional regressions are reported in Table 3. The summary statistics are computed separately for each year, then averaged (equal weights) across all years. Except for the debt/equity ratio, means and medians are roughly equal. Debt/equity is strongly positively skewed. The median firm has a debt/equity ratio of less than one-third while the mean ratio exceeds one-half. The mean and median values of log size are not particularly informative because no adjustment is made for inflation. No inflation adjustment is needed in the cross-sectional regressions because market capitalizations are all measured on the same date.

The cross-sectional regression is

$$\begin{aligned}\lambda_{i,j,k} &= b_{0,j,k} + b_{1,j,k}\hat{\beta}_i + b_{2,j,k}BE_i/ME_i + b_{3,j,k}D_i/ME_i + b_{4,j,k}\log(ME_i) \\ &+ b_{5,j,k}D\_DEV_i + \zeta_{i,j,k}, \quad j = \{m, I\},\ k = 0, \ldots, 3.\end{aligned}$$

The estimates for daily returns are displayed in Table 4 and those for monthly returns are displayed in Table 5. There are four main results that are worth highlighting.

The first main result is that cross-sectionally, firms with higher betas have a stronger positive contemporaneous relation between market returns and idiosyncratic volatility. (The relevant regressions are the first row in each table.) The statistical significance is overwhelming; the respective t-statistics on beta for daily and monthly return horizons are 7.5 and 3.5. Moreover, the magnitudes of the coefficients on beta are roughly what we expect if the contemporaneous return-volatility relation is driven by balance-sheet effects. A comparison of the mean estimates in Tables 2 with these cross-sectional results reveals that if a firm has a zero beta, then (holding everything else in the regression constant) it exhibits no clear relation between market returns and idiosyncratic volatility. (The relation is slightly positive with daily returns and slightly negative with monthly returns.)

Viewed in isolation, this result strongly supports the conclusion that balance-sheet effects drive the positive short-run relation between returns and idiosyncratic volatility. However, the results of the regressions that explain cross-sectional variations in the relation between market returns and future idiosyncratic volatility cast some doubt on this view. (These are the next three rows in the tables.) Balance-sheet effects should be persistent, but the predictive power of beta disappears after the next day. Unless this can be explained away, it is strong evidence against the balance-sheet effect story.

My interpretation of this pattern is that beta plays two roles in the relation between market returns and idiosyncratic volatility. The first role is the one emphasized in Hypothesis 2: The effect of a market return on a firm's balance sheet depends on the firm's beta. The second role is a cross-sectional relation between beta and the volatility asymmetry built into a firm's balance sheet. This additional role is the subject of the second main result in Tables 4 and 5.

Firms with higher betas have a less positive overall volatility asymmetry. The evidence is clear in the cross-sectional regressions that explain the strength of the relation between idiosyncratic returns and idiosyncratic return volatility. (These are the bottom four rows in each table.) For daily returns, higher betas correspond to less positive asymmetric volatility at all lags. The statistical strength of this cross-sectional relation is extremely strong, with t-statistics ranging from -2.6 to -4.1. For monthly returns, higher betas correspond to less positive asymmetric volatility at lags zero and one. This direct relation between beta and asymmetric volatility contaminates the indirect role that is the subject of Hypothesis 2. The relation between beta and volatility asymmetry was not predicted (and not ruled out) by the theory of Section 3. In the context of that theory, I could posit a negative cross-sectional relation between a firm's beta and the dispersion among the volatilities of its assets. But this is simply an after-the-fact story without any testable implications.

The third main result is that book-to-market ratios are strongly positively associated with asymmetric volatility. For daily returns, the coefficients on BE/ME for all eight regressions are positive, and five are significant at the one percent level. For monthly returns, the statistical significance is concentrated in the first two months. Three of these four regressions have a coefficient on BE/ME that is significant at the one percent level and the remaining coefficient is significant at the five percent level.

The point estimates on BE/ME imply a significant economic effect. Consider, for example, a typical firm with a BE/ME ratio that is one standard deviation above the mean in a given year. Using the summary statistics in Table 3, the firm has a BE/ME ratio of 1.07. Combining this figure with the mean point estimates for monthly returns in Table 5, the firm will have an elasticity of idiosyncratic volatility with respect to contemporaneous idiosyncratic returns of 0.54. This is over three times the implied elasticity of 0.17 for a typical firm with a book-to-market ratio of 0.329 (one standard deviation below the mean).

