Strategic Risk Shifting and the Idiosyncratic Volatility Puzzle*

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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, underperformed firms have more incentives to take on high idiosyncratic risk investments. Using three different measures of idiosyncratic volatility, we show that firms increase their idiosyncratic risk in response to negative return on assets (RoAs) at least twice as much as they do in response to positive RoAs. Second, the increased idiosyncratic volatility reduces the sensitivity of stocks to assets and results in low future stock returns. Only the strategic risk-shifting component of idiosyncratic volatility predicted from the past RoAs has a significantly *negative* impact on future stock returns. Specifically, the strategic component alone explains 77.21% of the negative impact of monthly idiosyncratic volatility on monthly stock returns, which dominates other alternative explanations.

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1 Introduction

Ang, Hodrick, Xing and Zhang (2006, 2009) document a strong negative relation between idiosyncratic volatility and subsequent stock returns. They find that firms with low stock idiosyncratic volatility outperform firms with high volatility by 1.06% per month in both domestic and international stock markets.[1] Standard asset pricing models in general do not generate such implications. A variety of economic mechanisms have been proposed to explain the idiosyncratic volatility puzzle. Recently, Hou and Loh (2012) conduct a comprehensive comparison of explanations for the puzzle and conclude that even when all the explanations are combined, a significant portion of the puzzle is still left unexplained.

In this paper, we offer a new perspective on the idiosyncratic volatility 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 agency conflict into the stock return and volatility dynamics and study the implications for the idiosyncratic volatility puzzle. The well-known agency conflict we consider is the risk shifting behavior (Jensen and Meckling, 1976) due to the asymmetric risk-sharing between equity and debt holders. Within this framework, we investigate: 1) How do equity holders strategically decide about the levels of idiosyncratic risk? 2) Do firms' strategic risk-shifting policies have an impact on stock returns, which might help explain the negative relation between idiosyncratic volatility and stock returns?

To answer the first question, we build a risk-shifting model based on Leland (1998).

[1] Jiang, Xu, and Yao (2009) confirm the negative relation and further argue that idiosyncratic volatility is related to future negative earning shocks. Huang (2009) finds similar results that firms with high *cash flow* volatility earn abnormally lower stock returns than their counterparts with low volatility by 1.35% per month.

Because equity holders are not obligated to pay back debt holders from their pockets at bankruptcy, they have limited downside risk but unlimited upside profits. After debt is in place, equity holders, can strategically increase their risk to maximize their *own* wealth. Leland exogenously specifies the amount of *total* volatility increment, while allowing the firms to endogenously choose the timing of risk-shifting. We also allow the firms to choose the timing of risk-shifting. In addition, unlike Leland (1998), we distinguish idiosyncratic volatility from systematic volatility and allow equity holders to choose privately optimal idiosyncratic volatility. Our first testable prediction is that, when the firm's profitability declines, equity holders choose to invest in projects with high idiosyncratic volatility.

To address the second question, we obtain closed-form solutions for equity returns before and after the risk-shifting. Intuitively, levered equity is a long position on a call option, and its value increases with idiosyncratic volatility. Therefore, equity holders become less sensitive to declining cash flows and asset values. In other words, the equity holders have lower exposure to downside risk, and they demand lower risk premium. As a result, firms with higher idiosyncratic volatility receive lower stock returns than those of a similar firm with lower idiosyncratic volatility. Our second prediction is: The negative relation between idiosyncratic volatility and stock returns is driven by the firm's strategic risk-shifting behavior, particularly for firms in low-risk states that are more likely to increase idiosyncratic risk.

We find strong empirical support for both theoretical predictions. We use three proxies for idiosyncratic asset risk to examine our first prediction, including research & 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, which is consistent with Hirshleifer, Low, and Teoh (2012).

However, this negative relation in both good and low-risk times does not necessarily suggest the opportunistic risk-shifting behavior, because taking more risks in good times has a smaller likelihood of putting debt holders in danger. 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 the three idiosyncratic risk measures is much more significant when the firms receive negative shocks than when they receive positive shocks. To our knowledge, we are the first to demonstrate the asymmetric effect of profitability on risk-taking policies.[2] This strategic risk-taking reaction to negative cash flow shocks is crucial in testing our second prediction.

