# Strategic Risk Shifting and the Idiosyncratic Volatility Puzzle: An Empirical Investigation*

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**Abstract**

We find strong empirical support for the risk-shifting mechanism to account for the puzzling negative relation between idiosyncratic volatility and future stock returns documented by Ang, Hodrick, Xing, and Zhang (2006). First, equity holders take on high idiosyncratic risk investments when their firms receive negative cash flow shocks, are in distress, have positive debt or have more long-term debt. Second, the strategically increased idiosyncratic volatility decreases the sensitivity of stocks to assets and results in low stock returns. Specifically, this strategic component alone explains 66.06 to 89.96% of the negative impact of total idiosyncratic volatility on future stock returns.

**Keywords**: risk-shifting, agency conflicts, idiosyncratic volatility puzzle

**JEL codes**: G12, G32

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# 1 Introduction

Do agency conflicts affect stock prices? Our answer is yes. In this article, we demonstrate that the well-known risk-shifting problem between equity and debt holders provides a new perspective for the negative relation between idiosyncratic volatility and subsequent stock returns. Ang, Hodrick, Xing and Zhang (2006, 2009) find that firms with low idiosyncratic stock volatility outperform firms with high volatility by 1.06% per month in both domestic and international stock markets, which is referred to as the idiosyncratic volatility puzzle. A variety of economic mechanisms have been proposed to explain the idiosyncratic volatility puzzle. Recently, Hou  Loh (2015) conduct a comprehensive comparison of explanations for the puzzle and conclude that most of the explanations account for less than 10% of the puzzle. Even when all the explanations are combined, only 29 to 54% of the puzzle has been explained. In contrast, our proxy for the risk-shifting behavior alone is able to explain 66.06 to 89.96% of the puzzle.

Traditional asset pricing models typically exclude any role agents might play in determining stock returns and volatility dynamics. Nevertheless, agency conflicts between equity and debt holders could affect expected stock returns in a significant manner. We introduce the well-known risk-shifting problem (Jensen  Meckling, 1976) into asset volatility dynamics and study its implications for the idiosyncratic volatility puzzle. Within this framework, equity is considered a call option on the underlying firm's assets (Merton, 1974). Because of limited liability, equity holders do not have to pay anything out of their pockets at bankruptcy. Therefore, they have incentives to delay bankruptcy, which is an American put option according to the put-call parity. This put option protects equity holders from downside risk, and therefore makes them less sensitive to the changes in asset values. To fully take advantage of this option, equity holders have incentives to strategically take on high risk investments to increase the underlying assets' volatility when their firm's profitability is deteriorating. Hence, equity holders who increase asset volatility more become less sensitive to the changes in asset values, which in turn results in a lower equity risk and therefore stock returns.

This risk-shifting mechanism connects a firm's profitability with its idiosyncratic volatility level, as well as the expected return on stocks. To investigate how and to what extend this risk-shifting behavior helps to explain the negative relation between idiosyncratic volatility and subsequent stock returns, we test the following two hypotheses. Our first hypothesis is that, when a firm's profitability declines, equity holders would choose to invest in projects with high volatility. More importantly, we focus on idiosyncratic volatility because equity holders do not have incentives to ride on the market when their firm is approaching bankruptcy. Our second hypothesis follows the first hypothesis: The firm's strategic risk-shifting behavior leads to a negative relation between idiosyncratic volatility and stock returns. To be more specific, when a firm increases more idiosyncratic volatility while experiencing deteriorating profits, this particular risk-shifting action decreases the stock value's sensitivity to underlying asset value. Given the same market risk premium of assets, the lower stock-asset sensitivity leads to lower expected stock returns.

We find strong empirical support for both hypotheses. To examine our first prediction, we use three proxies for idiosyncratic asset risk, including research and development expenditure, idiosyncratic volatility of asset returns, and idiosyncratic volatility of stock returns. We find that our profitability proxy, return on assets (RoA), has a negative impact on the firm's future risk-taking. This negative impact shows that equity holders increase their idiosyncratic risk-taking when their firm' profitability declines, providing strong support for the notion of risk-shifting.

To ensure the risk-shifting is one of the important, sufficient conditions for the changes in idiosyncratic volatility, we further show that equity holders are more likely to take on investments with high idiosyncratic risk when their firms receive negative RoA shocks, are in distress, have positive debt and have more long-term debt. The first condition, negative RoA shocks, is a simple, straightforward indicator that a firm is likely to enter distress, because RoA is a very persistent proxy of profitability. Additionally, we use a composite index, $o$-score (Ohlson (1980)), as our second proxy for financial distress, which relies on a historical estimation for relative weights of other accounting variables. To our knowledge, we are the first to demonstrate the negative association between RoA and idiosyncratic risk is much more significant when the firms receive negative RoA shocks or are in distress. The asymmetric association is important because taking more risks in good times does not necessarily put debt holders in danger. The third condition, positive debt, is an important and necessary condition for equity holders to shift risk. Without debt, equity holders have no incentives to take on additional idiosyncratic risk, even if their firms experience negative shocks, because they have to bear all the risk themselves. Therefore, risk-shifting behavior is less likely to occur among zero-leverage firms. The last condition is based on the result of Leland (1998) that equity holders are likely to increase risk early when they have more long-term debt. Overall, we find strong evidence that equity holders strategically take high idiosyncratic risk under these four conditions.

To verify our second prediction that *strategic* risk-shifting actions adversely impact stock returns, we use the component of idiosyncratic return volatility predicted from past RoA under the four aforementioned conditions to proxy for strategic risk-taking behavior. It worth to note that our empirical risk-shifting proxy is not only based on the past profitability, but also conditional on four scenarios where risk-taking are more likely to occur. We demonstrate that our risk-shifting proxy has a significantly negative effect on future stock returns. Specifically, using the decomposition method of Hou  Loh (2015), we find that the risk-shifting proxy component can explain majority of the negative impact of idiosyncratic volatility on future stock returns. When we include all the alternative explanations, our risk-shifting proxy stays highly significant and still accounts for 45.39 to 59.20% of the overall predictive power of idiosyncratic volatility.

The risk-shifting behavior of corporations has been studied extensively in previous research. Recent theoretical works introduce into Leland (1998) various costs of taking excess risk. Hennessy  Tserlukevich (2008) introduce a direct cost of the firm taking excess, value-destroying asset risk. Chen, Miao,  Wang (2010) show that, because of the precautionary saving incentive, an entrepreneur is less likely to risk-shift in normal times in an incomplete market, but she might still do so when her firm is close to default. Panageas (2010) introduces the bailout into the risk-shifting problem. The implicit cost of increasing risk is the loss of the opportunity to be bailed out, as potential bailouters will be reluctant to save a high-risk firm. Empirically, Eisdorfer (2008) is the first to use a large sample of firms to identify distressed firms' risk-shifting behavior. He identifies a positive relation between capital investment and uncertainty among distressed firms, which is empirically proxied by stock return volatility. Different from Eisdorfer (2008), we emphasize the *idiosyncratic* risk-taking in this paper, because distressed firms are less likely to ride on the market, because riding on the marketing during the firm's bad times cause a lower risk-adjusted asset growth rate and asset value. Using R&D investments, idiosyncratic volatility of RoA shocks and stock returns as our three proxies for idiosyncratic risk, we find that distressed firms make more investments with high idiosyncratic risk.

Our paper belongs to an emerging literature that examines the implications of agency conflicts for asset prices. Davydenko  Strebulaev (2007) demonstrate that strategic default decisions by equity holders have an adverse effect on bond prices. Albuquerue  Wang (2008) examine the impacts of corporate governance on stock valuation and show that countries with weaker investor protection have more incentives to overinvest, lower Tobin's $q$, and larger risk premia. Carlson  Lazrak (2010) show that managerial stock compensation induces risk-shifting behavior that helps explain the rates of credit default swaps (CDS) and leverage choices. Huang, Sialm,  Zhang (2011) find mutual funds that increase risk perform worse than funds with stable risk levels and conclude that agency issues might cause risk shifting by fund managers. Favara, Schroth,  Valta (2011), Garlappi  Yan (2011) and Hackbarth, Haselmann, Schoenherr (2015) study the effect of equity holders' bargaining power at bankruptcy on stock returns. By studying another agency conflict, we demonstrate that the negative association between idiosyncratic volatility and the future stock return might be driven by strategic risk-shifting behavior.

Our paper is also related to two contemporaneous papers that connect operating profitability with cross-sectional equity returns. Hou, Xue, Zhang (2015) show that an empirical $q$-factor model explains more about one half of 80 anomalies, including the idiosyncratic volatility anomaly, but do not explicitly explain why their profitability factor determines the association between idiosyncratic volatility and future returns. Fama French (2016) propose a five-factor model to explain the idiosyncratic volatility puzzle as well, and provide additional empirical evidence that "the returns of high volatility stocks behave like those of firms that are relatively unprofitable but nevertheless invest aggressively". Nevertheless, Fama French (2016) do not provide an economic story to explain their finding, either. We complement their study by providing a risk-shifting story to connect the aggressive investment behavior of unprofitable firms with their high volatility but low stock returns. More important, while they infer the relation between a firm's profitability and real investments from the stock portfolios, we provide additional empirical evidence on corporate real investments.

As reviewed in Hou Loh (2015), many explanations have been proposed in previous literature to explain the idiosyncratic volatility puzzle. Barberis Huang (2008) discuss the lottery preferences of investors, and Boyer, Mitton, Vorkink (2010) provide empirical supporting evidence for this behavioral theory for explaining the idiosyncratic volatility puzzle. A few papers focus on the relation between idiosyncratic volatility and firms' operating performance. Jiang, Xu, Yao (2009) show that idiosyncratic volatility contains information about future earnings. Avramov, Chordia, Jostova, Philipov (2013) use credit ratings to classify firms' financial status and provide evidence that the idiosyncratic volatility puzzle exists only in distressed firms. Market frictions, such as the one-month return reversal effect (Fu (2009) and Huang, Liu, Rhee, Zhang (2010)), illiquidity (Han Lesmond, 2011), price delay (Hou Moskowitz, 2005), short-sale constraints (Boehme, Danielsen, Kumar, Sorescu, 2009) and limits to arbitrage (STAMBAUGH, YU, YUAN, 2015), are also examined as potential reasons for the idiosyncratic volatility puzzle. Galai Masulis (1976), Johnson (2004), Bhamra Shim (2013) and Babenko, Boguth, Tserlukevich (2016) link asset growth volatility with the idiosyncratic volatility puzzle. These studies model growth options and do not consider the options of strategically increasing idiosyncratic volatility and going into bankruptcy. Our empirical decompositions show that the growth option can only account for about 2.84–5.68% of the puzzle.

The remainder of the paper proceeds as follows. We present a simple model and generate two predictions in Section 2. Data and empirical measures are introduced in Section 3. Section 4 contains the empirical results. Section 5 concludes the paper.

# 2 Empirical Hypothesis Development

We present a simple, modified model based on Leland (1998) in Section 2.1. We develop two testable predictions from the model in Section 2.2. The detail of the model and the formal derivation of the two hypotheses are provided in the Appendix.

## 2.1 Model Setup

The economy consists of a large number of firms. Consider a representative firm that operates in two states of risk, i.e., a high- and low-risk state. That is, the state, $s$, can take two values, H (high) or L (low). Before the firm goes bankrupt, the firm's assets produce instantaneous cash flows $X_t$ over the two states, governed by the following stochastic process:

$$\frac{dX_t}{X_t} = \hat{\mu}_s dt + \sigma_s d\hat{W}_t, \tag{1}$$

where $\hat{\mu}_s$ is the expected growth rate of the cash flow in state $s$, $\sigma_s$ is the total volatility of the cash flow growth rate, and $\hat{W}_t$ is a standard Brownian motion. The total volatility of the cash flow growth rate is $\sigma_s = \sqrt{\sigma_m^2 + \nu_s^2}$, where $\sigma_m$ is the constant systematic volatility across the two states and $\nu_s$ is the idiosyncratic volatility of the cash flow growth rate in state $s$.

According to Gordon's growth model under the risk-neutral measure $Q$, the asset value is as follows:

$$V_{s,t} \equiv V(s, X_t) = \mathbb{E}^Q \left[ \int_t^\infty X_\tau e^{-r\tau} d\tau \right] = \frac{X_t}{r - \mu_s}. \tag{2}$$

where $\mu_s = \hat{\mu}_s - \lambda$ is the risk-neutral counterpart of $\hat{\mu}_s$, and $\lambda$ is the constant risk premium over the two states. Specifically, $\lambda = \theta\sigma_m$, where $\theta$ is the market price of risk. Note that this partial equilibrium model is silent on the systematic structure of the risk premium $\lambda$.

Because $V_{s,t}$ is linear in $X_t$ in each state, it follows that

$$\frac{dV_{s,t}}{V_{s,t}} = \hat{\mu}_s dt + \sigma_s d\hat{W}_t. \tag{3}$$

Hence, the assets and their generated cash flows share the same dynamics in each state. To be consistent, we refer to $\hat{\mu}_s$ as the expected asset growth rate (or asset return), $\lambda$ as the asset risk premium, $\sigma_s$ as total asset growth volatility, and $\nu_s$ as idiosyncratic asset growth volatility throughout the rest of the paper.

The timeline is as follows. In the low-risk state $s = L$, the firm invests in assets at time 0 and produces cash flows that are characterized by a physical growth rate, $\hat{\mu}_L$, and a volatility parameter, $\sigma_L$. The firm uses the cash flows to pay taxes to the government (with effective tax rate $\tau$) and dividends to equity holders. The dividend received by equity holders is the entire cash flow $X_t$ net of coupon payments $c$ to debt holders and tax payments, $D_t = (1-\tau)(X_t - c)$. If cash flows $X_t$ decline to a low threshold $X_r$, the firm chooses to invest in high-risk assets and enter a high-risk state, hoping that the increased asset volatility might lead to a cash flow windfall, which might save the firm. At the risk-shifting threshold $X_r$, given a proportional cost $\eta \geq 0$, equity holders choose an optimal increment in asset volatility, $\epsilon^*$, to maximize the equity value $E_{H,r}$. In the high-risk state $s = H$, high-risk assets produce cash flows with a low expected growth rate $\hat{\mu}_H$, but high volatility $\sigma_H$. Lastly, if the firm's condition deteriorates further, equity holders decide to go bankrupt at $X_d$. Bankruptcy leads to immediate liquidation, in which equity holders receive nothing.

To focus on the idiosyncratic volatility puzzle, we assume that, after a firm with a low expected rate of asset growth has entered the high-risk state, the equity holders only increase the idiosyncratic volatility irreversibly (instead of systematic volatility $\sigma_m$) from $\nu_L$ to $\nu_H$ by $\epsilon = \sqrt{\nu_H^2 - \nu_L^2} \geq 0$. The intuition for this is twofold. First, given that an increase in the systematic volatility ($\sigma_m$) reduces the risk-adjusted (risk-neutral) expected growth rate, i.e., $\mu_s = \hat{\mu}_s - \theta\sigma_m$, and therefore the asset value as in equation (2), equity holders have more incentives to increase idiosyncratic volatility than total (or systematic) volatility. Second, the equity holders will have no incentives to ride on the market if the firm's declining performance is due to the contracting economy.[1]

The increment of asset volatility is optimal. We assume that the total lump-sum cost is $\eta\epsilon^2 V_{H,r}(1-\tau)$, where $V_{H,r}$ is the asset value at $X_r$. The proportional adjustment cost is intuitive. First, the cost to search capable workers with certain special expertise for idiosyncratic investments is higher than those for common projects. Second, firms with a lower asset value $V_{H,r}$ have less cash to spend on job advertisements. Compared to the original Leland's model that assumes an exogenous increase in the total volatility, our model endogenously determines the optimal amount of excess risk-taking. Meanwhile, we make two simplifications by assuming exogenous debt financing and irreversible risk-shifting decisions, which allow us to obtain closed-form solutions for stock returns. However, as demonstrated by Chen (2011), our economic insights and main predictions remain the same in a fully fledged dynamic model that allows endogenous debt refinancing and reversible risk-shifting.

To summarize, the expected asset growth rate $\hat{\mu}_s$ and idiosyncratic asset growth volatility

[1] An asset is more idiosyncratic if it can not be easily redeployed by other firms for common operations. For example, R&D investment is generally regarded as less redeployable (Titman, 1984). Practically, a firm can invest more in R&D projects to increase its idiosyncratic risk-taking. For example, Research in Motion (RIM), the manufacturer of Blackberry smart phones, has increased its R&D expenditure more than fourfold since 2008, while its annual revenue growth rate has declined from 100% to –34%.

$\nu_s$ are constant within each state, but differ across the two states. We have $\hat{\mu}_H \leq \hat{\mu}_L$ and $\nu_H \geq \nu_L$ because equity holders increase idiosyncratic volatility from $\nu_L$ to $\nu_H$ given the decrease in asset return from $\hat{\mu}_L$ to $\hat{\mu}_H$. We assume that $\hat{\mu}_H$, $\hat{\mu}_L$ and $\nu_L$ are public information and are exogenously given, while $\nu_H$ is controlled by the owners of the firm – equity holders.