This evidence on BE/ME is important because it supports the view that balance-sheet effects are positive and persistent, but obscured at longer lags by the presence of some other effect. In Table 2 the positive relation between daily idiosyncratic returns and daily idiosyncratic return volatility dies out after the first lag, but in Table 4 the predictive power of BE/ME does not. Table 2 also indicates that the positive relation between monthly idiosyncratic returns and monthly idiosyncratic return volatility is reversed at the first lag, but in Table 5 the predictive power of BE/ME remains positive and significant. One bit of evidence that points away from a balance-sheet effect is that the predictive power of BE/ME dies off after the first monthly lag. Although some decrease is to be expected if balance-sheet effects drive the return-volatility relation (as firms adjust their balance sheets over time), if we take these results at face value they indicate that firms adjust their balance sheets within a few months. That seems a little too fast. (This argument is adapted from a similar one in Figlewski and Wang (2000).)

The positive sign on BE/ME is explained by the model of growth options in Section 3.2. The positive sign indicates that firms with more of their value tied up in growth options have more negative relations between returns and volatility. This is consistent with the view that as options are more in-the-money, their return volatility falls. If the valuable growth options held by firms tend to have short maturities (say, once an option is deep in the money, the firm needs to act quickly before another firm grabs the opportunity), the model is also consistent with the decreasing significance of BE/ME as lag length increases.

The problem with the growth option interpretation is that it is a weak test. Hypothesis 3a allows for either a positive or negative relation between book-to-market and asymmetric volatility; it simply says there should be some relation. These results do, however, allow us to draw one firm conclusion. We cannot say that high book-to-market firms are typically financially distressed, and therefore have more operating leverage. If Hypothesis 3b were true, these firms should exhibit a more negative relation between returns and volatility, which is overwhelmingly rejected in the data.

The role of BE/ME in predicting variations in volatility asymmetry can be used to explain an empirical result in Chen et al. (2001). They find that stocks that have increased in value over the past three years exhibit a more negative relation between returns and volatility than do stocks that have decreased in value. Increases in stock prices typically correspond to decreases in BE/ME (working through the denominator). The lower BE/ME corresponds to a more negative relation between returns and volatility.

The fourth and final main result is that debt/equity ratios have no statistically significant link to asymmetric volatility. Across the daily and monthly regressions, none of the coefficients on debt/equity is statistically significant at the five percent level. This conclusion differs from those of Christie (1982), Cheung and Ng (1992), and Duffee (1995). One possible reason for the conflicting results is that the earlier work did not take into account cross-sectional correlations among the firm-level regressions. Another possibility is that the linear framework of (4) and (5) is misspecified. The earlier research focused more on rank correlations than on a parametric relation.

Overall, these results lend support to the hypothesis that the positive short-run relation between firm-level returns and idiosyncratic volatility is the result of balance-sheet effects. But are any hypotheses are ruled out by these results? The question is a little hard to answer because, as discussed by Chen et al. (2001), there are no economic models that naturally generate a positive return-volatility relation. They suggest that firms' managers may attempt to hide bad news and trumpet good news. However, a story about manager behavior is hard to reconcile with the predictive role of beta in the relation between market returns and contemporaneous idiosyncratic return volatility (the top two rows of the tables). In order to explain this result, managers must choose to release news of any kind (good or bad) when the firm's stock price rises owing to a general increase in the market, and refrain from releasing the news when the market is falling. It is not clear why such behavior would benefit managers.

Another possible story is that returns and idiosyncratic volatility move together because news about firms' projects is inherently positively skewed. Either a firm finds a positive NPV project, or it doesn't. No news is bad news, because an advance was not made, and a project was not started. Although plausible, this story has the same problem with the market return–idiosyncratic volatility relation. Why should a positive market return correspond to greater revelation of firm-specific news? In addition, why should BE/ME predict the strength of the relation between returns and future idiosyncratic volatility? Only a model of balance-sheet effects appears to fit all of this evidence.

5.3 Asymmetric correlations

Correlations among equity returns tend to be higher when the returns are negative than when they are positive. At the international equity market level this was first documented by Erb, Harvey, and Viskanta (1994). Additional evidence is in Longin and Solnick (2001) and Ang and Bekaert (1999). In the U.S. market, Ang and Chen (2002) find the same result for portfolios. The evidence in Tables 1 and 2 cast some light on the source of asymmetric correlations.