To verify our second prediction that the *strategic* risk-shifting actions adversely impact stock returns, we use the component of idiosyncratic stock return volatility predicted from past RoA to proxy for strategic risk-taking behavior. We demonstrate that only the predicted component of idiosyncratic volatility from past RoA has a significantly negative effect on the future stock returns. Specifically, using the decomposition method of Hou and Loh (2012), we find that the predicted component alone can explain 77.21% of the negative impact of idiosyncratic volatility on future stock returns.

Our paper belongs to an emerging literature that uses dynamic models to examine the implications of agency conflicts for asset pricing.[3] Albuquerue and Wang (2008) examine the impacts of corporate governance on stock valuation and show that countries with weaker in-

[2]Eisdorfer (2008) is the first who uses a large sample of firms and identify the positive relation between capital investment and uncertainty among distressed firms, which is empirically proxied by stock return volatility. However, his control variable, cash flows (operating cash flows normalized by PP&E), is positively related to capital investments. The abnormal investment of distressed firms is a manifestation of risk-shifting because it is in contrast with standard real options theory, which predicts investments of a healthy firm decline with uncertainty because the firm wants to wait until more information available.

[3]A nonexclusive list of papers that study the cross section of stock returns in a dynamic model includes Berk, Green, and Naik (1999); Carlson, Fisher, and Giammarino (2004); Gomes, Kogan, and Zhang (2003); and Zhang (2005). However, they do not consider agency conflicts.

vestor protection have more incentives to overinvest, lower Tobin's q, and larger risk premia. Davydenko and Strebulaev (2007) demonstrate that strategic default decisions by equity holders have adverse effect on bond prices. Carlson and Lazrak (2010) show that managerial stock compensation induces risk-shifting behavior that helps explain the rates of credit default swaps (CDS) and leverage choices. Favara, Schroth, and Valta (2011) and Garlappi and Yan (2011) study the effect of renegotiation at bankruptcy between equity and debt holders on stock returns. By studying another agency conflict, we demonstrate that the negative association between idiosyncratic volatility and future stock return might be driven by strategic risk-shifting behavior.

Existing explanations for the idiosyncratic volatility puzzle fall into three categories.[4] The first category is related to lottery preference. Barberis and Huang (2008) argue that investors overweight small chances of large gains and prefer positively skewed stocks. The excess demand on those stocks causes them to be overpriced and results in low subsequent returns. Empirical studies that find supporting evidence for this behavioral theory include Boyer, Mitton, and Vorkink (2010) and Bali, Cakici, and Whitelaw (2011). The second category is related to firms' operating profitability. Jiang et al. (2009) show that idiosyncratic volatility contains information content of future earnings. Avramov, Chordia, Jostova, and Philipov (2013) provide evidence that the idiosyncratic volatility puzzle exists only in distressed firms. The third category is associated with market frictions. Fu (2009) and Huang, Liu, Rhee, and Zhang (2010) find that the one-month return reversal effect drives this puzzle, and that the reversal effect is likely to be induced by bid-ask bounces and microstructure biases. Illiquidity (Han and Lesmond, 2011), price delay (Hou and Moskowitz, 2005) and short sale constraints (Boehme, Danielsen, Kumar, and Sorescu, 2009) can also induce the negative

[4] Our classification is largely based on Hou and Loh (2012).

idiosyncratic volatility-return relation. We conduct a formal comparison between our theory and other alternatives. Our variable, which is a proxy for strategic risk-shifting behavior, dominates variables from all three above categories.

There are other papers that link asset growth volatility with returns. Galai and Masulis (1976) show the negative impact of asset growth volatility on stock returns. Along the same line as Galai and Masulis (1976), Johnson (2004) introduces uncertainty of asset growth volatility into Merton (1974). The uncertainty of asset growth volatility makes asset processes more volatile for investors, therefore amplifying the negative association between asset growth volatility and stock returns shown in Galai and Masulis (1976). Additionally, two other recent working papers, Babenko, Boguth, and Tserlukevich (2013) and Bhamra and Shim (2013), link cash flow idiosyncratic volatility with equity risk. However, they model growth options and do not consider the options of strategically increasing idiosyncratic volatility and going into bankruptcy. Our paper differs from Galai and Masulis (1976) and other papers in two significant respects. First, asset growth volatility in these other papers is exogenously specified, while our models allow volatility to be endogenously chosen, depending on how firms adjust their risk-taking policy in response to their financial status. Second, the default timing in Galai and Masulis (1976) is exogenous, while it is endogenous in our model. In their model, default is realized only if the asset value falls below the principal of debt at the expiration date in the European option framework of Merton (1974). Given recent empirical evidence from Davydenko (2008) that the mean (median) of the market value of assets at default is only 66% (61.6%) of the face value of debt, we adopt the American option framework of Leland (1994, 1998), in which equity holders delay filing for bankruptcy and choose optimal bankruptcy timing. This strategic delay in bankruptcy can be considered as another form of opportunistic risk-shifting behavior.