## 2.2 Testable Predictions

The model we present is for one representative firm. To generate cross-sectional predictions for stock returns, we perform comparative statics analysis across firms. Suppose that there are three identical firms that start with the same $\hat{\mu}_L = 0.05$ and $\hat{\nu}_L = 0.1$ at $X_0 = 1$ in the low-risk state, but have different $\hat{\mu}_H = 0.02$, 0.03, and 0.04 respectively. We are interested in the optimal increment in idiosyncratic volatility, $\epsilon^*$, at $X_r$ and the subsequent impacts of $\epsilon^*$ on expected stock returns after $X_r$.

We obtain the parameter values from extant works, such as Carlson, Fisher, Giammarino (2004) and Strebulaev (2007). For the proportional cost of excess risk $\eta$, we choose $\eta = 0.20$ to produce a reasonable value of $\nu_H$. The specific choice of $\eta$ has no material impact on the qualitative implications of the model. The parameter values are listed in Table 1.

The following two predictions summarize how the firms strategically increase their idiosyncratic volatilities, and how the increased volatility impacts upon the stock-asset sensitivity and expected stock returns.

**Prediction 1**: *Equity holders of a firm with a lower expected growth rate of assets choose a greater increment $\epsilon^*$ and therefore have a higher idiosyncratic asset growth volatility $\nu_H$.*

Figure 1 plots the optimal $\epsilon^*$ against the expected $\hat{\mu}_H$. For the firm with the lowest $\hat{\mu}_H = 0.02$, the optimal increment $\epsilon^*$ is 0.751, while for the firm with the highest $\hat{\mu}_H = 0.04$, the optimal increment $\epsilon^*$ becomes 0.606. It is evident that the equity holders of the firm with a low expected asset return choose investments with high idiosyncratic asset growth volatility, which illustrates the prominent risk-shifting problem. Admittedly, the idiosyncratic volatility can be determined by other firm characteristics, and be even given exogenously. We emphasize the expected asset growth in this paper as it is one of the important sufficient conditions that determine a firm's optimal risk-taking policy.

**Prediction 2**: *The greater the strategically increased idiosyncratic volatility, the lower the sensitivity of stocks to underlying assets, and the lower the expected stock return.*

This prediction is based on our first prediction that equity holders choose the optimal amount of idiosyncratic risk-taking, $\epsilon^*$, in response to a lower value of $\hat{\mu}_H$. In our contingent claims framework, the expected excess stock return is simply the *market* risk premium of assets $\lambda$ scaled by the stock-asset sensitivity $\gamma_{s,t}$ for the pre- and post-shifting firms, respectively in equations (A14) and (A22) in the Appendix. With lowers stock-asset sensitivity $\gamma_{H,t}$, the expected stock return is simply lower. The optimal $\epsilon^*$ affects the stock return via the stock-asset sensitivity, $\gamma_{s,t}$. As shown in equation (A14), the increased $\epsilon^*$ increases the value of the put option to equity holders of troubled firms, which in turn lowers the sensitivity and stock returns.

We are interested in the cross-sectional stock-asset sensitivity $\gamma_{s,t}$, which varies across firms with different levels of idiosyncratic volatility $\nu_s$. We plot the stock-asset sensitivity $\gamma_{s,t}$ against $X_t$ in Figure 2. To emphasize the negative impact of the increased idiosyncratic volatility on stock returns, our discussion focus on the sensitivity, $\gamma_{H,t}$, after the risk-shifting. For $X_t < X_r$ in Figure 2, all three firms have already increased their idiosyncratic risk by $\epsilon^*$ given a lower expected $\hat{\mu}_H$. It is evident that, given a certain level of cash flows $X_t$, firms that choose lower increment $\epsilon^*$ and $\nu_H = \sqrt{\nu_L^2 + (\epsilon^*)^2}$ have higher sensitivity $\gamma_{H,t}$. For instance, when $X_t = 0.15$, Firm 3, with a greater increment $\epsilon^* = 0.744$, has a lower sensitivity $\gamma_{H,t}$ than does Firm 1 that has a smaller increment $\epsilon^* = 0.598$. Suppose the annual risk premium $\lambda = 0.1$. The difference in expected stock returns between Firm 3 and firm Firm 1 is about 0.09 per year at $X_t = 0.15$, which is comparable to the magnitude of the original idiosyncratic volatility puzzle. In short, consistent with our closed-form solutions for equity returns, Figure 2 shows that only the strategically increased idiosyncratic volatility by equity holders has a negative impact on stock returns.

# 3 Data

We obtain stock returns from the Center for Research in Security Prices (CRSP) and accounting information from quarterly Compustat industrial data. Due to the availability of quarterly ComputStat data, our sample period is from January 1975 to December 2013. We restrict the sample to firm-quarter observations with non-missing values for operating income and total assets, with positive total assets. We include common stocks listed on the NYSE, AMEX, and NASDAQ with CRSP share code 10 or 11. We exclude firms from the financial and utility sectors. The Fama-French factors and the risk-free rates are obtained from the website of Kenneth French.

## 3.1 Variable Definitions

We use the quarterly accounting data to test the first prediction, and merge the quarterly accounting data with the monthly stock return and idiosyncratic volatility to examine the second prediction.

Our measure of firm performance is RoA, which closely follows our theoretical definition of asset growth, $dV_t/V_t = X_t/V_t$. We calculate the RoA by dividing the sum of income before extraordinary items (or net income, Composted item IBQ), interest (XINTQ) and depreciation (DPQ) by the assets (ATQ) of the previous quarter. RoA values are winsorized at the upper and lower one-percentiles in order to reduce the impact of outliers and lessen the power of potential errors.[2]

We compute three proxies for subsequent idiosyncratic risk-taking for each firm $i$ at quarter $t$ or month $t$. As argued in Irvine  Pontiff (2009), increases in idiosyncratic volatility can be attributed to increases in the idiosyncratic volatility of fundamental cash flows. Our first measure for risk-taking is the annualized standard deviation of 12 quarterly RoA residuals. To get rid of market-wide fluctuations in RoA, we first obtain firm-specific RoA, $u_{i,t}^{RoA}$, by regressing firm-level RoA on market-level RoA for the whole sample,

$$RoA_{i,t} = a_i + b_i RoA_{M,t} + u_{i,t}^{RoA}, \tag{4}$$

where $RoA_{M,t}$ is the market-level RoA, proxied by the average of RoA values across all the firms at quarter $t$. We then compute $\nu_{i,t}^{RoA}$ as the standard deviation of the residual RoA from the future 12 quarters.

Our second risk-taking measure is research & development investments, $R\&D_{i,t}$. Chun, Kim, Morck,  Yeung (2008) and Comin  Philippon (2006) link idiosyncratic volatility to research intensity and spending, arguing that a more intensive use of information technology leads to higher idiosyncratic volatility. Moreover, R&D investment is likely to be idiosyncratic because present values of R&D-related cash flows are less related to systematic risk exposure. To mitigate the potential seasonality problem due to the quarterly data, we use the average of the ratio of R&D expenses (Item XRDQ) to assets (ATQ), from quarter $t$ to $t+3$. Following Hirshleifer, Low,  Teoh (2012), we set negative or missing values of R&D to zero.

The third measure is the idiosyncratic volatility of stock returns. The previous literature, including Eisdorfer (2008) and Hirshleifer et al. (2012), uses stock return volatility to proxy for the underlying asset growth volatility. Since our goal is to explain the idiosyncratic volatility puzzle, we follow Ang, Hodrick, Xing,  Zhang (2006) and estimate the idiosyncratic volatility of stock returns as the standard deviation of the residuals of daily stock returns.

We use daily stock returns to construct time series of idiosyncratic volatilities over one month and three months. We first estimate the daily stock return residuals from the Fama-

[2] Our results are very similar if we use the other firm performance measures, such as return on equity (RoE).

French (1993) three-factor model for quarter or month $t$ as follows:

$$r_{i,d}^{E} = \alpha_{i,t} + \beta_{i,t}^{MKT} r_{d}^{MKT} + \beta_{i,t}^{SMB} r_{d}^{SMB} + \beta_{i,t}^{HML} r_{d}^{HML} + u_{i,d}, \tag{5}$$

where $r_{i,d}^{E}$ is the daily stock return for firm $i$ at day $d$, and $r_{d}^{MKT}$, $r_{d}^{SMB}$, and $r_{d}^{HML}$ are the daily market, size, and value factors, respectively. To ensure an accurate estimate of idiosyncratic volatility, we require at least 50 daily return observations within one quarter for the three-month idiosyncratic volatility, and at least 15 observations within one month for the one-month volatility. We then compute the stock return idiosyncratic volatility, $\nu_{i,t}^{E}$, as the standard deviation of daily residuals for each firm-quarter and each firm-month, respectively.

The three idiosyncratic risk proxies are closely related. Empirically, the three proxies are measured over different horizons, with $\nu_{i,t}^{RoA}$ computed over three years, $R\&D_{i,t}$ over one year, and $\nu_{i,t}^{E}$ over one quarter or one month. Our first prediction is not restricted to any particular horizon, so we make use of all three proxies in testing the first hypothesis. For our second prediction, to be consistent with the existing literature on the idiosyncratic volatility puzzle, we mainly use the idiosyncratic volatility of stock returns, to test the negative relation between idiosyncratic risk and future stock returns.

When testing the first prediction, we control for firm size, growth opportunity and financial leverage. We use the logarithmic value of sales, $log(Sales)$, to proxy for the firm size; book-to-market equity, $BE/ME$, for the growth opportunity; and market leverage, $MktLev$, for the financial leverage. The book-to-market equity ratio, BE/ME, is the ratio of book equity to market equity.[3] Observations with negative BE/ME are excluded. Market leverage, MktLev, is measured as a ratio of total debt to the sum of total debt and the market value of equity, where book debt is the sum of short-term debt (Computstat item DLCQ) and long-term debt (item DLTTQ).

In addition, we follow Hirshleifer et al. (2012) and control for managerial compensations because stock-based compensations have an effect on managerial risk-taking. Using Standard and Poor's Execucomp database, we calculate delta and vega using the one-year approximation method of Core  Guay (1999) and take the natural logarithms of these two variables. Delta is defined as the dollar change in a CEO's stock and option portfolio given a 1% change in stock price, which measures the managerial incentive to increase the stock price. Vega is the dollar change in a CEO's option holdings in response to a 1% change in

[3]Book equity is the book value of equity (Computstat item CEQQ), plus balance sheet deferred taxes (item TXDBQ) and investment tax credit (ITCBQ, if available), minus the book value of preferred stock. Depending on availability, we use redemption (item PSTKRVQ), liquidation (item RSTKLQ), or par value (item PSTKQ) in that order to estimate the book value of preferred stock.

stock return volatility, which measures the risk-taking incentives generated by the managerial stock option holdings.

When testing the second prediction, we follow the literature and control for monthly contemporaneous factor loadings and lagged firm characteristics in our regressions. Factor loadings are the firm-level monthly estimates of $\beta_{i,t}^{MKT}$, $\beta_{i,t}^{SMB}$ and $\beta_{i,t}^{HML}$ from equation (5). Firm characteristics include size (the natural logarithm of market equity ME), book-to-market equity (BE/ME), market leverage (MktLev), and previous six months' cumulative stock return (PreRets).

## 3.2 Summary Statistics

Table 2 presents summary statistics of both the monthly and quarterly key and control variables we use in this study. We report the number of firms per quarter/month, the mean, the standard deviation (STD), and the first-order autocorrelation coefficients.

The quarterly data in Panel A are used to test the first prediction. On average, our sample includes 2913 to 3582 firms per quarter. As shown in the first row, the annualized $RoA$ has a mean of 3.86% and a STD of 16.2%. $RoA$ is also highly persistent, with an autocorrelation of 0.68. For the three proxies of idiosyncratic risk, the volatility of 12-quarter RoA has a mean of 12.52% with a STD of 6.03%, the R&D proxy has a mean of 4.23% with a STD of 2.54%, and the annualized idiosyncratic return volatility computed over three months has a mean of 56.79% with a STD of 29.90%. All three proxies are highly persistent, as indicated by their AR(1) coefficients, which are all at least 0.69. To avoid spurious regression issues, we include the lags of the idiosyncratic risk variables to control for the persistence in our regression analysis. As discussed earlier, the three proxies should be positively correlated. From results not included here, all three proxies are cross-sectionally correlated with a correlation coefficient of around 20 to 30%. The average logarithm of firm sales is 3.44 million dollars. Market-to-book assets ($MABA$) and market leverage ($MktLev$) have a mean of 1.96 and 0.23, respectively, and are both highly persistent.

Panel B presents the monthly data we use to test the second prediction. The annualized monthly stock return has an average of 15.72% and is slightly negatively serially correlated. The average annualized idiosyncratic volatility computed over one month has an average of 51.87%. The average size and book-to-market equity ratio in our monthly data are 111.05 ($e^{4.71}$) million dollars and 0.78, respectively, both of which are about the same as those of a median firm in the US stock markets. The average firm leverage ratio is 0.24. The average annualized lagged six-month cumulative returns after skipping a month ($PreRets$) is 15.66% with a standard deviation of 89.49%. The average firm-level betas on the market factor, size factor, and value factor are 0.90, 0.77 and 0.15, respectively. Overall, the statistics of our main variables are largely consistent with the empirical literature.

# 4 Empirical Results

In this section, we report the tests of our two theoretical predictions. In Section 4.1, we test the prediction that, given a low expected growth rate of assets, equity holders choose to take on high-idiosyncratic-risk projects to increase their own wealth. In Section 4.2, we further illustrate that firms are more likely to increase idiosyncratic risk-taking under four specific scenarios, and the risk-taking actions decrease the stock-asset sensitivity. In Section 4.5, we show that the component of idiosyncratic volatility predicted from risk-taking behavior has a negative and significant impact on future stock returns. We compare our findings with the existing literature in Section 4.6.

## 4.1 Impacts of RoA on Subsequent Risk-Shifting Behavior

Our first prediction is that equity holders who expect a low asset return take on investments with high idiosyncratic risk. Given that $RoA_{i,t}$ is highly persistent in Table 2, we assume that the expected RoA of the current quarter, conditioned on that of the previous quarter, is the RoA of previous quarter. That is, $\mathbb{E}_{t-1}(RoA_{i,t}) = RoA_{i,t-1}$. We empirically test whether idiosyncratic risk significantly increases at quarter $t$, given a decrease in $RoA_{i,t-1}$.

We perform the standard two-stage Fama-MacBeth regressions to examine the firms' risk-taking policy in response to the changing asset values at the firm level. Our results are very similar when we use a panel regression with firm fixed effects. At the first stage, we regress the idiosyncratic risk proxies on the lagged RoA and other control variables to obtain the time series of the coefficients. At the second stage, we make statistical inferences based on the time series of the coefficients from the first stage. We adjust the t-statistics using the Newey-West method with four lags.

Our first-stage estimation is conducted at each quarter $t$ as follows:

$$y_{i,t} = a_t + b_t RoA_{i,t-1} + d_t control_{i,t-1} + e_{i,t}, \tag{6}$$

where the dependent variable $y_{i,t}$ is our idiosyncratic volatility proxy.

We report Fama-MacBeth regression results in Table 3. In Panel A, the idiosyncratic volatility proxy is the volatility of the RoA over the next 12 quarters, $\nu_{i,t}^{RoA}$. In Panel B, we use R&D expenditure as a proxy for idiosyncratic volatility. In Panel C, we use the idiosyncratic return volatility over the next three months, $\nu_{i,t}^{E}$. For each dependent variable, we consider three alternative specifications, namely Reg I, II and III. Reg I is the baseline model that considers the effect of $RoA_{i,t-1}$ only. In the second regression (Reg II), we control for firm characteristics from the previous literature, such as industry averages, the logarithmic value of sales, book-to-market equity, and the market leverage ratio, delta and vega of managerial stock options, as well as $RoA_{i,t-2}$. In the third regression (Reg III), we include $y_{i,t-1}$ to control for the persistence in the dependent variables.

In Panel A, we use $\nu_{i,t}^{RoA}$ to proxy for idiosyncratic risk. For Reg I, the coefficient on $RoA_{i,t-1}$ is –0.27 (t = –17.74). This negative coefficient shows that, when $RoA_{i,t-1}$ decreases by 1%, future idiosyncratic risk increases by 0.27%. The coefficient of $RoA_{i,t-1}$ becomes –0.11 (t = –22.10) in Reg II and –0.09 (t = –24.10) in Reg III.

When we use $R\&D$ in Panel B and daily idiosyncratic return volatility in Panel C, as proxies for idiosyncratic risk, we obtain similar results. For instance, in the third regression in Panel B, the coefficient on $RoA_{i,t-1}$ is –0.03 (t= –13.50). That is, $R\&D$ increases by 0.03% in response to a 1% decrease in RoA shocks. For Reg III in Panel C, the coefficient on $RoA_{i,t-1}$ is –0.08 (t = –15.71), which indicates that the increase in $\nu_{i,t}^{E}$ in response to a 1% decrease in RoA is 0.08%.

In short, we verify our first prediction of a negative relation between the asset growth rate and future idiosyncratic risk-taking. Our results are also robust to the inclusion of lagged dependent variables and other lagged firm characteristics.

## 4.2 Risk Shifting and its Impact on Stock-Asset Sensitivity under Different Circumstances

Results in previous section show that firms take on more idiosyncratic risk when expecting lower RoA. But optimal level of idiosyncratic volatility might depend on many other variables, and risk-shifting might not be the only driving force. In this subsection, we further investigate four scenarios where equity holders are more inclined to shift risk and take more idiosyncratic volatility. We also show that the additional idiosyncratic risk-taking lowers the exposure of equity holders to the downside risk and the stock-asset sensitivity, which is our second prediction.