A little formalism will help. Consider returns to two firms, r_1 and r_2, and the return to the entire stock market, r_m. To make this example as simple as possible, all returns are mean zero, and firm-level returns consist of a common factor and an idiosyncratic factor,

$$r_i = r_m + \ {}_i, \ \ i = 1, 2.$$

Their correlation, conditioned on some information Ω, is

$$\text{Cor}(r_1, r_2|\Omega) = \frac{\text{Var}(r_m|\Omega)}{\text{Var}(r_m|\Omega) + \text{Var}(\ {}_i|\Omega)}. \tag{13}$$

Asymmetric return correlations are produced if either $\text{Var}(r_m|r_m < 0) > \text{Var}(r_m|r_m > 0)$ or $\text{Var}(\ _i|r_m > 0) > \text{Var}(\ _i|r_m < 0)$.

Researchers, especially in the literature on international stock markets, have typically focused their interpretations of asymmetric correlations on the latter inequality–the behavior of $\text{Var}(F_c)$. For example, Das and Uppal (1999) assume that a common factor can periodically jump. If the mean jump size is negative, correlations in down markets can be higher than correlations in up markets. This emphasis on common shocks in explaining correlations in international stock markets is not unreasonable, given the recent behavior of these markets. The negative skewness of aggregate U.S. stock market returns is also consistent with a model in which common shocks occasionally exhibit downward jumps.

The results in Table 2 point to the conclusion that, at least for individual stocks, a positive covariance between market returns and idiosyncratic volatility also drives asymmetric correlations. The question I address here is how much of the asymmetry in daily stock return correlations is the result of variability in idiosyncratic volatility. I use (13) to decompose changes in correlations. Implicitly, I am considering correlations between two firms with betas of one. Because the nonlinearity of (13) I use a first-order approximation:

$$\Delta\text{Cor}(r_1, r_2) \approx \frac{\text{Var}(r_m)}{\text{Var}(r_m) + \text{Var}(\ _i)} \frac{\text{Var}(\ _i)}{\text{Var}(r_m) + \text{Var}(\ _i)} \left[\frac{\Delta\text{Var}(r_m)}{\text{Var}(r_m)} - \frac{\Delta\text{Var}(\ _i)}{\text{Var}(\ _i)} \right.$$

The term in brackets tells us that the change in volatility is driven equally by the percentage changes in the variances of the market return and the idiosyncratic return. Therefore the fraction of the difference between up-day correlations and down-day correlations that is due to idiosyncratic volatility is approximately (using down-market variances as the starting point)

$$F \equiv \frac{(\text{Var}(\ _i|down) - \text{Var}(\ _i|up))/\text{Var}(\ _i|down)}{\text{Var}(r_m|up)/\text{Var}(r_m|down) - \text{Var}(\ _i|up)/\text{Var}(\ _i|down)} \tag{14}$$

To estimate this ratio I construct, for each firm i, measures of idiosyncratic variance conditioned on the market return. They are

$$VAR_i(up) = \text{mean}[\ ^2_i|r_m(d) > \overline{r_m}],\ VAR_i(down) = \text{mean}[\ ^2_i|r_m(d) < \overline{r_m}].$$

The corresponding ratio is

$$RATIO_i \equiv VAR_i(up)/VAR_i(down).$$

Similarly, I construct measures of the conditional variance of market returns:

$$VAR_m(up) = \text{mean}[\tilde{r}_m^2 | r_m(d) > \overline{r_m}],\ VAR_m(down) = \text{mean}[\tilde{r}_m^2 | r_m(d) < \overline{r_m}],$$

$$RATIO_m \equiv VAR_m(up)/VAR_m(down).$$

Then an estimate of the fraction in (14) for firm i is

$$\hat{F}_i = \frac{1 - RATIO_i}{RATIO_m - RATIO_i}. \tag{15}$$

I follow the procedure used throughout this paper and construct these variances and ratios for each year from 1965 through 2001. I calculate cross-sectional statistics for each year, then report the time-series means of these cross-sectional statistics. The results are in Table 6. Panel A reports conditional variances for the market return. For the typical year, the ratio of up-day variance to down-day variance is 0.92. The ratio tends to be lower in years when variances are higher, which is why the ratio of the mean up-day variance to the mean down-day variance is only 0.81.