Our paper is also related to the literature that links firm profitability to cross-sectional equity returns. Hou, Xue, and Zhang (2012) show that an investment-based factor model which includes a ROE factor can price portfolios sorted on idiosyncratic volatility among others. Fama and French (2013) propose a five-factor model which includes an operating profitability factor. Both papers illustrate the importance of firm profitability to equity returns. In our paper, we highlight one important channel how firm profitability affects idiosyncratic volatility and thus returns through firms strategic risk-shifting.

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

2 The Model

In this section, we build a risk-shifting model to explain the puzzling negative relation between idiosyncratic volatility and stock returns. We start with the setup of the model in Section 2.1. We derive the expected stock return after risk-shifting and before risk-shifting in Section 2.2 and 2.3, respectively. Lastly, we discuss testable predictions from the model in Section 2.4.

2.1 Setup

We develop a partial equilibrium model with a pricing kernel, m_t, following:[5]

$$\frac{dm_t}{m_t} = -rdt - \theta dZ_t, \tag{1}$$

[5] Similar pricing kernels are used in Berk et al. (1999), Carlson et al. (2004), Gomes and Schmid (2010) and Garlappi and Yan (2011).

where r is the constant risk-free rate, θ is the market price of risk, and Z_t is a standard Brownian motion.

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

$$\frac{dX_t}{X_t} = \hat{\mu}_s dt + \sigma_s d\hat{W}_t, \tag{2}$$

where $\hat{\mu}_s$ is the expected growth rate of cash flow in the state of s, σ_s is the total volatility of cash flow growth rates, and $\hat{W}_t$ is a standard Brownian motion. We use $\hat{}$ to denote physical measure. We define $\hat{\mu}_s = \mu_s + \lambda$, where μ_s is the risk neutral counterpart of $\hat{\mu}_s$, and λ is the constant risk premium over the two states. Specifically, $\lambda = \theta\rho_s\sigma_s$, where ρ_s is the correlation coefficient between the cash flows growth rates and the pricing kernel in the state of s. The total volatility of cash flow growth rates is $\sigma_s = \sqrt{(\rho_s\sigma_s)^2 + \nu_s^2}$, where ν_s is the idiosyncratic volatility of cash flow growth rates in the state of s. As Garlappi and Yan (2011) point out, this partial equilibrium model is silent on the systematic structure of the risk premium λ. The risk premium can be modeled in the consumption-based framework (Bhamra, Kuehn, and Strebulaev, 2010) or in the capital asset pricing model (Galai and Masulis, 1976).

The value of assets-in-place, $V_{s,t}$, under the risk-neutral Q measure, is

$$V_{s,t} \equiv V(s, X_t) = \mathbb{E}^Q \left[\int_t^\infty X_\tau e^{-r\tau} d\tau \right] = \frac{X_t}{r - \mu_s}. \tag{3}$$

Because $dV_{s,t}/V_{s,t} = dX_t/X_t$ in each state, it follows that

$$\frac{dV_{s,t}}{V_{s,t}} = \hat{\mu}_s dt + \sigma_s d\hat{W}_t. \tag{4}$$

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 expected asset growth rate (or asset return), λ as asset risk premium, ρ_s as the asset correlation coefficient between the asset return and the pricing kernel, ν_s as idiosyncratic asset growth volatility, and σ_s as total asset growth volatility throughout the rest of the paper.

The firm pays taxes to the government and dividends to equity holders. The effective tax rate is τ. The dividend received by equity holders is the entire cash flow X_t net of coupon payments c to debt holders and tax payments, $D_t = (1-\tau)(X_t - c)$. We assume that the firm can costlessly issue new equity to cover its debt service (Leland, 1994).