The first scenario for more risk-shifting is when the firm receives negative RoA shocks. This is a natural choice as the risk shifting is more likely to occur when the firm's asset value is declining and the firm is expected to enter distress. We use negative RoA to emphasize the asymmetric effect. Without loss of generality, we simply use negative RoA shocks of the last quarter to indicate that the firm is likely to increase idiosyncratic risk. To demonstrate that equity holders' incentives to take more risk are stronger in bad times, we further show that the negative association between RoA and idiosyncratic risk is much more significant when the firms receive negative RoA shocks or are in distress.

The second scenario for more risk-shifting is when the firm has a high $o$-score, which is a composite index estimated and proposed by Ohlson (1980) for a firm's financial status. Hillegeist, Keating, Cram, Lundstedt (2004) re-estimate the $o$-score using the new data. We report the results using the updated estimation of $o$-score, and our results are very similar when using the original estimation of Ohlson (1980). We calculate the $o$-score as follows:

$$\begin{aligned} O - score_{i,t} = & -5.91 + 0.04\ln(TA_{i,t}) + 0.08TL_{i,t}TA_{i,t} + 0.01WC_{i,t}TA_{i,t} - 0.01\frac{CL_{i,t}}{CA_{i,t}} \\ & + 1.59I(TL_{i,t} > TA_{i,t}) + 1.2\frac{NI_{i,t}}{TA_{i,t}} + 0.18\frac{FFO_{i,t}}{TL_{i,t}} \\ & + 0.01I(\text{Continuous two-quarter net loss}) - 1.1\frac{NI_{i,t} - NI_{i,t-1}}{|NI_{i,t}| - |NI_{i,t-1}|} \end{aligned}$$

where $TA$ is total assets, $TL$ is total liabilities, $WC$ is working capital, $CL$ is current liabilities, $CA$ is current assets, the indicator $I(.)$ equals one if the condition is met and equals zero otherwise, $NI$ is net income, and $FFO$ is funds from operations. The greater $o$-score, the more distressed the firm is. We sort all the firms into terciles based on the $o$-score of the previous quarter and classify the firms in the top tercile as distressed firms.

The third scenario for potentially more risk-shifting behavior is when the firms have positive financial leverage. Debt is an embedded put option for equity holders, protecting them from downside risk. Without such protection (i.e., in the case of zero debt), equity holders have no incentives to increase their risk-taking if they have to bear all the downside risk themselves. Around 20% of the firm-quarter observations in our sample have no debt.[4] Alternatively, we exclude the observations with zero-leverage and find that our results remain qualitatively the same. We include all the observations to be consistent with the sample used by Ang et al. (2006). While our study emphasizes the risk-shifting from equity holders to debt holders, firms are likely to shift the operating risk to their workers and operating material suppliers if they are not able to make payments for contractual wages and fixed long term operating costs. Defaults on those fixed costs raise operating leverage risk, which we can be easily incorporated into our model.

The last scenario we consider is based on debt maturity. Equity holders have greater incentives to take more risk if the time at which they will have to repay the debt holders is far away. Leland (1998) shows that the risk-shifting threshold increases with debt maturity (or decreases with debt retirement frequency). The more the long-term debt, the greater

[4] Strebulaev Yang (2013) find that zero-leverage firms have higher market-to-book ratios and higher cash balances, are more profitable, and pay more taxes and dividends.

likelihood of risk shifting. We use the ratio of long-term debt (Compustat item DLTTQ) to total debt (DLTTQ + DLCQ) to proxy for the relative fraction of long-term debt. We choose a median value, 2/3, as a cutoff to identify a greater composition of long-term debt.

## 4.3 Asymmetric Risk Shifting under Different Circumstances

To examine the asymmetric impacts of RoA on idiosyncratic risk-taking, we include a dummy variable, $I(.)$, to identify the four aforementioned scenarios in which risk shifting is more likely to occur, in the following regression:

$$y_{i,t} = a_t + b_t RoA_{i,t-1} + c_t RoA_{i,t-1} I(.) + d_t control_{i,t-1} + e_{i,t}, \tag{7}$$

where $y_{i,t} = \nu^E_{i,t}$,[5] and the dummy variable $I(.)$ takes a value of one if the RoA of the last quarter is negative ($RoA < 0$), the $o$-score is in the top tercile ($os = 3$), the firm has positive debt ($Debt > 0$), or the fraction of long-term debt in the total debt is more than 2/3 ($DM > 2/3$). While $b_t$ measures idiosyncratic risk-taking in response to RoA regardless of the likelihood of risk shifting, $c_t$ measures the additional effect when risk shifting is highly likely to occur. That is, $b_t + c_t$ captures the impact of $RoA_{i,t-1}I(.)$ on future idiosyncratic volatility when risk shifting is more likely, i.e., $I(.) = 1$. Finally, we include various control variables, $control_{i,t-1}$.

Table 4 reports the results. The first regression (Reg I) shows that the estimated coefficients of $RoA_{i,t-1}$ and $RoA_{i,t-1}I(RoA_{i,t-1} < 0)$ are –0.02 (–2.28) and –0.19 (t=–6.79), respectively. Those two estimates indicate that the increase in $\nu^E_{i,t}$ in response to a negative RoA is –0.21 (–0.02–0.19), which is is about ten times its response to a positive RoA (–0.02). The second regression that uses the $o$-score to proxy for financial distress confirms that firms take on more investments with high idiosyncratic risk when they are in bad times.

When the firms have positive debt (Reg III) and more long-term debt (Reg IV), we obtain similar results. For instance, in Reg III, the coefficient on $RoA_{i,t-1}$ is –0.05 (t= –6.99) and the coefficient on $RoA_{i,t-1}I(debt > 0)$ is –0.04 (t= –5.55). That is, $\nu^E_{i,t}$ increases by 0.05% in response to a 1% *decrease* in RoA shocks among the firms with zero debt, but it increases by 0.09% (0.05% + 0.04%) in response to the same decrease in RoA among the firms with positive debt. As we explained early, the firms of zero leverage are likely to shift risk to their works and operating material suppliers. The above result shows the firms with positive leverage have nearly doubled their risk-taking appetite relative of firms with zero leverage. For Reg IV, the coefficient on $RoA_{i,t-1}$ is –0.07 (t = –13.25) and the coefficient on

[5] To save space, we do not report results on $\nu^{RoA}_{i,t}$ and $R\&D_{i,t}$. The results are qualitatively similar to those presented here and are available upon request.

$RoA_{i,t-1}I(DM > 2/3)$ is –0.03 (t = –6.39). This confirms that firms with more long-term debt are likely to take more idiosyncratic risk than their counterparts.

## 4.4 Stock-Asset Sensitivity under Different Circumstances

Having demonstrated that equity holders take on more idiosyncratic risk under four scenarios, we proceed to show the consequent effect of risk shifting on the sensitivity of stocks to assets, which is $\gamma_{s,t}$ defined in equation (A16). The baseline regression of Reg I is as follows:

$$r_{i,t}^{E} = a_t + (b_t + c_t * \nu_{i,t-1})RoA_{i,t-1} + d_t control_{i,t-1} + e_{i,t}. \tag{8}$$

In our specification, the stock-asset sensitivity is $b_t + c_t * \nu_{i,t-1}$. According to our second prediction that idiosyncratic volatility reduces the stock-asset sensitivity, we expect $c_t < 0$.

Table 5 reports the results. Consistent with our prediction, the estimated coefficient of the interaction term $RoA_{i,t-1} * \nu_{i,t-1}$ is –0.21 (t = –2.12) in Reg I, indicating that the higher idiosyncratic volatility provides equity holders with more protection and weakens the sensitivity of stocks to assets.

We expect idiosyncratic volatility to further reduce the stock-asset sensitivity in the four high-risk-shifting scenarios. Therefore, we include the indicator $I(.)$ to consider the four high-risk-shifting scenarios in Reg II, III, IV and V in the following regression:

$$r_{i,t}^{E} = a_t + (b1_t + c1_t * \nu_{i,t-1})RoA_{i,t-1} + (b2_t * I(.) + c2_t * I(.) * \nu_{i,t-1})RoA_{i,t-1} + d_t control_{i,t-1} + e_{i,t}. \tag{9}$$

We expect to see $c2_t < 0$.

We consider the four high-risk-shifting scenarios in the next four columns of Table 5. For Reg II where the firms receive negative RoA shocks, the coefficient of $RoA_{i,t-1} * \nu_{i,t-1} * I(.)$ is –0.69 (t = 1.68), indicating that the reduction in the stock-asset sensitivity is largely driven by firms receiving negative RoA and taking on additional idiosyncratic risk. The result is similar in Reg III where the firms have high $o$-scores, with an estimate of –0.26(t = 1.67). Our results for the other two scenarios have the same implications. The estimates of $RoA_{i,t-1} * \nu_{i,t-1} * I(.)$ in Reg IV and V are –0.28 (t = –1.78) and –0.45 (t = –3.66), respectively. They consistently confirm that the decreases in the stock-sensitivity due to the idiosyncratic volatility are from the firms with a high probability of risk-shifting.

In summary, we demonstrate that the increased idiosyncratic volatility causes stock holders to become less sensitive to the changes in the underlying asset values. More importantly, the reduction effect of idiosyncratic volatility on the stock-asset sensitivity is more significant among firms with greater incentives to shift risk.

## 4.5 Negative Relation between Idiosyncratic Volatility and Stock Returns

In this subsection, we first decompose idiosyncratic return volatility into two components, one strategic risk-shifting component predicted from the past RoA, and one orthogonal component. We show that it is the strategic risk-shifting component that negatively impacts the future stock returns. In addition, we apply the decomposition method of Hou  Loh (2015) to quantify the magnitude of this risk-shifting component's effect on the negative relation between idiosyncratic volatility and stock return.

### 4.5.1 Decomposing the Negative Impacts of Risk Shifting on Stock Returns

Our model states that, when the asset value decreases, equity holders choose to increase idiosyncratic risk, which in turn results in lower stock-asset sensitivity and stock returns. The idiosyncratic volatility at month $t$ is computed using current one-month daily returns and three-month daily returns from the beginning of the current month, respectively.

To decompose the idiosyncratic volatility of stock returns $\nu_{i,t}^{E}$ into the strategic risk-shifting component in response to the past RoA, and the orthogonal residual component, we estimate the following cross-sectional regression month by month:

$$\nu_{i,t-1}^{E} = a_{t-1} + b_{t-1} RoA_{i,t-1} + c_{t-1} RoA_{i,t-1} I(.) + u_{i,t-1} \tag{10}$$

where $u_{i,t-1}$ is the error term. The indicator $I(.)$ takes a value of one if the $RoA$ of the last quarter is negative ($RoA < 0$), the $o$-score is classified into the top tercile ($os = 3$), the firm has positive debt ($Debt > 0$), or the fraction of long-term debt in the total debt is more than 2/3 ($DM > 2/3$).

Based on the estimated coefficients each month, we then have the following decomposition:

$$\begin{aligned} \nu_{i,t-1}^{E} &= \nu_{i,t-1}^{Pred} + \nu_{i,t-1}^{Rsd} \\ &= (\hat{b}_{t-1} RoA_{i,t-1} + \hat{c}_{t-1} RoA_{i,t-1} I(.)) + (\hat{a}_{t-1} + u_{i,t-1}). \end{aligned} \tag{11}$$

The predicted component $\nu_{i,t-1}^{Pred}$ is determined by the strategic risk-shifting behavior predicted by RoA, while the residual component $\nu_{i,t-1}^{Rsd}$ captures the rest. By design, $\nu_{i,t-1}^{Pred}$ and $\nu_{i,t-1}^{Res}$ are orthogonal to each other. We expect that it is the $\nu_{i,t-1}^{Pred}$ rather than the $\nu_{i,t-1}^{Res}$ that drives the negative relation between idiosyncratic volatility $\nu^{E}_{i,t-1}$ and next-period stock returns $r_{i,t}$.[6]

We follow Ang, Hodrick, Xing, Zhang (2009) and estimate the two-stage Fama-MacBeth regression for stock returns at the firm level, month by month. The first-stage estimation is specified as follows:

$$r^{E}_{i,t} = a_t + b_t\nu^{E}_{i,t-1} + c_t control_{i,t-1} + u_{i,t} = a_t + b1_t\nu^{Pred}_{i,t-1} + b2_t\nu^{Rsd}_{i,t-1} + c_t control_{i,t-1} + u_{i,t}, \quad (12)$$

where the control variables, $control_{i,t-1}$, include size, the book-to-market ratio, previous returns, market leverage and factor loadings on market, size and value factors. We draw statistical inferences in the second stage using the time series of coefficients, we obtain from the first stage. Standard errors are adjusted using the Newey-West method with four lags. In the first equation, we establish the negative relation between idiosyncratic volatility and future stock returns. In the second equation, we investigate which component, $\nu^{Pred}_{i,t-1}$ or $\nu^{Res}_{i,t-1}$, drives the negative relation between idiosyncratic volatility and future stock returns.

Table 6 reports the estimation results. For robustness, we present two sets of results. In Panel A, $\nu^{E}_{i,t-1}$ is computed using the future one-month daily returns, while in Panel B $\nu^{E}_{i,t-1}$ is computed using the future three-month daily returns. For the first regression in Panel A, the coefficient on $\nu^{E}_{i,t-1}$ is –0.11 (t = –3.96). That is, if annualized volatility increases by 10%, then the stock return for the next month decreases by 1.1%, which confirms the finding in Ang et al. (2006) that idiosyncratic volatility $\nu^{E}_{i,t-1}$ has a negative impact on future stock returns $r_{i,t}$.

In the next four regressions, we replace $\nu^{E}_{i,t-1}$ with the predicted component, $\nu^{Pred}_{i,t-1}$, and the residual component, $\nu^{Res}_{i,t-1}$. Across all four regressions, the negative impact of the predicted component, $\nu^{Pred}_{i,t-1}$, on stock returns is economically and statistically significant, with a coefficient of –1.36 (t = –11.83), –1.41 (t = 10.33), –1.56 (t = –8.36) and –1.54 (t = –8.34), respectively. In sharp contrast, the estimated coefficients of the residual component $\nu^{Rsd}_{i,t-1}$ are only about –0.05, and more importantly, are far less statistically significant with t-statistics from 2.10 to 2.24. This sharp contrast indicates that the firm's risk-shifting behavior, captured by $\nu^{Pred}_{i,t}$, is the driving force behind the negative relation between idiosyncratic volatility and future stock returns.

Among the control variables, size and market leverage are negatively associated with future stock returns, the book-to-market ratio is positively associated with future returns, and the lagged six-month cumulative stock return is positively related to future returns. Consistent with the findings in the literature, all these characteristics are highly statisti-

[6] To be consistent with the decomposition method proposed by Hou Loh (2015), we use the contemporaneous $RoA_{i,t-1}$ to decompose $\nu^{E}_{i,t-1}$. The results using further lagged RoA are very similar and are available upon request.

cally significant. Additionally, the contemporaneous loading on the market factor carries a significant positive coefficient while the loadings on the size factor and the value factor are insignificant. The coefficients on the control variables remain highly consistent across all four regressions.

The results are quite similar when $\nu^E_{i,t-1}$ is computed using three-month daily returns in Panel B. To save space, we focus our future discussion on the one-month horizon, which is adopted in most of the existing literature.

To summarize, by decomposing the idiosyncratic volatility into the predicted and residual components, we have shown that its predictive power for subsequent returns comes primarily from the strategic component that is predicted from $RoA_{i,t-1}$ and $RoA_{i,t-1}I(.)$.

#### 4.5.2 Quantifying the Negative Impacts of Risk Shifting on Stock Returns in the Hou  Loh (2015) Decomposition

In a recent paper, Hou  Loh (2015) evaluate a large number of existing explanations for the negative relation between idiosyncratic volatility and subsequent stock returns. They propose a methodology for decomposing the negative relation between idiosyncratic volatility and returns into two components: one component related to suggested candidate variables and another residual component unrelated to the candidate variables. Their method helps to quantify the magnitudes of the impacts of the candidate variables. Hou  Loh (2015) show that many suggested explanations explain less than 10% of the idiosyncratic volatility puzzle. They find that explanations based on investors' lottery preferences, short-term reversal and earnings shocks show greater promise in explaining the puzzle and that together they account for 60 to 80% of the negative coefficient. We adopt their procedure to examine quantitatively how well our proxy for risk shifting explains the idiosyncratic volatility puzzle.

The procedure proposed by Hou  Loh (2015) is as follows. First, for each month $t$, stock returns are regressed on lagged idiosyncratic volatility cross-sectionally,

$$r^E_{i,t} = \alpha_t + \kappa_t \nu^E_{i,t-1} + u_{i,t}. \tag{13}$$

Next, idiosyncratic volatility is regressed on a candidate variable,

$$\nu^E_{i,t-1} = a_{t-1} + \delta_{t-1} Candidate_{i,t-1} + u_{i,t-1}. \tag{14}$$

The component $\delta_{t-1} Candidate_{i,t-1}$ is essentially the same as our predicted component $\nu^{Pred}_{i,t}$ in equation (11). Lastly, $\kappa_t$ is decomposed into two components, $\kappa^c_t$, explained by the candidate and, $\kappa_t^r$, explained by the residual:

$$\kappa_t = \frac{Cov\left(r_{i,t}^E, \nu_{i,t-1}^E\right)}{Var\left(\nu_{i,t-1}^E\right)} = \frac{Cov\left(r_{i,t}^E, \delta_{t-1}Candidate_{i,t-1}\right)}{Var\left(\nu_{i,t-1}^E\right)} + \frac{Cov\left(r_{i,t}^E, a_{t-1} + u_{i,t-1}\right)}{Var\left(\nu_{i,t-1}^E\right)} = \kappa_t^c + \kappa_t^r. \tag{15}$$

Our candidate variable is $RoA_{i,t-1}$, combined with an indicator $I(.)$ that identifies the circumstances in which equity holders are more likely to shift risk. To be consistent with Hou  Loh (2015), we exclude observations with a stock price lower than one dollar.