Panel B reports results for idiosyncratic volatility. It reports cross-sectional results for two groups: All firms in the sample and the 500 largest firms in the sample. The two groups have similar mean ratios of up-market variance to down-market variance (about 1.14). These mean results are for the typical firm in the typical year. However, years in which variances are higher are also years in which the up-day and down-day idiosyncratic variances are closer together. Therefore the ratio of the mean up-day variance to the mean down-day variance is closer to one (about 1.06).

I use (13) to estimate yearly cross-correlations between firm-level stock returns. The mean of these estimates are reported in the Table. The implied correlations are, not surprisingly, higher on down days. I also compute (15) for each firm. A few firms have $RATIO_i$ very close to $RATIO_m$, which blows up $\hat{F}_i$. Therefore I report the median value instead of the mean. (This is also why I report separate results for the largest 500 firms instead of reporting value-weighted means.) For both the sample of all firms and the sample of the largest firms, over 40 percent of the difference in correlations between down days and up days is due to higher idiosyncratic volatility on up days. Again, these results are for the typical firm in the typical year. In high-variance years market asymmetries are larger and idiosyncratic asymmetries are less smaller, thus (15) calculated using the time-series means of the variances is 0.35 for all firms and 0.21 for the largest 500 firms. Regardless of which set of estimates is used, the conclusion is that asymmetric idiosyncratic volatilities play a significant, but not dominant, role in explaining asymmetric correlations.

6 Concluding comments

The most robust conclusion in this paper is that asymmetric volatility has multiple causes. Balance-sheet effects are a potential source of asymmetric volatility, and the evidence in this paper is broadly supportive of the hypothesis that such effects drive a positive relation between returns and volatility. But balance-sheet effects are incapable of explaining either the negative relation between aggregate stock return and aggregate stock return volatility or the quick reversal of the positive relation between firm-level idiosyncratic returns and idiosyncratic return volatility. The success of the balance-sheet hypothesis lies in its ability to explain two previously undocumented facts: the strength of asymmetric volatility varies cross-sectionally with beta and book/market.

This cross-sectional predictability is fairly short-lived, which poses a problem for the balance-sheet hypothesis. This feature of the data needs to be explored in more detail. Perhaps it says something about the time to expiration of in-the-money growth options. Alternatively, it may reflect the speed at which firms adjust their asset mix over time. However, we cannot rule out the possibility that it means we need a theory other than balance-sheet effects to explain the empirical evidence in this paper.

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	Lag of return			
Horizon	0	1	2	3
Daily	−8.522	−10.585	−9.917	−6.812
	(3.655)	(2.060)	(2.357)	(2.095)
Monthly	−1.602	−1.381	−0.426	0.530
	(0.579)	(0.432)	(0.413)	(0.450)

Table 1: The relation between aggregate stock returns and aggregate stock return volatility

Aggregate stock return volatility is regressed on either contemporaneous or lagged aggregate stock returns. Daily volatility is measured with the absolute demeaned return to the CRSP value-weighted index and monthly volatility is measured by the square root of the sum of squared demeaned returns in the month. The regressions are

$$\frac{|\tilde{r}_m(d)|}{\overline{|\tilde{r}_m|}} = c + \lambda r_m(d - \text{lag}) + v(d),\ \text{lag} = 0, \ldots, 3 \qquad \text{(Daily)}$$

$$\log \sigma_m(t) = c + \lambda r_m(t - \text{lag}) + v(t),\ \text{lag} = 0, \ldots, 3 \qquad \text{(Monthly)}$$

Separate regressions are run for each year from 1965 through 2001. The table reports the mean estimates of λ. Standard errors are computed from the sample standard deviations of the yearly estimates.