Table 7 shows the results from the Hou-Loh decomposition. As in Table 6, we present results using one-month daily stock return idiosyncratic volatility in the left panel, and results using three-month daily stock return idiosyncratic volatility in the right panel. Panels A, B and C report the estimation results for the three steps of the Hou-Loh decomposition, respectively.

For the one-month idiosyncratic volatility, for the first step shown in Panel A, the coefficient of $\nu_{i,t-1}^E$ is –0.15 when we use the whole sample to predict the idiosyncratic volatility under the first three situations of $I(RoA < 0)$, $I(os = 3)$ and $I(DM > 2/3)$, and it is –0.17 when we use the subsample of positive debt for the case of $I(DM > 2/3)$. These negative coefficients confirm the negative relation between idiosyncratic volatility and the future stock return. In the second step, shown in Panel B, we regress idiosyncratic volatility on $RoA_{i,t-1}$ and $RoA_{i,t-1}I(.)$. Both variables are significantly negatively related to idiosyncratic volatility, especially the asymmetric part, $RoA_{i,t-1}I(.)$, which is consistent with our findings in previous section. In the last step of the decomposition shown in Panel C, the component $\kappa_t^c$ predicted from $RoA_{i,t-1}$ and $RoA_{i,t-1}I(.)$ explains at least 66.06% of the negative impact of idiosyncratic volatility on the stock return, and the predicted component using the condition $I(Debt > 0)$ has the most significant explanatory power. The residual component, $\kappa_t^r$, suggests that a proportion of 27.83 to 33.94% remains unexplained under the four risk-shifting scenarios. In addition, all the t-statistics of $\kappa_t^c$ are above 11.96 in absolute value and highly statistically significant, while all the t-statistics of $\kappa_t^r$ are insignificant. We report the decomposition of Hou  Loh (2015) using three-month idiosyncratic volatility in the right panel. The results are similar to the left panel.

Many existing explanations examined in Hou  Loh (2015) explain less than 10% of the idiosyncratic volatility puzzle. In sharp contrast, our results in Table 6 show that while the risk-shifting induced by negative RoA, high $o$-score, positive debt can explain a striking 71.92, 71.45 or 72.17% of the idiosyncratic volatility puzzle, the risk-shifting caused by more long-term debt (relative to short term debt) explain 66.06% of the puzzle.

In Hou  Loh (2015), the most promising variable is the maximum daily return, proposed by Bali, Cakici,  Whitelaw (2011) as an indicator for stocks preferred by lottery-seeking investors. Although this variable can explain almost the entire volatility puzzle, those authors recognize that the performance is due to high correlation between the maximum daily return and idiosyncratic volatility, and they report a correlation coefficient of 88.3% between them. In fact, one can argue that the maximum daily return is simply a variant of the range-based volatility measure. The maximum daily return naturally appears to explains a large portion of the idiosyncratic volatility puzzle simply due to its high correlation with idiosyncratic volatility. Hence, we exclude the maximum daily return from our exercise and from our future discussion.

## 4.6 Alternative Explanations

In this section, we examine alternative explanations offered in the literature and compare our risk-shifting explanation with them.

### 4.6.1 Summary of Alternative Explanations for the Idiosyncratic Volatility Puzzle

Bekaert, Hodrick, Zhang (2010) provide a summary of existing studies of how firm fundamentals affect idiosyncratic risk, and thus possibly affect stock returns. Cao, Simin, Zhao (2008) show that both the level and variance of corporate growth options are significantly related to idiosyncratic volatility. To capture this growth option, they use market assets over book assets ($MABA$) as a proxy. Irvine Pontiff (2009) and Gaspar Massa (2006) argue that idiosyncratic return volatility is related to the idiosyncratic volatility of fundamental cash flows, or intense product market competition. Following the literature, we use two measures to proxy for competition: the industry turnover, $IndTurn$, and industry-level earnings dispersion, $Dispers$. To compute $IndTurn$, we take the percentage of the market cap of firms entering and exiting the same industry at the 48-industry level each month, and then assign this percentage to each individual firm in each of the industries. For $Dispers$, we use the first-order difference in earnings per share (EPS) to proxy for innovations in earnings, and then compute a cross-sectional variance of this for each of the 48 industries and assign this earnings dispersion measure to each individual firm.

In addition, we include all the alternatives cited in Hou Loh (2015). First, Jiang et al. (2009) show that high idiosyncratic volatility stocks have negative earnings shocks both before and after portfolio formation, and argue that it is the reason for the poor stock performance of those stocks. As a result, we use the most recent quarter's standardized unexpected earnings, SUE, as a candidate. It is also possible that the negative association between idiosyncratic volatility and stock returns is a reflection of illiquidity. To address this concern, we adopt the transaction cost/liquidity measure developed in Lesmond, Ogden, Trzcinka (1999), $Zeros$, calculated using the proportion of daily returns equal to zero each month. Huang et al. (2010) show that the idiosyncratic effect on future stock returns is driven merely by short-term return reversals. Therefore, we include the lagged one-month return, $Reversal$, for the reversal effect. Barberis Huang (2008) provide the lottery preference explanation and argue that firms with high idiosyncratic skewness have low returns, which drives the idiosyncratic volatility puzzle. To accommodate this alternative, we include the monthly expected skewness (Boyer et al., 2010), $ESkew$, obtained from the website of Brian Boyer. Finally, Johnson (2004) uses the dispersion of the forecast on earnings to proxy for the uncertainty of volatility parameter. Using a similar approach, we follow Diether, Malloy, Scherbina (2002) and use the number of analysts ($Analysts$) who provide current fiscal-year annual earnings estimates in the I/B/E/S database to proxy for the dispersion of earnings forecasts. Instead of excluding observations with missing I/B/E/S values, we include all observations and use $I_{MissAnalyst}$ as an indicator for the missing I/B/E/S observations. The only alternative we do not explicitly test is the maximum daily return over the past month. As we explained earlier, the maximum daily return has a high collinearity with idiosyncratic volatility.

### 4.6.2 The Significance of the Risk-Shifting Proxy in the Presence of Alternatives

In this section, we estimate the standard Fama-MacBeth two-stage regression, with the following specification:

$$r_{i,t}^{E} = a_t + b_t \nu_{i,t-1}^{Pred} + c_t \nu_{i,t-1}^{Rsd} + d_t Alternative_{i,t-1} + e_t control_{i,t-1} + u_{i,t}, \tag{16}$$

where $Alternative_{i,t-1}$ stands for a vector of alternative variables. If the risk-shifting story is robust to alternative explanations, we expect the coefficient $b_t$ to remain significantly negative.

Table 8 presents the results in the presence of different alternatives. As before, we use the one-month idiosyncratic volatility in Panel A and the three-month idiosyncratic volatility in Panel B. In Panel A, across the four risk-shifting scenarios, the coefficients on $\nu_{i,t-1}^{Pred}$ range between –1.11 and –1.31, with t-statistics of at least 7.25 in absolute terms. This finding clearly demonstrates that the risk-shifting theory we propose is a robust explanation for the idiosyncratic volatility, which remains highly significant when we include alternative explanations. Meanwhile, the coefficients on $\nu_{i,t-1}^{Rsd}$ are about 0.03 and statistically insignificant in all four cases.

We briefly discuss the coefficients on the alternative variables. The first alternative is $MABA$, proxying for growth options. The coefficient on $MABA$ is low, possibly because $MABA$ is usually highly correlated with the book-to-market ratio. Next are the two competition proxies, $IndTurn$ and $Dispers$. The coefficients on $IndTurn$ are statistically insignificant. For the proxy for earnings shocks, $SUE$, and the proxy for the illiquidity, $Zeros$, both coefficients are positive and statistically significant, implying that positive earnings shocks and low liquidity lead to high future stock returns. The coefficient on $Reversal$ is negative, indicating that firms with a strong return reversal effect tend to have lower future stock returns. Additionally, the coefficient of $ESkew$ is positive. Finally, the number of analysts and the indicator for missing records of analysts are both insignificant. Our results in Panel B are largely the same.

To summarize, in the presence of all the alternative explanations, the strategic component of idiosyncratic volatility predicted by $RoA_{i,t-1}$ and $RoA_{i,t-1}I(.)$ under the four risk-shifting scenarios is always highly significant, while the coefficient of the residual component is mostly insignificant. This evidence lends support to our risk-shifting explanation in the presence of alternative explanations.

### 4.6.3 Contribution of the Risk-Shifting Explanation in the Hou Loh (2015) Decomposition

In the previous section, we have showed that alternative explanations do not attenuate the significance or explanatory power of risk-shifting behavior, proxied by RoA and an indicator of high risk-shifting possibility scenarios. In this section, we take a step further to compare the performance of our risk-shifting proxy with other alternatives. In other words, we are interested in quantifying the marginal contribution of our risk-shifting explanation, in comparison with competing variables. We adopt the Hou-Loh decomposition introduced in Section 4.5.2. In this section, the Hou-Loh decomposition includes all alternative variables, and we expect the best explanatory variable to account for the highest proportion of $\kappa_t$.

Table 9 presents the results for the multivariable decomposition. The left panel contains the results for idiosyncratic volatility computed from one-month daily stock returns, and the right panel contains results for idiosyncratic volatility computed from three-month daily stock returns. Panel B shows that the estimates of $K_t^j$ for our risk-shifting proxy $RoA_{i,t-1}$ + $RoA_{i,t-1} * I(.)$ are all economically and statistically significant. In Panel C where we use one-month idiosyncratic volatility, the same risk-shifting variable alone captures45.39 to 51.98% of the puzzle under the four risk-shifting scenarios. Compared to Table 7, where we include only the risk-shifting variable, the inclusion of alternative explanatory variables in this table slightly reduces the explanatory power of the risk-shifting theory. However, it remains by far the most dominant explanation when compared with the alternatives.

The time-series average $\kappa_t^j$ divided by $\kappa_t$ measures the fraction of the negative impact of idiosyncratic volatility on stock returns explained by any other candidate variable $j$. For example, when the firm receives negative RoA shocks, MABA, industry turnover, earnings dispersion, SUE, short-term reversal, expected idiosyncratic skewness and the number of analysts explain 2.84%, 0.54%, 1.38%, 5.47%, –8.11%, 22.69%, 2.53% and 2.93%, respectively. Among all the competing explanations, reversal makes the highest contribution. Lastly, the residual component indicates that 24.33% of the puzzle remains unexplained.

The right panel presents results using three-month idiosyncratic volatility. It shows a similar pattern to the left panel but a stronger one. The risk-shifting variable itself explains 55.64 to 59.78% of the negative relation between idiosyncratic volatility and stock returns.

In summary, the results in Table 9 strongly demonstrate that, compared to other explanations, the risk-shifting variables under various scenarios explain the largest portion of the idiosyncratic volatility puzzle. This suggests that agency conflict between equity and debt holders plays a key role in the dynamic relation between idiosyncratic volatility and future stock returns.

# 5 Concluding Remarks

In this article, we examine a prominent agency conflict problem, the risk-shifting behavior of equity holders, and its implications for the negative relation between idiosyncratic volatility and future stock returns. We build a simple risk-shifting model based on Leland (1998), which intuitively connects firm's profitability, optimal risk-taking and future stock returns.

We conduct extensive tests for our empirical predictions. Our first testable prediction is that when firms expect lower profitability, the equity holders would shift risk by taking on more idiosyncratic risk. In testing our first prediction, we carefully use the R&D investments, volatility of RoA, and idiosyncratic volatility of stock returns as our risk-taking proxies. We show that the negative relation between profitability, proxied by the past RoA, and risk-shifting behavior is amplified when firms receive negative cash flow shocks, are in distress, have positive debt or have more long-term debt.

Our second prediction is that the risk-shifting strategy reduces the downside risk exposure of equity holders. By taking on high idiosyncratic risk investments and shifting downside risk to debt holders, equity holders become less sensitive to changing asset values, therefore demanding lower risk premiums and receiving lower stock returns. We empirically confirm that only the risk-shifting component of idiosyncratic volatility predicted from the past RoA, under our four risk-shifting scenarios, has an adverse impact on stock returns. Specifically, the proportion of the negative impact from this risk-shifting component ranges from 66.06 to 89.96%. The main results still hold in the presence of alternative explanatory variables. Hence, our results show that strategic risk shifting plays a significant role in driving firm-level volatility dynamics, and largely explains the negative relation between idiosyncratic volatility and future stock returns. In summary, we demonstrate that the well known risk-shifting problem could help explain why unprofitable firms have high volatility but low stock returns, via the channel of aggressive investment behavior.

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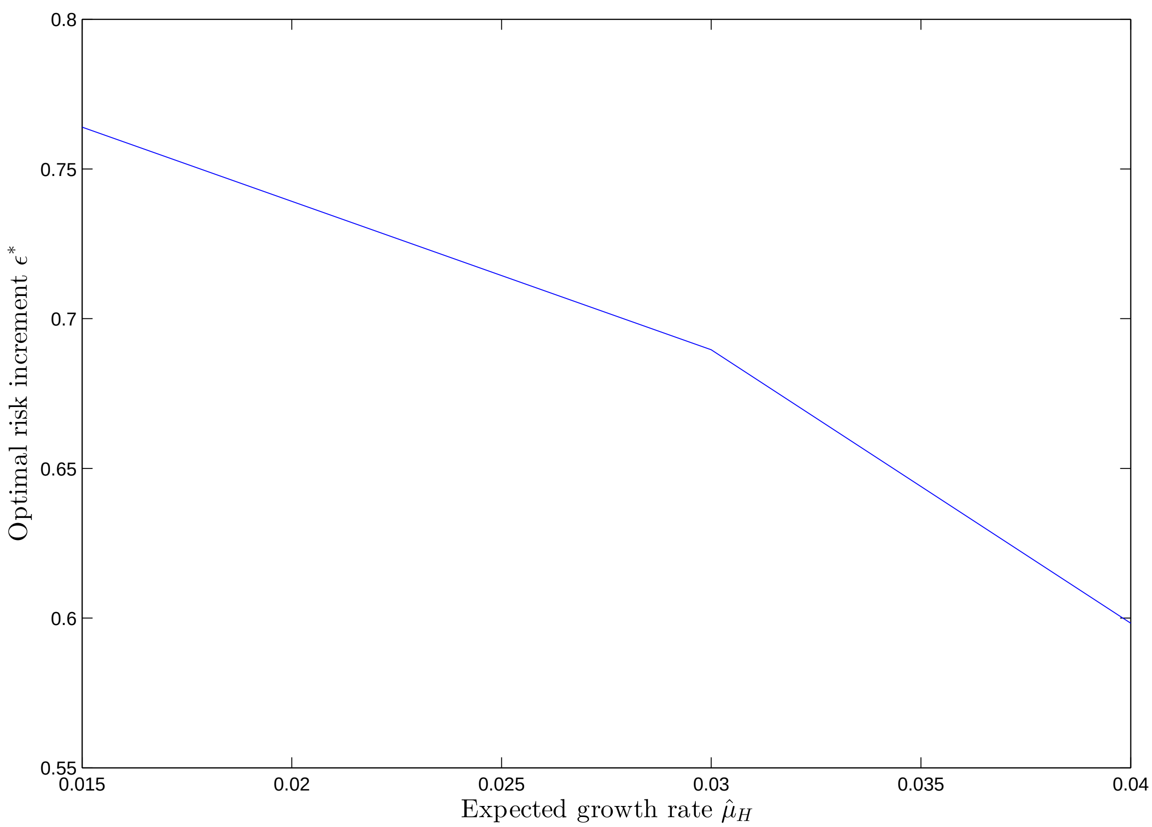


Figure 1: **Expected Growth Rate vs. Optimal Risk Increment.**
This figure plots the optimal risk increment $\epsilon^*$ against the expected growth rate $\hat{\mu}_H$ for three firms that are entering a high-risk state. These three firms start with the same $\hat{\mu}_L = 0.05$ and $\hat{\nu}_L = 0.1$ at $X_0 = 1$ in the low-risk state. When their conditions deteriorate, these firms have different expected $\hat{\mu}_H = 0.02, 0.03, 0.04$, respectively. Given their expected $\hat{\mu}_H$'s, they choose different optimal $\epsilon^*$'s.