Horizon	Mean number of firms	Coefs on market return (lag) 0	1	2	3	Coefs on idiosyncratic return (lag) 0	1	2	3
Daily	1341								
Equal weights		3.056	1.311	−0.362	−0.254	3.349	0.715	0.071	−0.106
		(0.572)**	(0.589)*	(0.484)	(0.453)	(0.420)**	(0.171)**	(0.101)	(0.069)
Value weights		3.034	1.274	−0.398	−0.285	3.251	0.686	0.060	−0.115
		(0.574)**	(0.593)*	(0.485)	(0.454)	(0.420)**	(0.173)**	(0.102)	(0.069)
Monthly	1336								
Equal weights		0.143	−0.208	−0.065	−0.035	0.356	−0.181	−0.129	−0.078
		(0.194)	(0.134)	(0.136)	(0.122)	(0.060)**	(0.023)**	(0.020)**	(0.024)**
Value weights		0.136	−0.216	−0.065	−0.029	0.342	−0.185	−0.128	−0.080
		(0.195)	(0.135)	(0.137)	(0.124)	(0.060)**	(0.023)**	(0.020)**	(0.024)**

Table 2: The firm-level relation between stock returns and the volatility of idiosyncratic stock returns

Idiosyncratic daily stock returns for firm i are residuals from regressions of firm-level stock returns on the market return. Daily idiosyncratic volatility is measured with the absolute value of daily residuals. Monthly idiosyncratic returns are sums of daily returns and monthly idiosyncratic volatility DEV_i is measured by the square root of the sum of squared residuals in the month. Denoting the market return by r_m and idiosyncratic returns by $_i$, the volatility-return regressions are

$$\frac{|\ _i(d)|}{\overline{|\ _i|}} = c_i + \lambda_{i,m} r_m(d - \text{lag}) + \lambda_{i,I}\ _i(d - \text{lag}) + v_i(d),\ \text{lag} = 0, \ldots, 3 \qquad \text{(Daily)}$$

$$\log DEV_i(t) = c_i + \lambda_{i,m} r_m(t - \text{lag}) + \lambda_{i,I}\ _i(t - \text{lag}) + v_i(t),\ \text{lag} = 0, \ldots, 3 \qquad \text{(Monthly)}$$

Separate regressions are run for each firm and year from 1965 through 2001. Equally-weighted and market cap-weighted cross-sectional means of $\lambda_{i,m}$ and $\lambda_{i,I}$ are then computed across firms for each year. The table reports the means, across years, of these cross-sectional means. Standard errors are computed from the sample standard deviations of the yearly cross-sectional means. Asterisks denote t-statistics that exceed the 5% and 1% significance levels (2-tailed).

Firm-level statistic	Mean	Median	Std dev	Cross-correlation with Beta	BE/ME	D/ME	log(ME)
Beta	1.064	1.008	0.482	1			
BE/ME	0.699	0.639	0.370	−0.185	1		
D/ME	0.552	0.328	0.715	−0.149	0.424	1	
log(ME)	13.008	12.795	1.279	−0.113	−0.175	−0.091	1
log(D_DEV)	−3.974	−3.983	0.366	0.621	−0.139	−0.096	−0.545

Table 3: Summary statistics for explanatory variables used in cross-sectional regressions

For each year-end from 1964 through 2000, stock return betas, book/market and debt/equity ratios, market capitalizations, and the standard deviation of daily returns are calculated for a sample of stocks. The mean sample size (across years) is 921 stocks. Year-end cross-sectional summary statistics are computed for each year. This table reports the time-series means, across years, of these cross-sectional statistics.

1st stage						
Explanatory variable	Lag	2nd stage regression coefs: Beta	B/ME	D/ME	log(ME)	log(D_DEV)
Market return	0	2.591	0.528	0.088	0.162	0.759
		(0.343)**	(0.324)	(0.135)	(0.119)*	(0.491)
	1	1.065	0.390	0.097	−0.257	−0.206
		(0.219)**	(0.297)	(0.162)	(0.106)*	(0.400)
	2	−0.076	1.181	−0.044	−0.135	0.563
		(0.239)	(0.374)**	(0.150)	(0.079)	(0.375)
	3	−0.152	1.106	−0.178	−0.011	1.078
		(0.223)	(0.346)**	(0.143)	(0.095)	(0.402)**
Idiosyncratic return	0	−1.032	4.466	−0.110	−0.381	0.847
		(0.357)**	(0.458)**	(0.247)	(0.188)*	(0.648)
	1	−0.424	1.117	−0.025	−0.137	0.049
		(0.102)**	(0.137)**	(0.119)	(0.056)*	(0.250)
	2	−0.232	0.562	0.080	−0.065	−0.144
		(0.077)**	(0.107)**	(0.079)	(0.037)	(0.199)
	3	−0.197	0.224	0.140	−0.012	0.109
		(0.076)**	(0.097)*	(0.071)*	(0.036)	(0.152)