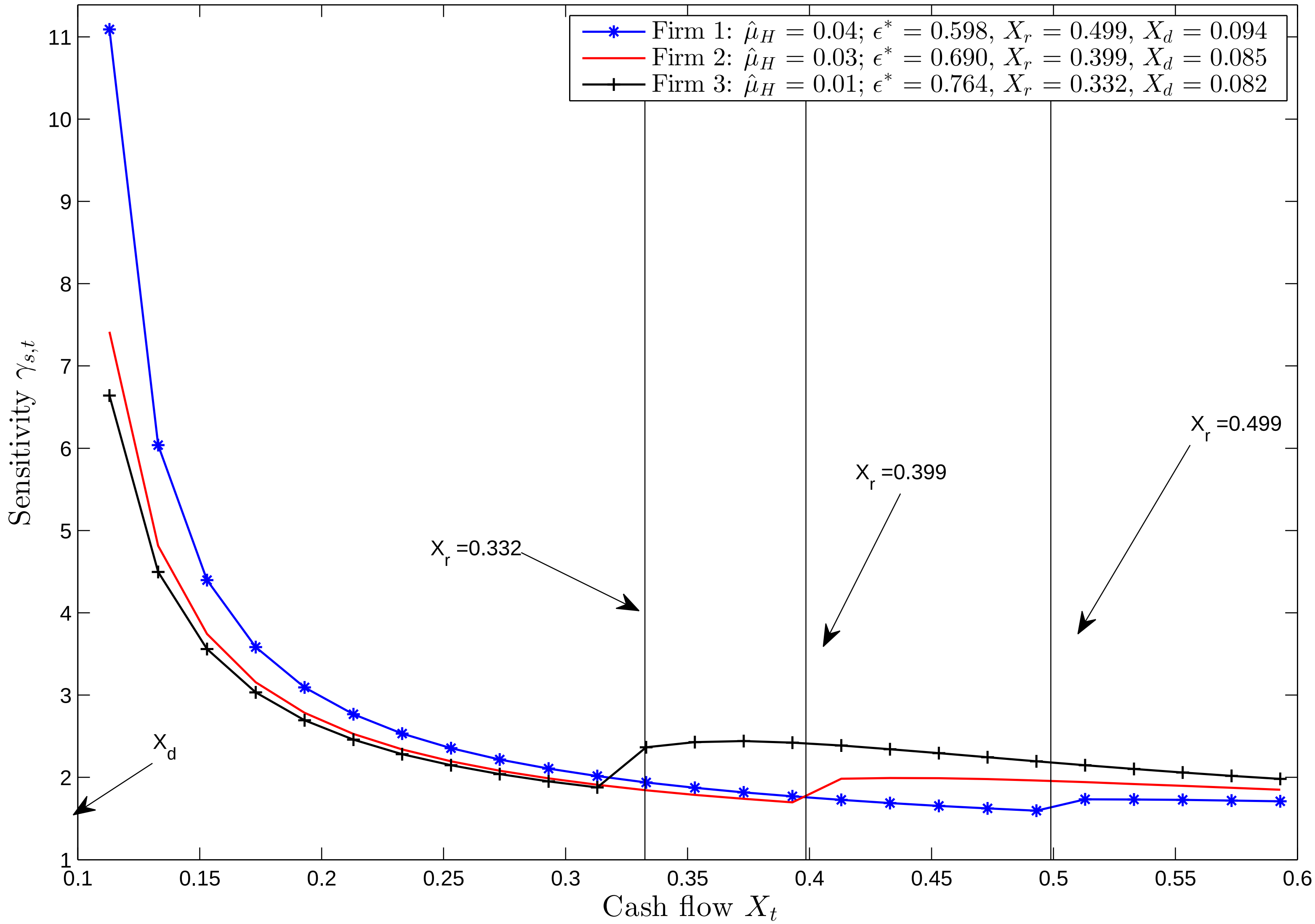


Figure 2: **Stock-Asset Sensitivity**

This figure plots the stock-asset sensitivity $\gamma_{s,t}$ against cash flows $X_t$ for three firms. They start with the same $\hat{\mu}_L = 0.05$ and $\hat{\nu}_L = 0.1$ at $X_0 = 1$ in the low-risk state. When their conditions deteriorate, these firms have different expected $\hat{\mu}_H = 0.02, 0.03, 0.04$, respectively. Given the $\hat{\mu}_H$'s, they choose different optimal values of $\epsilon^*$, $X_r$ and $X_d$. We calculate $\gamma_{s,t}$ according to equation (A16) for $X_t < X_r$ and equation (A24) for $X_t \geq X_r$ for each firm.

Table 1: **Parameter Values**

This table presents the parameter values for the model. The economy-wide and firm-specific parameters of the model are obtained from the extant literature, except for the cost of excess volatility $\eta$.

| Parameters | Symbols | Values |
|---|---|---|
| Risk-free rate | $r$ | 0.06 |
| Effective tax rate | $\tau$ | 0.15 |
| Market return volatility | $\sigma_M$ | 0.2 |
| Market price of risk | $\theta$ | 0.5 |
| Initial output | $X_0$ | 1 |
| Initial asset value | $V_{L,0}$ | $X_0/(r_f - \mu_L)$ |
| Coupon | c | 0.3 |
| Physical growth rate | $\hat{\mu}_L$ | 0.05 |
| Physical growth rate | $\hat{\mu}_H$ | 0.02, 0.03, 0.04 |
| Idio. Vol. (Low-risk state) | $\nu_L$ | 0.1 |
| Total Vol. (Low-risk state) | $\sigma_L$ | 0.2059 |
| Correlation coefficient | $\rho_L$ | 0.8742 |
| Cost of excess volatility | $\eta$ | 0.20 |

Table 2: **Summary Statistics of Empirical Measures**

This table reports the number of observations, means, standard deviations (STD), and the first autocorrelation coefficients (AR(1)) for quarterly variables in Panel A and monthly variables in Panel B. The quarterly variables include return on assets ($RoA_{i,t}$), research and development ($R\&D_{i,t}$), idiosyncratic volatility of 12-quarter RoA ($\nu_{i,t}^{RoA}$), idiosyncratic stock return volatility ($\nu_{i,t}^{E}$), the natural logarithm of sales ($log(sales)_{i,t}$), market-to-book assets ($MABA_{i,t}$), market leverage ($MktLev_{i,t}$) and the natural logarithm of delta and vega of managerial stock options. The monthly variables include the stock return ($r_{i,t}^{E}$), monthly idiosyncratic stock return volatility ($\nu_{i,t}^{E}$), the logarithmic value of market capitalization ($Size_{i,t}$), book-to-market equity ($BE/ME_{i,t}$), cumulative six-month stock returns ($PreRets_{i,t}$) and market leverage ($MktLev_{i,t}$) as well as the factor loadings on the market factor ($\beta_{i,t}^{mkt}$), size factor ($\beta_{i,t}^{SMB}$) and value factor ($\beta_{i,t}^{HML}$). All the variables are expressed in annual percent.

| Panel A. Quarterly Data | | | | |
|---|---|---|---|---|
| | Obs./Qtr | Mean | STD | AR(1) |
| $RoA_{i,t}$ | 3395 | 3.86 | 16.02 | 0.68 |
| $\nu_{i,t}^{RoA}$ | 2913 | 12.52 | 6.03 | 0.97 |
| $R\&D_{i,t}$ | 3582 | 4.23 | 2.54 | 0.94 |
| $\nu_{i,t}^{E}$ | 3582 | 56.79 | 29.90 | 0.69 |
| $log(sales)_{i,t}$ | 3435 | 3.44 | 0.59 | 0.99 |
| $MABA_{i,t}$ | 3345 | 1.96 | 0.91 | 0.92 |
| $MktLev_{i,t}$ | 3469 | 0.23 | 0.11 | 0.96 |
| $log(1+Delta)_{i,t}$ | 3582 | 0.77 | 0.39 | 0.96 |
| $log(1+Vega)_{i,t}$ | 3582 | 0.55 | 0.27 | 0.97 |

| Panel B. Monthly Data | | | | |
|---|---|---|---|---|
| | Obs./Month | Mean | STD | AR(1) |
| $r_{i,t}^{E}$ | 3525 | 15.72 | 70.92 | −0.04 |
| $\nu_{i,t}^{E}$ | 3525 | 51.87 | 36.71 | 0.58 |
| $Size_{i,t}$ | 3525 | 4.71 | 0.65 | 1.00 |
| $BE/ME_{i,t}$ | 3437 | 0.78 | 0.40 | 0.96 |
| $PreRets_{i,t}$ | 3457 | 15.66 | 89.49 | 0.80 |
| $MktLev_{i,t}$ | 3496 | 0.24 | 0.10 | 0.99 |
| $\beta_{i,t}^{mkt}$ | 3525 | 0.90 | 2.38 | 0.10 |
| $\beta_{i,t}^{SMB}$ | 3525 | 0.77 | 3.22 | 0.06 |
| $\beta_{i,t}^{HML}$ | 3525 | 0.15 | 3.98 | 0.03 |

Table 3: **Negative Impacts of Return on Assets (RoA) on Subsequent risk-taking**
This table reports the results from Fama-MacBeth regressions at the firm level. We regress subsequent risk measures on a constant, the lagged quarterly return on assets (RoA), and lagged firm characteristics, quarter-by-quarter, as follows:
$y_{i,t} = a_t + b_t RoA_{i,t-1} + d_t control_{i,t-1} + e_{i,t}$,
where the dependent variable, $y_{i,t}$, is the quarterly idiosyncratic volatility of RoAs $\nu^{RoA}_{i,t}$ in Panel A, quarterly research and development expenditure $R\&D_{i,t}$ in Panel B, and monthly three-month idiosyncratic stock return volatility $\nu^{E}_{i,t}$ in Panel C. We include industry averages, $R\&D^{Ind}_{i,t-1}$, to control for industry effects. The past firm characteristics include the natural logarithm of sales $log(sales)_{i,t-1}$, market-to-book assets $MABA_{i,t-1}$, and market leverage $MktLev_{i,t-1}$ as well as the natural logarithm of the delta and vega of managerial stock options. If the delta and vega from ExecuComp are missing, they are replaced with zero and the indicator $I_{missingExec}$ is set to one. We also include $RoA_{i,t-2}$ and the lagged dependent variable $y_{i,t-1}$. The t-statistics in parentheses are adjusted using the Newey-West method with four lags. Adj. $R^2$ is the time-series average of the adjusted $R^2$'s.

| | Panel A. $y_{i,t} = \nu^{RoA}_{i,t}$ | | | Panel B. $y_{i,t} = R\&D_{i,t}$ | | | Panel C. $y_{i,t} = \nu^{E}_{i,t}$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | Reg I | Reg II | Reg III | Reg I | Reg II | Reg III | Reg I | Reg II | Reg III |
| Intercept | 12.78 | 15.04 | 10.65 | 6.28 | 6.06 | 1.85 | 55.35 | 68.09 | 28.31 |
| (t) | (20.25) | (19.64) | (16.15) | (37.36) | (17.94) | (8.47) | (27.71) | (26.30) | (19.83) |
| $RoA_{i,t-1}$ | −0.27 | −0.11 | −0.09 | −0.19 | −0.08 | −0.03 | −0.53 | −0.12 | −0.08 |
| (t) | (−17.74) | (−22.10) | (−24.10) | (−17.96) | (−14.36) | (−13.50) | (−31.06) | (−11.55) | (−15.71) |
| $R\&D^{Ind}_{i,t-1}$ | | 0.08 | 0.03 | | 0.02 | −0.04 | | 0.32 | 0.18 |
| (t) | | (0.84) | (0.40) | | (0.26) | (−0.94) | | (1.29) | (1.52) |
| $log(sales)_{i,t-1}$ | | −1.61 | −1.15 | | −0.56 | −0.21 | | −7.26 | −2.96 |
| (t) | | (−19.99) | (−15.54) | | (−10.94) | (−7.65) | | (−17.00) | (−18.69) |
| $MABA_{i,t-1}$ | | 1.39 | 0.89 | | 1.77 | 0.58 | | −0.27 | −0.25 |
| (t) | | (19.34) | (15.07) | | (19.84) | (12.79) | | (−0.57) | (−1.26) |
| $MktLev_{i,t-1}$ | | 1.23 | 1.08 | | −7.28 | −1.97 | | 28.47 | 13.33 |
| (t) | | (2.82) | (2.95) | | (−22.87) | (−11.36) | | (16.79) | (15.05) |
| $log(1+Delta)_{i,t-1}$ | | −0.14 | −0.10 | | −0.30 | −0.14 | | 0.88 | 0.43 |
| (t) | | (−3.52) | (−2.82) | | (−5.68) | (−3.98) | | (4.38) | (4.52) |
| $log(1+Vega)_{i,t-1}$ | | 0.33 | 0.26 | | 0.60 | 0.21 | | 0.04 | −0.05 |
| (t) | | (4.77) | (4.52) | | (8.29) | (5.77) | | (0.24) | (−0.83) |
| $\mathbf{1}_{MissingExec}$ | | 0.61 | 0.53 | | 0.17 | −0.18 | | 5.94 | 2.64 |
| (t) | | (2.78) | (2.91) | | (0.76) | (−1.51) | | (4.34) | (4.46) |
| $RoA_{i,t-2}$ | | −0.11 | −0.07 | | −0.09 | −0.02 | | −0.19 | −0.08 |
| (t) | | (−19.56) | (−15.29) | | (−15.50) | (−9.07) | | (−15.43) | (−13.62) |
| $y_{i,t-1}$ | | | 0.36 | | | 0.73 | | | 0.58 |
| (t) | | | (17.36) | | | (35.35) | | | (33.26) |
| $Adj.R^2$ | 0.14 | 0.25 | 0.33 | 0.18 | 0.37 | 0.73 | 0.09 | 0.31 | 0.53 |
| Total N. of Obs. | 501320 | | | 362924 | | | 1503668 | | |

Table 4: **Idiosyncratic Risk Shifting under Different Circumstances**

This table reports the idiosyncratic risk-shifting results from month-by-month Fama-MacBeth regressions at the firm level. We regress three-month idiosyncratic stock return volatility $\nu_{i,t}^{E}$ on a constant, the lagged quarterly return on assets (RoA), and lagged firm characteristics, as follows:
$y_{i,t} = a_t + b_t RoA_{i,t-1} + c_t RoA_{i,t-1} I(.) + d_t control_{i,t-1} + e_{i,t}$
where $I(.)$ is an indicator that identifies a situation in which a firm is more likely to shift risk. The indicator takes a value of one if the $RoA$ of the last quarter is negative ($RoA < 0$), $o$-score of the last quarter is classified into the top tercile ($OS = 3$), the firm has positive debt ($Debt > 0$), and the fraction of long-term debt in the total debt is more than 2/3 ($DM > 2/3$). We include industry averages, $R\&D_{i,t-1}^{Ind}$, to control for industry effects. The past firm characteristics include the natural logarithm of sales $log(sales)_{i,t-1}$, market-to-book assets $MABA_{i,t-1}$, and market leverage $MktLev_{i,t-1}$ as well as the natural logarithm of the delta and vega of managerial stock options. If the delta and vega from ExecuComp are missing, they are replaced with zero and the indicator $I_{missingExec}$ is set to one. We also include $RoA_{i,t-2}$ and the lagged dependent variable $y_{i,t-1}$. The t-statistics in parentheses are adjusted using the Newey-West method with 12 lags. Adj. $R^2$ is the time-series average of the adjusted $R^2$'s.

| | Reg I: $RoA < 0$ | Reg II: $OS = 3$ | Reg III: $Debt > 0$ | Reg IV: $DM > 2/3$ |
|---|---|---|---|---|
| Intercept | 27.83 | 28.27 | 28.37 | 28.33 |
| (t) | (27.27) | (28.75) | (28.84) | (28.73) |
| $RoA_{i,t-1}$ | −0.02 | −0.07 | −0.05 | −0.07 |
| (t) | (−2.28) | (−14.79) | (−6.99) | (−13.25) |
| $RoA_{i,t-1} * I(.)$ | −0.19 | −0.04 | −0.04 | −0.03 |
| (t) | (−6.79) | (−6.71) | (−5.55) | (−6.39) |
| $R\&D_{i,t-1}^{Ind}$ | 0.29 | 0.19 | 0.17 | 0.18 |
| (t) | (1.56) | (1.69) | (1.67) | (1.65) |
| $log(sales)_{i,t-1}$ | −2.97 | −2.96 | −2.96 | −2.95 |
| (t) | (−27.65) | (−27.76) | (−27.87) | (−27.81) |
| $MABA_{i,t-1}$ | −0.45 | −0.23 | −0.26 | −0.25 |
| (t) | (−3.42) | (−1.77) | (−1.94) | (−1.93) |
| $MktLev_{i,t-1}$ | 13.39 | 13.35 | 13.40 | 13.42 |
| (t) | (22.62) | (22.65) | (22.71) | (22.62) |
| $log(1 + Delta)_{i,t-1}$ | 0.41 | 0.43 | 0.43 | 0.43 |
| (t) | (6.95) | (7.28) | (7.25) | (7.25) |
| $log(1 + Vega)_{i,t-1}$ | −0.05 | −0.04 | −0.04 | −0.05 |
| (t) | (−1.14) | (−0.98) | (−1.02) | (−1.20) |
| $\mathbf{1}_{MissingExec}$ | 2.58 | 2.67 | 2.65 | 2.65 |
| (t) | (7.09) | (7.28) | (7.32) | (7.30) |
| $RoA_{i,t-2}$ | −0.08 | −0.09 | −0.08 | −0.08 |
| (t) | (−17.32) | (−18.01) | (−17.78) | (−17.55) |
| $y_{i,t-1}$ | 0.58 | 0.58 | 0.58 | 0.58 |
| (t) | (47.91) | (48.26) | (48.24) | (48.26) |
| $Adj.R^2$ | 0.53 | 0.53 | 0.53 | 0.53 |

Table 5: **Stock-Asset Sensitivity**

This table estimates the stock-asset sensitivity from month-by-month Fama-MacBeth regressions at the firm level. In baseline regressions, we regress monthly stock returns on a constant, the lagged return on assets (RoA), the interaction between RoA and three-month idiosyncratic volatility $\nu^E_{i,t-1}$, and lagged firm characteristics, as follows:
$r^E_{i,t} = a_t + b1_t RoA_{i,t-1} + c1_t RoA_{i,t-1} * \nu_{i,t-1} + b2_t RoA_{i,t-1} * I(.) + c2_t RoA_{i,t-1} * \nu_{i,t-1} * I(.) + d_t control_{i,t-1} + e_{i,t}$,
where $I(.)$ is an indicator that identifies a situation in which risk shifting is more likely to occur and reduce the stock-asset sensitivity. This indicator takes a value of one if the $RoA$ of the last quarter is negative ($RoA < 0$), $o$-score of the last quarter is classified into the top tercile ($OS = 3$), the firm has positive debt ($Debt > 0$), and the fraction of long-term debt in the total debt is more than 2/3 ($DM > 2/3$). The past firm characteristics include market capitalization ($size_{i,t-1}$), book-to-market equity ($BE/ME_{i,t-1}$), market leverage ($MktLev_{i,t-1}$) and six-month cumulative stock returns ($PreRets_{i,t-1}$). The t-statistics in parentheses are adjusted using the Newey-West method with 12 lags. Adj. $R^2$ is the time-series average of the adjusted $R^2$'s.

| | Reg I: Baseline | Reg II: $RoA < 0$ | Reg III: $OS = 3$ | Reg IV: $Debt > 0$ | Reg V: $DM > 2/3$ |
|---|---|---|---|---|---|
| Intercept | 17.33 | 2.05 | 17.13 | 17.60 | 17.85 |
| (t) | (3.18) | (0.40) | (3.14) | (3.23) | (3.28) |
| $RoA_{i,t-1}$ | 0.93 | 1.54 | 0.91 | 0.58 | 0.74 |
| (t) | (8.95) | (10.68) | (8.92) | (6.91) | (8.38) |
| $RoA_{i,t-1} * \nu_{i,t-1}/100$ | −0.28 | 0.18 | −0.21 | −0.01 | −0.04 |
| (t) | (−3.26) | (0.91) | (−2.12) | (−0.08) | (−0.32) |
| $RoA_{i,t-1} * I(.)$ | | −0.60 | 0.07 | 0.41 | 0.35 |
| (t) | | (−1.26) | (1.17) | (5.58) | (4.91) |
| $RoA_{i,t-1} * \nu_{i,t-1} * I(.)/100$ | | −0.69 | −0.26 | −0.28 | −0.45 |
| (t) | | (−1.68) | (−1.67) | (−1.78) | (−3.66) |
| $size_{i,t-1}$ | −3.15 | −2.71 | −3.12 | −3.22 | −3.28 |
| (t) | (−6.38) | (−5.94) | (−6.33) | (−6.52) | (−6.74) |
| $BE/ME_{i,t-1}$ | 14.25 | 17.12 | 14.33 | 14.24 | 14.23 |
| (t) | (9.75) | (11.00) | (9.79) | (9.74) | (9.76) |
| $MktLev_{i,t-1}$ | −17.82 | −15.45 | −17.79 | −18.49 | −18.65 |
| (t) | (−4.49) | (−4.00) | (−4.49) | (−4.73) | (−4.77) |
| $PreRets_{i,t-1}$ | 0.01 | 0.00 | 0.01 | 0.01 | 0.01 |
| (t) | (0.49) | (−0.05) | (0.47) | (0.43) | (0.44) |
| $Adj.R^2$ | 0.04 | 0.04 | 0.04 | 0.04 | 0.04 |

Table 6: **Decomposing the Impact of Idiosyncratic Volatility on Stock Returns**

This table reports the decomposition of the impact of idiosyncratic volatility on stock returns from the month-by-month Fama-MacBeth regressions at the firm level. In the baseline regression, we regress the monthly raw stock return in annual percent ($r^E_{i,t}$) on a constant, the lagged return on assets ($RoA_{i,t-1}$), the lagged idiosyncratic volatility ($\nu^E_{i,t-1}$), and other past firm characteristics. The lagged idiosyncratic volatility is computed using previous one-month and three-month daily returns, respectively. The past firm characteristics include market capitalization ($size_{i,t-1}$), book-to-market equity ($BE/ME_{i,t-1}$), market leverage ($MktLev_{i,t-1}$) and six-month cumulative stock returns ($PreRets_{i,t-1}$) as well as the factor loadings on the market factor ($\beta^{mkt}_{i,t}$), size factor ($\beta^{SMB}_{i,t}$) and value factor ($\beta^{HML}_{i,t}$). To decompose $\nu^E_{i,t-1}$ into a predicted component $\nu^{Pred}_{i,t-1}$ and a residual component $\nu^{Rsd}_{i,t-1}$, we run the following cross-sectional regression, month by month: $\nu^E_{i,t-1} = a_{t-1} + b_{t-1}RoA_{i,t-1} + c_{t-1}RoA_{i,t-1}I(.) + u_{i,t-1}$
where the indicator $I(.)$ takes a value of one if the $RoA$ of the last quarter is negative ($RoA < 0$), $o$-score of the last quarter is classified into the top tercile ($OS = 3$), the firm has positive debt ($Debt > 0$), and the fraction of long-term debt in the total debt is more than 2/3 ($DM > 2/3$). The predicted component is calculated as $\nu^{Pred}_{i,t-1} = \hat{b}_{t-1}RoA_{i,t-1} + \hat{c}_{t-1}RoA_{i,t-1}I(.)$ for the three situations in which risk shifting is more likely to occur, and the residual component as $\nu^{Rsd}_{i,t-1} = \nu^E_{i,t-1} - \nu^{Pred}_{i,t-1}$. The t-statistics in parentheses are adjusted using the Newey-West method with 12 lags. Adj. $R^2$ is the time-series average of the adjusted $R^2$'s.

| | Panel A. One-month $\nu^E_{i,t-1}$ | | | | | Panel B. Three-month $\nu^E_{i,t-1}$ | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Baseline | $RoA < 0$ | $OS = 3$ | $Debt > 0$ | $DM > 2/3$ | Baseline | $RoA < 0$ | $OS = 3$ | $Debt > 0$ | $DM > 2/3$ |
| Intercept | 18.34 | 18.35 | 18.25 | 17.00 | 17.38 | 20.48 | 18.20 | 18.11 | 16.80 | 17.14 |
| (t) | (3.38) | (3.63) | (3.76) | (3.52) | (3.61) | (3.98) | (3.77) | (3.90) | (3.63) | (3.72) |
| $\nu^E_{i,t-1}$ | −0.11 | | | | | −0.13 | | | | |
| (t) | (−3.96) | | | | | (−4.01) | | | | |
| $\nu^{Pred}_{i,t-1}$ | | −1.36 | −1.41 | −1.56 | −1.54 | | −1.21 | −1.27 | −1.40 | −1.38 |
| (t) | | (−11.83) | (−10.33) | (−8.38) | (−8.34) | | (−11.49) | (−10.06) | (−8.41) | (−8.31) |
| $\nu^{Rsd}_{i,t-1}$ | | −0.05 | −0.06 | −0.05 | −0.05 | | −0.05 | −0.06 | −0.05 | −0.05 |
| (t) | | (−2.10) | (−2.24) | (−2.16) | (−2.16) | | (−1.80) | (−1.97) | (−1.85) | (−1.84) |
| $size_{i,t-1}$ | −2.44 | −3.72 | −3.72 | −3.67 | −3.75 | −2.63 | −3.66 | −3.69 | −3.63 | −3.71 |
| (t) | (−3.99) | (−6.80) | (−6.72) | (−6.71) | (−6.82) | (−4.59) | (−7.01) | (−6.95) | (−6.95) | (−7.06) |
| $BE/ME_{i,t-1}$ | 14.76 | 13.70 | 13.75 | 13.90 | 14.01 | 14.67 | 13.69 | 13.77 | 13.91 | 14.03 |
| (t) | (9.52) | (9.21) | (9.58) | (9.80) | (9.82) | (9.59) | (9.31) | (9.70) | (9.91) | (9.94) |
| $MktLev_{i,t-1}$ | −15.44 | −18.65 | −18.53 | −18.35 | −19.38 | −15.50 | −18.85 | −18.73 | −18.56 | −19.61 |
| (t) | (−4.12) | (−5.01) | (−4.98) | (−4.92) | (−5.26) | (−4.16) | (−5.09) | (−5.05) | (−4.99) | (−5.34) |
| $\beta^{mkt}_{i,t}$ | 6.02 | 6.12 | 6.13 | 6.10 | 6.10 | 6.08 | 6.13 | 6.14 | 6.11 | 6.11 |
| (t) | (5.35) | (5.60) | (5.58) | (5.58) | (5.59) | (5.51) | (5.70) | (5.68) | (5.68) | (5.69) |
| $\beta^{SMB}_{i,t}$ | 0.79 | 0.82 | 0.82 | 0.82 | 0.83 | 0.79 | 0.82 | 0.82 | 0.82 | 0.83 |
| (t) | (1.83) | (1.87) | (1.89) | (1.89) | (1.90) | (1.83) | (1.87) | (1.89) | (1.90) | (1.91) |
| $\beta^{HML}_{i,t}$ | −0.96 | −1.00 | −0.99 | −0.98 | −0.98 | −1.00 | −1.02 | −1.01 | −1.00 | −1.00 |
| (t) | (−1.78) | (−1.86) | (−1.85) | (−1.84) | (−1.83) | (−1.89) | (−1.92) | (−1.91) | (−1.90) | (−1.89) |
| $PreRets_{i,t-1}$ | 0.03 | 0.01 | 0.01 | 0.01 | 0.01 | 0.03 | 0.01 | 0.01 | 0.01 | 0.01 |
| (t) | (2.14) | (0.68) | (0.86) | (0.74) | (0.72) | (2.44) | (0.87) | (1.04) | (0.92) | (0.90) |
| $Adj.R^2$ | 11.61 | 12.84 | 12.78 | 12.71 | 12.71 | 11.72 | 12.87 | 12.83 | 12.76 | 12.76 |

Table 7: **Quantifying the Impact of the Strategic Component of Idiosyncratic Volatility on Stock Returns**

This table reports the impact of the strategic component of idiosyncratic volatility on stock returns. We follow Hou Loh (2015) and decompose a negative coefficient obtained from the Fama-MacBeth regression of stock returns on past idiosyncratic volatility $\nu^E_{i,t-1}$. The past idiosyncratic volatility is computed using previous one-month and three-month daily returns, respectively. The procedure is as follows. First, for each month $t$, stock returns are regressed on lagged idiosyncratic volatility cross-sectionally, i.e., $r^E_{i,t} = \alpha_t + \kappa_t \nu^E_{i,t-1} + u_{i,t}$. Second, idiosyncratic volatility is regressed on a candidate variable, i.e., $\nu^E_{i,t-1} = a_{t-1} + \delta_{t-1} Candidate_{i,t-1} + u_{i,t-1}$. We obtain two orthogonal components, $\delta_{t-1} Candidate_{i,t-1}$ and $a_{t-1} + \varepsilon_{i,t-1}$. Then, $\kappa_t$ is decomposed into a strategic component, $\kappa^c_t$, that is related to the candidate variable, and a residual component, $\kappa^c_t$. Specifically, $\kappa_t = \frac{Cov\left(r^E_{i,t}, \nu^E_{i,t-1}\right)}{Var\left(\nu^E_{i,t-1}\right)} = \frac{Cov\left(r^E_{i,t}, \delta_{t-1} Candidate_{i,t-1}\right)}{Var\left(\nu^E_{i,t-1}\right)} + \frac{Cov\left(r^E_{i,t}, a_{t-1} + u_{i,t-1}\right)}{Var\left(\nu^E_{i,t-1}\right)} = \kappa^c_t + \kappa^r_t$. The time-series average $\kappa^c_t$ divided by $\kappa_t$ measures the fraction of the negative impact of idiosyncratic volatility on stock returns explained by the candidate variable. Our candidate variable is the combination of $RoA_{i,t-1}$ and $RoA_{i,t-1} I(.)$, where the indicator $I(.)$ takes a value of one if the $RoA$ of the last quarter is negative ($RoA < 0$), *o*-score of the last quarter is classified into the top tercile ($OS = 3$), the firm has positive debt ($Debt > 0$), and the fraction of long-term debt in the total debt is more than 2/3 ($DM > 2/3$). The t-statistics in parentheses are adjusted using the Newey-West method with 12 lags.

| Panel A. Regression of monthly stock returns $r^E_{i,t}$ on $\nu^E_{i,t-1}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | One-month $\nu^E_{i,t-1}$ | | | | Three-month $\nu^E_{i,t-1}$ | | | |
| | $RoA < 0$ | $OS = 3$ | $Debt > 0$ | $DM > 2/3$ | $RoA < 0$ | $OS = 3$ | $Debt > 0$ | $DM > 2/3$ |
| $\kappa_t$ | −0.15 | −0.15 | −0.15 | −0.17 | −0.14 | −0.14 | −0.14 | −0.16 |
| (t) | (−4.16) | (−4.25) | (−4.16) | (−4.59) | (−3.24) | (−3.40) | (−3.24) | (−3.65) |
| Panel B. Regression of $\nu^E_{i,t-1}$ on $RoA_{i,t-1}$ and $RoA_{i,t-1}I(.)$ | | | | | | | | |
| Intercept | 47.71 | 47.90 | 48.00 | 47.87 | 51.99 | 52.39 | 52.48 | 52.31 |
| (t) | (42.43) | (48.63) | (49.04) | (49.21) | (43.16) | (49.46) | (49.91) | (50.20) |
| $RoA_{i,t-1}$ | −0.45 | −0.43 | −0.41 | −0.41 | −0.47 | −0.47 | −0.44 | −0.44 |
| (t) | (−24.80) | (−41.76) | (−22.92) | (−37.50) | (−24.93) | (−45.11) | (−24.25) | (−41.86) |
| $RoA_{i,t-1} * I(.)$ | −0.33 | −0.09 | −0.06 | −0.10 | −0.38 | −0.09 | −0.06 | −0.12 |
| (t) | (−4.63) | (−9.66) | (−5.08) | (−12.29) | (−4.95) | (−8.62) | (−5.15) | (−13.94) |
| Panel C. Decomposition of the $\nu^E_{i,t-1}$ coefficient | | | | | | | | |
| $\kappa^c_t$ | −0.11 | −0.11 | −0.11 | −0.11 | −0.12 | −0.13 | −0.13 | −0.13 |
| (t) | (−11.96) | (−12.88) | (−12.21) | (−12.27) | (−11.34) | (−12.52) | (−11.87) | (−12.00) |
| $\kappa^c_t/\kappa_t(\%)$ | 71.92 | 71.45 | 72.17 | 66.06 | 88.56 | 87.56 | 89.96 | 80.51 |
| $\kappa^r_t$ | −0.04 | −0.04 | −0.04 | −0.06 | −0.02 | −0.02 | −0.01 | −0.03 |
| (t) | (−1.42) | (−1.45) | (−1.40) | (−1.88) | (−0.45) | (−0.51) | (−0.39) | (−0.86) |
| $\kappa^r_t/\kappa_t(\%)$ | 28.08 | 28.55 | 27.83 | 33.94 | 11.45 | 12.44 | 10.05 | 19.49 |

Table 8: **Alternative Explanations**

This table presents the results from month-by-month Fama-MacBeth regressions of the return on the predicted volatility $\nu_{i,t-1}^{Pred}$ and residual volatility $\nu_{i,t-1}^{Rsd}$ at the firm level, controlling for alternative explanations. The calculation of $\nu_{i,t-1}^{Pred}$ is the same as in Table 6 under three high-risk-shifting scenarios where the RoA of the last quarter is negative ($RoA < 0$), the firm has positive debt ($Debt > 0$), the fraction of long-term debt in the total debt is more than 2/3 ($DM > 2/3$), or *o*-score of the last quarter is classified into the top tercile ($Distr = 1$). $MABA_{i,t-1}$ is the ratio of market assets to book assets, $IndTurn_{i,t-1}$ is industry turnover, $Dispers_{i,t-1}$ is industry earnings dispersion, $SUE_{i,t-1}$ is standardized unexpected quarterly earnings, $Zeros_{i,t-1}$ is a measure of transaction costs using the proportion of daily returns that are equal to zero each month (Lesmond, Ogden, and Trzcinka, 1999), $Reversal_{i,t-1}$ is the lagged monthly return in annual percent proxying for the return reversal effect (Huang, Liu, Rhee and Zhang, 2010), $ESkew_{i,t-1}$ denotes the monthly expected stock return skewness obtained from Boyer et al. (2010), $Analysts_{i,t-1}$ is the number of analysts providing current-fiscal-year annual earnings estimates in the I/B/E/S database (Diether, Malloy andScherbina, 2002) and $I_{MissAnalyst}$ is the indicator for missing I/B/E/S records. The t-statistics in parentheses are adjusted using the Newey-West method with 12 lags.