Table 4: Cross-sectional variation in the daily stock return–volatility relation

In the first stage the following time-series regression is estimated for individual firms i.

$$\frac{|\ _i(d)|}{\overline{|\ _i|}} = c_i + \lambda_{i,m} r_m(d - \text{lag}) + \lambda_{i,I}\ \ _i(d - \text{lag}) + v_i(d),\ \text{lag} = 0, \ldots, 3$$

This table reports results from a second-stage cross-sectional regression. The estimates of $\lambda_{i,m}$ and $\lambda_{i,I}$ are regressed on firm i's beta, book equity/market equity, debt/market equity, log market equity, and log standard deviation of idiosyncratic daily returns. The first and second stage regressions are estimated for each year from 1965 through 2001. The second stage regressions have a mean of 921 firms. The table reports the means, across years, of these yearly parameter estimates. Standard errors are computed from the sample standard deviations of the yearly estimates. Asterisks denote t-statistics that exceed the 5% and 1% significance levels (2-tailed).

1st stage Explanatory variable	Lag	2nd stage regression coefs Beta	B/ME	D/ME	log(ME)	log(D_DEV)
Market	0	0.235	0.231	−0.040	0.013	0.184
return		(0.066)**	(0.104)*	(0.045)	(0.035)	(0.161)
	1	−0.103	0.277	−0.064	−0.006	0.195
		(0.065)	(0.092)**	(0.044)	(0.034)	(0.132)
	2	−0.023	0.055	−0.030	0.009	0.001
		(0.072)	(0.085)	(0.054)	(0.027)	(0.142)
	3	−0.038	0.113	−0.054	0.035	−0.164
		(0.068)	(0.075)	(0.054)	(0.030)	(0.131)
Idiosyncratic	0	−0.211	0.490	0.018	−0.070	0.122
return		(0.044)**	(0.060)**	(0.047)	(0.024)**	(0.101)
	1	−0.080	0.179	−0.021	−0.017	0.055
		(0.031)**	(0.046)**	(0.031)	(0.018)	(0.093)
	2	0.017	0.022	−0.001	0.011	0.022
		(0.040)	(0.038)	(0.043)	(0.014)	(0.084)
	3	−0.004	−0.091	−0.012	−0.025	−0.045
		(0.027)	(0.047)	(0.045)	(0.016)	(0.069)

Table 5: Cross-sectional variation in the monthly stock return–volatility relation

In the first stage the following time-series regression is estimated for individual firms i.

$$\log DEV_i(t) = c_i + \lambda_{i,m} r_m(t - \text{lag}) + \lambda_{i,I} \;\; {}_i(t - \text{lag}) + v_i(t), \;\; \text{lag} = 0, \ldots, 3$$

This table reports results from a second-stage cross-sectional regression. The estimates of $\lambda_{i,m}$ and $\lambda_{i,I}$ are regressed on firm i's beta, book equity/market equity, debt/market equity, log market equity, and log standard deviation of idiosyncratic daily returns. The first and second stage regressions are estimated for each year from 1965 through 2001. The second stage regressions have a mean of 918 firms. The table reports the means, across years, of these yearly parameter estimates. Standard errors are computed from the sample standard deviations of the yearly estimates. Asterisks denote t-statistics that exceed the 5% and 1% significance levels (2-tailed).

Panel A. Aggregate returns ($\times 10^2$)

$\mathrm{Var}(r_m \mid up)$	$\mathrm{Var}(r_m \mid down)$	$\mathrm{Var}(r_m \mid up)/$ $\mathrm{Var}(r_m \mid down)$
0.713	0.880	0.918
(0.088)	(0.153)	(0.055)

Panel B. Firm-level returns ($\times 10^2$)

	All firms	Largest 500 firms
Mean [Var($\mid up$)]	5.985	3.757
	(0.584)	(0.408)
Mean [Var($\mid down$)]	5.563	3.574
	(0.553)	(0.418)
Mean [$\mathrm{Cor}(r_i, r_j \mid up)$]	0.156	0.198
	(0.008)	(0.010)
Mean [$\mathrm{Cor}(r_i, r_j \mid down)$]	0.187	0.234
	(0.013)	(0.015)
Mean [Var($\mid up$)/Var($\mid down$)]	1.145	1.128
	(0.010)	(0.010)
Median fraction of asymmetric correlation due to asymmetric idiosyncratic volatility	0.467	0.429
	(0.058)	(0.056)