| | Panel A. One-month $\nu_{i,t-1}^{E}$ | | | | Panel B. Three-month $\nu_{i,t-1}^{E}$ | | | |
|---|---|---|---|---|---|---|---|---|
| | $RoA < 0$ | $OS = 3$ | $Debt > 0$ | $DM > 2/3$ | $RoA < 0$ | $OS = 3$ | $Debt > 0$ | $DM > 2/3$ |
| Intercept | 19.97 | 19.98 | 19.80 | 18.81 | 3.52 | 9.79 | 3.16 | 1.95 |
| (t) | (2.22) | (2.46) | (2.24) | (2.33) | (0.24) | (0.99) | (0.22) | (0.12) |
| $\nu_{i,t-1}^{Pred}$ | −1.11 | −1.18 | −1.31 | −1.28 | −1.26 | −1.20 | −1.40 | −1.40 |
| (t) | (−8.88) | (−8.81) | (−7.25) | (−7.30) | (−5.60) | (−8.19) | (−6.38) | (−5.69) |
| $\nu_{i,t-1}^{Rsd}$ | 0.03 | 0.03 | 0.03 | 0.03 | 0.04 | 0.03 | 0.04 | 0.07 |
| (t) | (1.08) | (0.98) | (1.13) | (1.10) | (0.70) | (0.55) | (0.73) | (0.84) |
| $size_{i,t-1}$ | −4.20 | −4.17 | −4.16 | −4.19 | −3.05 | −3.50 | −3.02 | −2.83 |
| (t) | (−4.38) | (−4.59) | (−4.35) | (−4.57) | (−2.88) | (−4.28) | (−2.85) | (−2.22) |
| $BE/ME_{i,t-1}$ | 10.17 | 10.25 | 10.18 | 10.55 | 13.42 | 12.53 | 13.44 | 13.74 |
| (t) | (4.07) | (4.35) | (4.12) | (4.58) | (6.58) | (7.87) | (6.67) | (6.47) |
| $MktLev_{i,t-1}$ | −14.46 | −14.38 | −14.34 | −15.19 | −13.40 | −13.70 | −13.29 | −14.42 |
| (t) | (−3.77) | (−3.72) | (−3.73) | (−3.96) | (−3.24) | (−3.41) | (−3.21) | (−3.57) |
| $\beta_{i,t}^{mkt}$ | 5.60 | 5.56 | 5.59 | 5.57 | 5.29 | 5.44 | 5.28 | 5.23 |
| (t) | (5.20) | (5.14) | (5.19) | (5.17) | (4.62) | (4.93) | (4.61) | (4.49) |
| $\beta_{i,t}^{SMB}$ | 1.18 | 1.22 | 1.18 | 1.26 | 1.58 | 1.46 | 1.59 | 1.27 |
| (t) | (2.13) | (2.13) | (2.14) | (2.11) | (1.85) | (1.95) | (1.86) | (2.10) |
| $\beta_{i,t}^{HML}$ | −0.94 | −0.92 | −0.93 | −0.91 | −0.87 | −0.90 | −0.86 | −0.91 |
| (t) | (−1.75) | (−1.71) | (−1.73) | (−1.70) | (−1.55) | (−1.64) | (−1.54) | (−1.68) |
| $PreRets_{i,t-1}$ | 0.01 | 0.01 | 0.01 | 0.01 | 0.03 | 0.03 | 0.03 | 0.03 |
| (t) | (0.47) | (0.88) | (0.58) | (0.80) | (1.20) | (1.35) | (1.23) | (1.24) |
| $MABA_{i,t-1}$ | −2.86 | −3.33 | −3.50 | −3.03 | −2.86 | −3.23 | −3.51 | −4.69 |
| (t) | (−1.76) | (−1.97) | (−2.04) | (−2.04) | (−1.70) | (−1.95) | (−1.98) | (−1.55) |
| $IndTurn_{i,t-1}$ | −2800.57 | −2662.87 | −2801.00 | −2916.19 | −3419.05 | −3516.17 | −3418.39 | −2857.96 |
| (t) | (−0.98) | (−0.98) | (−0.98) | (−0.99) | (−0.99) | (−0.99) | (−0.99) | (−0.99) |
| $Dispers_{i,t-1}$ | −10.09 | 5.34 | −9.64 | 1.98 | 158.42 | 104.35 | 158.73 | 162.93 |
| (t) | (−0.67) | (0.31) | (−0.64) | (0.13) | (0.97) | (0.95) | (0.97) | (0.97) |
| $SUE_{i,t-1}$ | 7.62 | 8.04 | 7.73 | 8.83 | 11.74 | 11.25 | 11.81 | 5.77 |
| (t) | (2.87) | (2.98) | (2.89) | (2.61) | (1.95) | (2.12) | (1.96) | (2.80) |
| $Zeros_{i,t-1}$ | 0.09 | 0.09 | 0.09 | 0.09 | 0.06 | 0.06 | 0.06 | 0.04 |
| (t) | (1.89) | (1.87) | (1.93) | (1.95) | (1.32) | (1.34) | (1.37) | (0.80) |
| $Reversal_{i,t-1}$ | −67.48 | −66.50 | −67.46 | −67.06 | −62.98 | −63.09 | −62.96 | −62.12 |
| (t) | (−11.07) | (−11.34) | (−11.16) | (−11.24) | (−10.80) | (−11.47) | (−10.80) | (−10.26) |
| $ESkew_{i,t-1}$ | 1.92 | 1.78 | 1.87 | 1.86 | 1.91 | 1.82 | 1.91 | 1.89 |
| (t) | (1.92) | (1.81) | (1.89) | (1.87) | (1.88) | (1.82) | (1.88) | (1.86) |
| $Analysts_{i,t-1}$ | 0.80 | 0.81 | 0.79 | 0.76 | 0.84 | 0.86 | 0.83 | 0.81 |
| (t) | (0.70) | (0.72) | (0.70) | (0.68) | (0.74) | (0.76) | (0.74) | (0.72) |
| $\mathbf{1}_{MissAnalyst}$ | −0.60 | −0.66 | −0.63 | −0.64 | −0.62 | −0.67 | −0.64 | −0.65 |
| (t) | −0.37 | −0.41 | −0.39 | −0.39 | −0.39 | −0.42 | −0.40 | −0.40 |
| $Adj.R^2$ | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 |

Table 9: **Comparing the Impact of the Strategic Component of Idiosyncratic Volatility on Stock Returns with Alternative Explanations**

This table reports the comparison between the impact of the strategic component of idiosyncratic volatility on stock returns and the impacts of other explanatory variables. We follow Hou Loh (2015) and decompose a negative coefficient obtained from the Fama-MacBeth regression of stock returns on past idiosyncratic volatility $\nu^E_{i,t-1}$. The past idiosyncratic volatility is computed using previous one-month and three-months of daily returns, respectively. The negative coefficient is decomposed into components that are related to candidate variables and a residual component. The procedure is as follows. First, each month $t$, stock returns are regressed on lagged idiosyncratic volatility cross-sectionally, i.e., $r^E_{i,t} = \alpha_t + \kappa_t \nu^E_{i,t-1} + u_{i,t}$. Second, idiosyncratic volatility is regressed on $n$ candidate variables indexed by $j$, i.e., $\nu^E_{i,t-1} = a_{t-1} + \sum_1^n \delta^j_{t-1} Candidate^j_{i,t-1} + u_{i,t-1}$. We obtain orthogonal components, such as $\delta^j_{t-1} Candidate^j_{i,t-1}$ and $a_{t-1} + \varepsilon_{i,t-1}$. Then, we decompose $\kappa_t$. Specifically, $\kappa_{i,t} = \frac{Cov\left(r^E_{i,t}, \nu^E_{i,t-1}\right)}{Var\left(\nu^E_{i,t-1}\right)} = \sum_1^n \frac{Cov\left(r^E_{i,t}, \delta^j_{t-1} Candidate^j_{i,t-1}\right)}{Var\left(\nu^E_{,t-1}\right)} + \frac{Cov\left(r^E_{i,t}, a_{i,t-1} + \varepsilon_{i,t-1}\right)}{Var\left(\nu^E_{i,t-1}\right)} = \sum_1^n \kappa^j_t + \kappa^r_{i,t}$. The time-series average $\kappa^j_t$ divided by $\kappa_t$ measures the fraction of the negative impact of idiosyncratic volatility on stock returns, the fraction explained by the candidate variable $j$. Our candidate variable is the combination of $RoA_{i,t-1}$ and $RoA_{i,t-1}I(.)$, where the indicator $I(.)$ takes a value of one if the $RoA$ of the last quarter is negative ($RoA < 0$), $o$-score of the last quarter is classified into the top tercile ($OS = 3$), the firm has positive debt ($Debt > 0$), and the fraction of long-term debt in the total debt is more than 2/3 ($DM > 2/3$). Alternative explanatory variables include $MABA_{i,t-1}$, $IndTurn_{i,t-1}$, $Dispers_{i,t-1}$, $SUE_{i,t-1}$, $Zeros_{i,t-1}$, $Reversal_{i,t-1}$, $ESkew_{i,t-1}$, and $Analysts_{i,t-1}$. The t-statistics in parentheses are adjusted using the Newey-West method with 12 lags.

| Panel A. Regression of monthly stock returns $r^E_{i,t}$ on $\nu^E_{i,t-1}$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | One-month $\nu^E_{i,t-1}$ | | | | Three-month $\nu^E_{i,t-1}$ | | | |
| | $RoA < 0$ | $OS = 3$ | $Debt > 0$ | $DM > 2/3$ | $RoA < 0$ | $OS = 3$ | $Debt > 0$ | $DM > 2/3$ |
| $\kappa_t$ | −0.12 | −0.12 | −0.12 | −0.14 | −0.13 | −0.13 | −0.13 | −0.14 |
| (t) | (−2.98) | (−2.89) | (−2.98) | (−3.25) | (−2.96) | (−2.87) | (−2.96) | (−3.23) |

Table 9: **Comparing the Impact of the Strategic Component of Idiosyncratic Volatility on Stock Returns with Alternative Explanations (con't)**

| Panel B. Decomposition of $\kappa_t$ into $\kappa_t^j$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | One-month $\nu^E_{i,t-1}$ | | | | Three-month $\nu^E_{i,t-1}$ | | | |
| | $RoA < 0$ | $OS = 3$ | $Debt > 0$ | $DM > 2/3$ | $RoA < 0$ | $OS = 3$ | $Debt > 0$ | $DM > 2/3$ |
| $RoA_{i,t-1} + RoA_{i,t-1} * I(.)$ | −0.06 | −0.06 | −0.06 | −0.07 | −0.07 | −0.08 | −0.08 | −0.08 |
| (t) | (−3.23) | (−3.31) | (−3.33) | (−7.04) | (−7.23) | (−7.34) | (−7.58) | (−10.01) |
| $MABA_{i,t-1}$ | −0.00 | −0.00 | −0.00 | −0.01 | −0.01 | −0.01 | −0.01 | −0.01 |
| (t) | (−0.85) | (−0.84) | (−1.05) | (−1.79) | (−1.40) | (−1.50) | (−1.59) | (−1.72) |
| $IndTurn_{i,t-1}$ | −0.00 | −0.00 | −0.00 | −0.00 | −0.00 | −0.00 | −0.00 | −0.00 |
| (t) | (−1.17) | (−1.61) | (−1.18) | (−0.91) | (−0.37) | (−0.46) | (−0.35) | (−0.15) |
| $Dispers_{i,t-1}$ | −0.00 | −0.00 | −0.00 | −0.00 | −0.00 | −0.00 | −0.00 | −0.00 |
| (t) | (−1.70) | (−1.86) | (−1.66) | (−1.40) | (−2.14) | (−2.40) | (−2.08) | (−1.91) |
| $SUE_{i,t-1}$ | −0.01 | −0.01 | −0.01 | −0.01 | −0.01 | −0.01 | −0.00 | −0.00 |
| (t) | (−3.27) | (−2.96) | (−3.01) | (−3.12) | (−2.44) | (−2.03) | (−2.06) | (−2.14) |
| $Zeros_{i,t-1}$ | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.00 |
| (t) | (1.50) | (1.54) | (1.50) | (1.50) | (1.04) | (1.13) | (1.04) | (0.89) |
| $Reversal_{i,t-1}$ | −0.03 | −0.03 | −0.03 | −0.01 | −0.02 | −0.02 | −0.02 | −0.01 |
| (t) | (−3.26) | (−3.20) | (−3.27) | (−0.45) | (−4.24) | (−4.26) | (−4.25) | (−1.34) |
| $ESkew_{i,t-1}$ | −0.00 | −0.00 | −0.00 | −0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| (t) | (−0.19) | (−0.18) | (−0.19) | (−0.50) | (0.88) | (0.91) | (0.88) | (0.46) |
| $Analysts_{i,t-1}$ | −0.00 | −0.00 | −0.00 | −0.00 | −0.00 | −0.00 | −0.00 | −0.00 |
| (t) | (−1.67) | (−1.63) | (−1.66) | (−1.94) | (−1.69) | (−1.64) | (−1.67) | (−1.91) |
| Residuals $\varepsilon_{i,t-1}$ | −0.03 | −0.03 | −0.03 | −0.04 | −0.03 | −0.03 | −0.03 | −0.04 |
| (t) | (−1.36) | (−1.16) | (−1.23) | (−1.65) | (−1.27) | (−1.02) | (−1.09) | (−1.52) |
| Panel C. Contribution of Each Alternative Variables, $\kappa_t^j/\kappa_t^c$ (%) | | | | | | | | |
| $RoA_{i,t-1} + RoA_{i,t-1} * I(.)$ | 45.39 | 48.24 | 47.50 | 51.98 | 55.64 | 59.78 | 59.20 | 57.87 |
| $MABA_{i,t-1}$ | 2.84 | 3.34 | 3.62 | 4.41 | 5.23 | 6.34 | 6.25 | 5.68 |
| $IndTurn_{i,t-1}$ | 0.54 | 0.71 | 0.54 | 0.35 | 0.23 | 0.28 | 0.21 | 0.08 |
| $Dispers_{i,t-1}$ | 1.38 | 1.40 | 1.35 | 1.09 | 1.78 | 2.03 | 1.75 | 1.57 |
| $SUE_{i,t-1}$ | 5.47 | 5.22 | 4.99 | 4.62 | 4.48 | 3.96 | 3.78 | 3.45 |
| $Zeros_{i,t-1}$ | −8.11 | −8.42 | −8.09 | −7.32 | −4.03 | −4.63 | −4.05 | −3.24 |
| $Reversal_{i,t-1}$ | 22.69 | 23.21 | 22.71 | 7.53 | 16.47 | 16.97 | 16.45 | 8.05 |
| $ESkew_{i,t-1}$ | 2.53 | 2.34 | 2.53 | 7.01 | −7.64 | −8.04 | −7.68 | −3.77 |
| $Analysts_{i,t-1}$ | 2.93 | 2.96 | 2.91 | 3.31 | 3.14 | 3.14 | 3.09 | 3.44 |
| Residuals $\varepsilon_{i,t-1}$ | 24.33 | 20.99 | 21.94 | 27.03 | 24.70 | 20.18 | 21.01 | 26.87 |

# Appendix

# A Model, Valuations and Stock Returns

We start with presenting a general asset valuation framework, and then provide the closed-form solutions for equity values and returns for firms after risk-shifting and for those prior to risk-shifting.

## A.1 Asset Valuation Framework

The model is partial equilibrium with a pricing kernel, $m_t$, as follows:[7]

$$\frac{dm_t}{m_t} = -rdt - \theta dZ_t, \tag{A1}$$

where $r$ is the constant risk-free rate, and $Z_t$ is a standard Brownian motion.

Under the risk-neutral measure, the Bellman equation describes the valuation of any claim $G(s, X_t)$ on operating cash flows $X_t$ in state, $s$, as follows:

$$G(s, X_t) = H_t dt + e^{-rdt}\mathbb{E}^Q(G(s, X_t + dX_t)), \tag{A2}$$

where $H_t$ denotes the cash flows accruing to claim holders. Standard dynamic programming suggests that $G(s, X_t)$ must satisfy the ordinary differential equation

$$\mu_s X G'_{s,t} + \frac{\sigma_s^2}{2} X^2 G''_{s,t} - rG_{s,t} + H_{s,t} = 0, \tag{A3}$$

where $G_{s,t} \equiv G(s, X_t)$, $G'_{s,t}$ and $G''_{s,t}$ denote the first and second-order derivatives of $G_{s,t}$ with respect to $X_t$, respectively.

Because the cash flows generated by the assets is $H_t = X_t$, the value of assets-in-place, $V_{s,t}$, under the risk-neutral measure $Q$, is

$$V_{s,t} \equiv V(s, X_t) = \frac{X_t}{r - \mu_s}. \tag{A4}$$

Given the cash flows $H_t = (X_t - c)(1 - \tau)$, the value function of equity is

$$E(s, X_t) = (1-\tau)\left(\frac{X_t}{r-\mu_s} - \frac{c}{r}\right) + e_{s,1}X_t^{\omega_{s,1}} + e_{s,2}X_t^{\omega_2}, \tag{A5}$$

$$= (1-\tau)\left(V_{s,t} - \frac{c}{r}\right) + e_{s,1}X_t^{\omega_{s,1}} + e_{s,2}X_t^{\omega_2} \tag{A6}$$

[7] Similar pricing kernels are used in Berk, Green, Naik (1999), and Carlson et al. (2004).

where $\omega_{s,1} < 0$ and $\omega_{s,2} > 1$ are the two roots of the characteristic equation in state $s$

$$\frac{1}{2}\sigma_s^2\omega_s(\omega_s - 1) + \mu_s\omega_s - r = 0. \tag{A7}$$

Ito's lemma implies that the equity value $E(s, X_t) \equiv E_{s,t}$ satisfies

$$\frac{dE_{s,t}}{E_{s,t}} = \frac{1}{E_{s,t}}\left(\frac{\partial E_{s,t}}{\partial t} + \hat{\mu}_s X_t \frac{\partial E_{s,t}}{\partial X_t} + \frac{\sigma_s}{2} X_t^2 \frac{\partial^2 E_{s,t}}{\partial X_t^2}\right) dt + \frac{1}{E_{s,t}} X_t \sigma_s \frac{\partial E_{s,t}}{\partial X_t}. \tag{A8}$$

The standard asset pricing argument gives

$$\mathbb{E}\left[\frac{dE_{s,t} + D_t dt}{E_{s,t}}\right] - rdt = -cov\left(\frac{dE_{s,t}}{E_{s,t}}, \frac{dm_t}{m_t}\right) = \frac{X_t}{E_{s,t}} \frac{\partial E_{s,t}}{\partial X_t} \sigma_m \theta dt. \tag{A9}$$

Denoting $(dE_{s,t} + D_t dt)/E_{s,t}$ by $r_{s,t}^E$ and $(X_t \partial E_{s,t})/(E_{s,t} \partial X_t)$ by $\gamma_{s,t}$, we have

$$\mathbb{E}[r_{s,t}^E] - rdt = \gamma_{s,t}\sigma_m\theta dt = \gamma_{s,t}\lambda dt. \tag{A10}$$

The sensitivity of the stock to the underlying assets $\gamma_{s,t}$ is

$$\begin{aligned}
\gamma_{s,t} =& \frac{X_t \partial E_{s,t}}{E_{s,t}\partial X_t} = \frac{V_{s,t}\partial E_{s,t}}{E_{s,t}\partial V_{s,t}} \\
=& \frac{1}{E_{s,t}}(X_t(1-\tau) + e_{s,1}\omega_{s,1}X_t^{\omega_{s,1}} + e_{s,2}\omega_{s,2}X_t^{\omega_{s,2}}) \\
=& \frac{1}{E_{s,t}}\left(E_{s,t} + \frac{c(1-\tau)}{r} - e_{s,1}X_t^{\omega_{s,1}} + e_{s,1}\omega_{s,1}X_t^{\omega_{s,1}} - e_{s,2}X_t^{\omega_{s,2}} + e_{s,2}\omega_{s,2}X_t^{\omega_{s,2}}\right) \\
=& 1 + \frac{c(1-\tau)}{rE_{s,t}} + \frac{(\omega_{s,1}-1)}{E_{s,t}}e_{s,1}X_t^{\omega_{s,1}} + \frac{(\omega_{s,2}-1)}{E_{s,t}}e_{s,2}X_t^{\omega_{s,2}}
\end{aligned} \tag{A11}$$

Because we solve the model by backward induction, we first show how a firm determines its optimal timing of bankruptcy after risk shifting, and then present the optimal risk-shifting policies for the same firm before it increases its idiosyncratic risk. We apply the general value function of equity of (A6) and equity return of (A10) to studying the pre- and post-shifting firms.

## A.2 The Firm After Risk Shifting

Equity holders choose the optimal default threshold $X_d$ to maximize their own equity value $E_{s,t} \equiv E(s, X_t)$. The two standard conditions are as follows:

$$E(s = H, X_t = X_d) = 0; \tag{A12}$$

$$E'(s = H, X_t = X_d) = 0, \tag{A13}$$

where $E'(s, X_t)$ denotes the first-order partial derivative of the equity value function $E(s, X_t)$ with respect to $X_t$ in state $s$. Equation (A12) is the value-matching condition, which states that equity holders receive nothing at bankruptcy.[8] Equation (A13) is the smooth-pasting condition that allows equity holders to choose their optimal bankruptcy threshold by facing a tradeoff between the costs of keeping the firm alive and the benefits from future tax shelter (Leland, 1994).

The following proposition states the expected stock return of post-shifting firms, $\mathbb{E}[r^E_{H,t}]$, and the default threshold $X_d$.

**Proposition 1** *When the firm is in the high-risk state but has not yet entered bankruptcy, $X_d \leq X_t < X_r$, the expected instantaneous stock return $\mathbb{E}[r^E_{H,t}]$ is*

$$\mathbb{E}[r^E_{H,t}] = rdt + \mathbb{E}[\gamma_{H,t}\lambda dt], \tag{A14}$$

*where the sensitivity of stocks to asset values, $\gamma_{H,t}$, is*

$$\gamma_{H,t} = \frac{\partial E_{H,t}/E_{H,t}}{\partial V_{H,t}/V_{H,t}} \tag{A15}$$

$$= 1 + \underbrace{\frac{c/r(1-\tau)}{E_{H,t}}}_{\textit{Leverage}} \underbrace{- (1-\omega_{H,1})\frac{(c/r - V_{H,d})}{E_{H,t}}\left(\frac{X_t}{X_d}\right)^{\omega_{H,1}}(1-\tau)}_{\textit{American Put Option of Delaying Bankruptcy (+)}}. \tag{A16}$$

*The optimal default threshold $X_d$ is*

$$X_d = \frac{c(r-\mu_H)\omega_{H,1}}{r(\omega_{H,1}-1)}, \tag{A17}$$

*and equity value $E_{H,t}$ is by*

$$E_{H,t} = \left[\underbrace{\left(V_{H,t} - \frac{c}{r}\right)}_{\textit{Equity-in-Place}} + \underbrace{\left(\frac{c}{r} - V_{H,d}\right)\left(\frac{X_t}{X_d}\right)^{\omega_{H,1}}}_{\textit{Option of Delaying Bankruptcy}}\right](1-\tau). \tag{A18}$$

**Proof**: The no-bubble condition implies $e_{H,2} = 0$, the value-matching condition of equation (A12) gives $e_{H,1} = -(V_H - c/r)(1-\tau)/X_d^{\omega_{H,1}}$. Simply substituting $e_{H,1}$ and $e_{H,2}$ into equations (A11) and (A6), we obtain equations (A16) and (A18), respectively. ∎

Equation (A14) shows that the expected stock return is the sum of the risk-free rate and the product of the *systematic* asset risk premium, $\lambda$, and the sensitivity of stocks to underlying assets, $\gamma_{H,t}$. The asset risk premium, $\lambda$, is assumed to be constant over time. The time-varying element for the expected stock return is then $\gamma_{H,t}$. We denote $\gamma_{H,t}$ the "stock-asset sensitivity" because,

[8] It is simple to introduce a Nash bargaining game at default as in Fan  Sundaresan (2000) and Garlappi  Yan (2011). However, the qualitative results remain unchanged.

strictly speaking, it measures how much the stock value changes in response to changes in asset values.[9]

Equation (A16) presents the stock-asset sensitivity, which consists of three components. The first is the baseline sensitivity, which is normalized to one. The second is related to financial leverage, as $c/r$ can be regarded as risk-free equivalent debt. Not surprisingly, the stock-asset sensitivity is positively associated with the financial leverage. Because the coupon $c$ is fixed after debt is in place, the increased excess risk $\epsilon$ increases $E_{H,t}$, thereby reducing the financial leverage and the stock-asset sensitivity.

The last component, the option of delaying bankruptcy, decreases the stock-asset sensitivity. The option of delaying bankruptcy, which is essentially an American put option, protects equity holders from downside risk. Given limited liability, equity holders choose to go bankrupt only when the asset value $V_{H,d}$ falls below the risk-free equivalent debt $c/r$.[10] Hence, $c/r - V_{H,d} > 0$. Moreover, the greater the asset growth volatility, the more opportunities equity holders have to receive a cash flow windfall. Therefore, equity holders of a firm with high idiosyncratic asset growth volatility have more incentives to delay bankruptcy, i.e., $\partial V_{H,d}/\partial \nu_H < 0$. Everything else being equal, the payoff of the put option $c/r - V_{H,d}$ increases with $\nu_H$. Therefore, the increase in the value of the put option due to strategically increased volatility, $\epsilon^*$, decreases the stock-asset sensitivity.

In short, idiosyncratic asset growth volatility, $\nu_H$, lowers the stock-asset sensitivity, $\gamma_{H,t}$, and therefore the expected stock returns, $\mathbb{E}[r^E_{H,t}]$, for firms in the high-risk state. Next, we take a step further to investigate how the firm increases its risk when it expects a low asset return in the high-risk state. We model this strategic risk-shifting behavior and study its implications for equity returns. In addition to the risk-shifting timing that has been studied by Leland (1998), we explicitly allow the firm to determine the amount of the risk increment.

## A.3 The Firm Prior to Risk Shifting

In the low-risk state, the firm chooses to invest in assets that generate cash flows, characterized by the growth rate and volatility pair ($\hat{\mu}_L$ and $\sigma_L$). Equity holders choose the optimal risk-shifting threshold $X_r$, at which they optimally switch to a higher-risk strategy, as well as the optimal excess idiosyncratic asset growth volatility $\epsilon^* \in [0, +\infty)$. The following two boundary conditions determine the threshold $X_r$:

$$E_{L,r} = E_{H,r} - \eta\epsilon^2 V_{H,r}(1-\tau), \tag{A19}$$

$$E'_{L,r} = E'_{H,r} - \eta\epsilon^2 (1-\tau)/(r-\mu_H). \tag{A20}$$

[9] Garlappi Yan (2011) label $\gamma_{H,t}$ as the "beta", but point out that their beta is not exactly the market beta as this stylized model does not assume a market model for the asset risk premium.

[10] Empirically, Davydenko (2008) documents that the majority of *negative*-net-worth firms do not default for at least a year and that the mean (median) of the market value of assets at default is only 66% (61.6%) of the face value of debt. This finding shows the importance of the option to delay bankruptcy.

The value-matching condition in equation (A19) is the no-arbitrage condition at $X_r$. Although the asset value decreases from $V_{L,t}$ to $V_{H,t}$ because $\mu_H < \mu_L$, equity holders are able to increase their own wealth to $E_{H,r} \equiv E(s = H, X_t = X_r)$ by increasing the idiosyncratic asset growth volatility from $\nu_L$ to $\nu_H$ at a cost of $\eta\epsilon^2 V_{H,r}(1-\tau)$. Equation (A20) is the smooth-pasting condition that determines the optimal risk-shifting threshold $X_r$.

In response to the expected decline from $\hat{\mu}_L$ to $\hat{\mu}_H$, equity holders strategically increase idiosyncratic volatility by $\epsilon^*$. Unlike the exogenous risk increment in Leland (1998), we allow equity holders to choose the optimal increment $\epsilon^*$ to maximize the equity value $E_{H,r}$ at $X_r$ after debt is in place:[11]

$$\epsilon^* = \underset{\epsilon}{argmax} \quad E_{H,r} - \eta\epsilon^2 V_{H,r}(1-\tau). \tag{A21}$$

On the one hand, the excess risk $\epsilon$ increases the equity value because of the option-like feature of equity. On the other hand, excess risk taking means greater proportional adjustment costs. Hence, equity holders make a cost-benefit tradeoff and determine the optimal excess risk taking $\epsilon^*$ so as to maximize their own wealth at $X_r$. After obtaining a semi-closed-form solution for $X_r$ as a function of $\epsilon^*$, we solve for $\epsilon^*$ and $X_r$ jointly.

The next proposition gives the expected stock return of the pre-shifting firms, $\mathbb{E}[r^E_{L,t}]$, and the optimal risk-shifting threshold, $X_r$.

**Proposition 2** *When the firm is in the low-risk state, $X_t \geq X_r$, the expected instantaneous stock return $\mathbb{E}[r^E_{L,t}]$ is*

$$\mathbb{E}[r^E_{L,t}] = rdt + \mathbb{E}[\gamma_{L,t}\lambda dt], \tag{A22}$$

*where the sensitivity of stock to asset, $\gamma_{L,t}$, is*

$$\gamma_{L,t} = \frac{\partial E_{L,t}/E_{L,t}}{\partial V_{L,t}/V_{L,t}} \tag{A23}$$

$$= 1 + \underbrace{\frac{c/r(1-\tau)}{E_{L,t}}}_{\text{Leverage}} + \underbrace{\frac{V_{L,r} - V_{H,r} + \eta\epsilon^2 V_{H,r}}{E_{L,t}} \left(\frac{X_t}{X_r}\right)^{\omega_{L,1}} (1-\tau)(1-\omega_{L,1})}_{\text{Option of increasing risk (+)}}$$

$$\underbrace{- \frac{c/r - V_{H,d}}{E_{L,t}} \left(\frac{X_r}{X_d}\right)^{\omega_{H,1}} \left(\frac{X_t}{X_r}\right)^{\omega_{L,1}} (1-\tau)(1-\omega_{L,1})}_{\text{Option of delaying bankruptcy (+)}}. \tag{A24}$$

*The optimal risk-shifting threshold $X_r$ is*

$$X_r = \left[\frac{(c/r - V_{H,d})(\omega_{H,1} - \omega_{L,1})}{X_d^{\omega_{H,1}} \left(\frac{1}{r-\mu_L} - \frac{1-\eta\epsilon^2}{r-\mu_H}\right)(1-\omega_{L,1})}\right]^{\frac{1}{1-\omega_{H,1}}}, \tag{A25}$$

[11] It makes no difference if we maximize $E_{L,r}$ because it equals $E_{H,r} - \eta\epsilon^2 V_{H,r}(1-\tau)$ according to the value-matching condition in equation (A19).

*and equity value $E_{L,t}$ is given by*

$$E_{L,t} = \left[\left(V_{L,t} - \frac{c}{r}\right) + (V_{H,r}(1-\eta\epsilon^2) - V_{L,r})\left(\frac{X_t}{X_r}\right)^{\omega_{L,1}} + (\frac{c}{r} - V_{H,d})\left(\frac{X_r}{X_d}\right)^{\omega_{H,1}}\left(\frac{X_t}{X_r}\right)^{\omega_{L,1}}\right](1-\tau). \tag{A26}$$

**Proof**: The no-bubble condition implies that $e_{L,2} = 0$ for equation (A6), and the value-matching condition of equation (A19) suggests

$$\begin{aligned}\left(V_{L,r} - \frac{c}{r}\right)(1-\tau) + e_{L,1}X_r^{\omega_{L,1}} = \left(V_{H,r} - \frac{c}{r}\right)(1-\tau) + \left(\frac{c}{r} - V_{H,d}\right)\left(\frac{X_r}{X_d}\right)^{\omega_{H,1}}(1-\tau) \\ - \eta\epsilon^2 V_{H,r}(1-\tau).\end{aligned} \tag{A27}$$

Hence,

$$e_{L,1} = \frac{(1-\tau)}{X_r^{\omega_{L,1}}}\left[(V_{H,r}(1-\eta\epsilon^2) - V_{L,r}) + \left(\frac{c}{r} - V_{H,d}\right)\left(\frac{X_r}{X_d}\right)^{\omega_{H,1}}\right]. \tag{A28}$$

Substituting $e_{L,1}$ and $e_{L,2}$ into equation (A11) and (A6), we obtain equations (A24) and (A26), respectively. Using smooth-pasting condition in equation (A20), we obtain the optimal risk-shifting threshold $X_r$ after some algebraic manipulation. ∎

Compared with the stock-asset sensitivity in equation (A16) for the post-shifting firm, the sensitivity in equation (A24) has four elements for a pre-shifting firm and the option to increase asset risk is a new element. First, everything else equal, a low idiosyncratic risk in this low-risk state implies a low equity value, a high financial leverage and stock-sensitivity. Second, the option to increase asset risk has a positive effect on the stock-asset sensitivity. Although the asset value *decreases* from $V_{L,r}$ to $V_{H,r}$ at $X_r$, the equity value *increases* from $E_{L,r}$ to $E_{H,r}$ due to the optimal increase in idiosyncratic risk $\epsilon^*$. This contrast implies that equity holders gain by taking on high-risk investments, and transfer wealth from debt holders to themselves. Lastly, the option to delay bankruptcy in (A24) is slightly different from that in equation (A16). Because the firm is still in the low-risk state, this out-of-the-money put option is less valuable to this healthy firm than it is to the underperforming firm in the high-risk state.

These two mechanisms have opposite effects on the stock-asset sensitivity. Their relative effects depend not only on their payoffs but also on the probability that they will be exercised. First, the potential increment in idiosyncratic volatility $\epsilon$ has a positive impact on the payoff from the option of increasing volatility. As shown in equation (A24), given the constant cost $\eta$, the greater the risk increment $\epsilon$, the greater the payoff $(V_{L,r} - V_{H,r} + \eta\epsilon^2 V_{H,r})$. Second, before the risk shifting, the likelihood of going bankrupt and the expected value of the option of going bankrupt are small because the firm is still in a low-risk state.[12]

[12]Mathematically, the probability of exercising those two options can be approximated by the distance of $X_t$ from their exercising thresholds. When the firm is approaching the high-risk state, $X_t \to X_r$, the risk-neutral probability $(X_t/X_r)^{\omega_{L,1}} \to 1$ for the option of increasing asset risk and the risk-neutral probability $(X_r/X_d)^{\omega_{H,1}}(X_t/X_r)^{\omega_{L,1}} \to (X_r/X_d)^{\omega_{H,1}} \leq 1$ for the option of delaying bankruptcy.

In short, the option of increasing idiosyncratic risk dominates the option of going into bankruptcy, and the potential increment of $\epsilon$ might positively impact the stock-asset sensitivity only among the pre-shifting firms.