Table 6: Daily stock return volatility conditional on the sign of the market return

Idiosyncratic daily stock returns for firm i, denoted , are residuals from regressions of firm-level stock returns on the market return. Days are sorted into 'up' and 'down' samples by whether the market return exceeds its sample mean. In each calendar year from 1965 through 2001, variances of market and idiosyncratic returns are computed for both samples. Panel A reports for the market the mean variances and mean ratio of up-day variance to down-day variance, where the means are taken over the 37 yearly observations. Panel B reports time-series means of cross-sectional mean variances, variance ratios, and implied cross-correlations between firms' stock returns. Correlations are estimated by the ratio of the market's variance to the sum of the market's variance and idiosyncratic variance. Panel B also reports the time-series mean of the cross-sectional median of equation (15) in the text. This equation estimates the fraction of the difference in up-day and down-day correlations that is due to changes in idiosyncratic volatility. Standard errors are computed from the sample standard deviations of the yearly values.

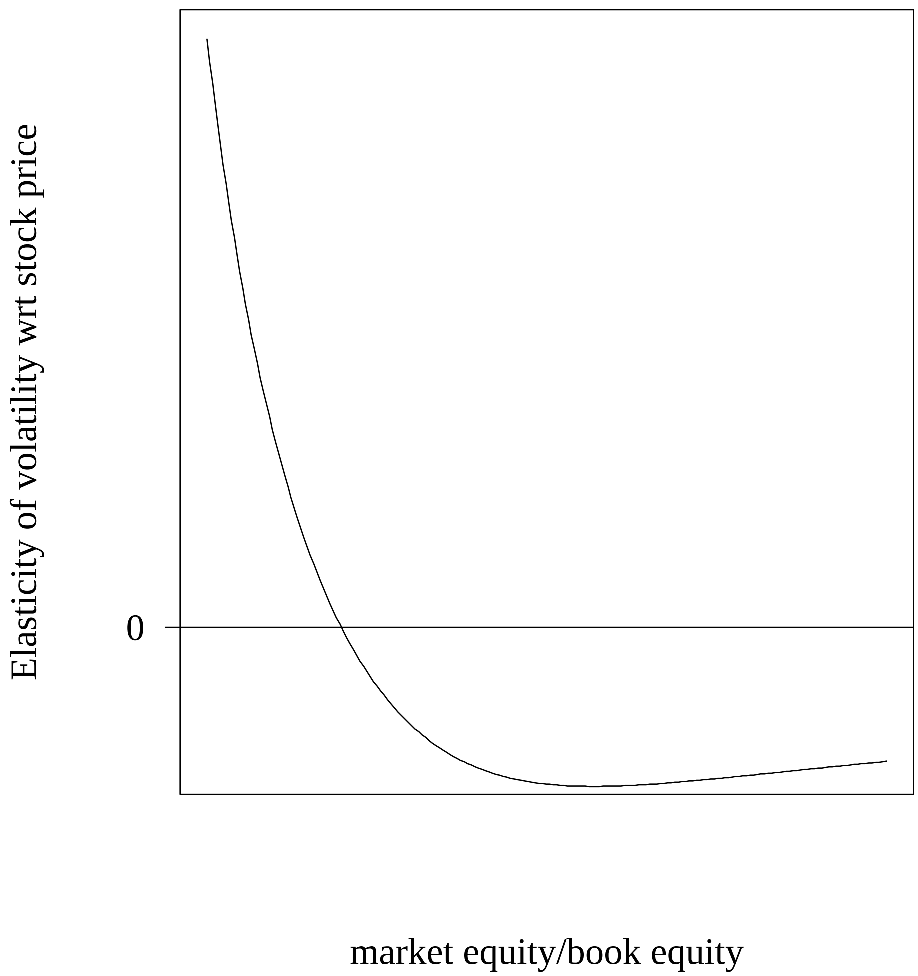

Figure 1: The return-volatility relation as a function of a firm's market-to-book ratio.

The figure assumes that a firm's book equity equals the value of an asset in place. Market equity V is the sum of its existing assets and an option to double the amount of its assets. The figure plots $\partial \log \sigma_V / \partial \log V$.