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, σ_L. If cash flows X_t decline to a low threshold X_r, the firm enters a high-risk state.[6] Equity holders thus choose to invest in high-risk assets that produce cash flows with a low expected growth rate $\hat{\mu}_H$, but high volatility σ_H, hoping that a cashflow windfall due to the increased σ_H might save the firm. For example, Research in Motion (RIM), the manufacturer of Blackberry smart phone, has increased its R&D expenditure more than four fold since 2008, while its annual revenue growth rate has declined from 100% to –34%. 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.

[6] Unlike Bhamra et al. (2010) and Chen (2009) who exogenously specify a Markov transition probability for the states of the economy, the probability of risk-shifting in this paper is endogenous because the risk-shifting threshold X_r is endogenously chosen by equity holders.

To focus on the idiosyncratic volatility puzzle, we assume that, after the firm enters the high-risk state with low expected asset returns, equity holders only increase the idiosyncratic volatility, ν_s, rather than the total volatility, σ_s, when they choose to increase volatility. The intuition for this is two-fold. First, given that an increase in the systematic volatility reduces the risk-adjusted (risk-neutral) expected growth rate μ_s and the asset value as in equation (3), risk-neutral equity holders have more incentives to increase idiosyncratic volatility rather than the total volatility. Second, the equity holders have no incentives to ride on the market if the firm's declining performance is due to the contracting economy.[7]

Equity holders face a lump-sum cost of $\eta\epsilon^2 V_{H,r}(1-\tau)$ to adjust their firm's risk profile at the risk-shifting threshold X_r, where $\eta \geq 0$ is the proportional cost of excess risk-taking, ϵ is the increment in asset growth volatility, and $V_{H,r}$ is the asset value at X_r.[8] Specifically, $\epsilon = \sqrt{\nu_H^2 - \nu_L^2} \geq 0$. The assumption that the adjustment costs are proportional to ϵ^2 is intuitive. First, research and development (R&D) expenses for higher idiosyncratic (or unique) projects are generally greater than those for lower idiosyncratic projects, because they demand more research inputs. Second, it is more costly for sinking firms to attract talented workers for their "idiosyncratic" projects. If those firms eventually go bankrupt, their workers would have difficulty finding new jobs, given that their specific skills might not be applicable to their new jobs (Titman, 1984).

In short, the expected asset return $\hat{\mu}_s$ and idiosyncratic asset growth volatility ν_s are constant within each state, but they are different across the two states. We have $\hat{\mu}_H \leq \hat{\mu}_L$

[7]This assumption is essentially the same as in Leland (1998) who assumes a constant risk-neutral growth rate across two states, while increasing the total asset growth volatility. To keep the risk-neutral growth rate constant in his setup, the increase in the total asset growth volatility has to derive entirely from the increase in the idiosyncratic component. Otherwise, the risk-adjusted rate would decrease.

[8]Hennessy and Tserlukevich (2008) assume a flow cost in the rate of asset growth. Alternatively, Panageas (2010) model the indirect, lump-sum cost by introducing the bailout to risk-shifting problem. The cost of increasing excess risk before bankruptcy potentially causes the firm lose the opportunity of being bailed out.

and $\nu_H \geq \nu_L$ because equity holders increase idiosyncratic volatility from ν_L to ν_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 ν_L are public information and they are exogenously given, while ν_H is controlled by the owners of the firm – equity holders.

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.

2.2 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:

$$E(s = H, X_t = X_d) = 0; \tag{5}$$

$$E'(s = H, X_t = X_d) = 0, \tag{6}$$

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 the state of s. Equation (5) is the value matching condition, which states that equity holders receive nothing at bankruptcy.[9] Equation (6) 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 next proposition states the expected stock return and the default threshold X_d.

Proposition 1 *When the firm is in the high-risk state but prior to bankruptcy,* $X_d \leq X_t <$

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

X_r, the expected instantaneous stock return $\mathbb{E}[r^s_{H,t}]$ is

$$\mathbb{E}[r^s_{H,t}] = rdt + \mathbb{E}[\gamma_{H,t}\lambda dt], \tag{7}$$

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

$$\gamma_{H,t} = \frac{\partial E_{H,t}/E_{H,t}}{\partial V_{H,t}/V_{H,t}} \tag{8}$$

$$= 1 + \underbrace{\frac{c/r(1-\tau)}{E_{H,t}}}_{\textit{Leverage}} \underbrace{- (1-\omega_{H,1})\frac{(c/r - V_{H,d})}{E_{H,t}}\left(\frac{X_t}{X_d}\right)^{\omega_{H,1}}(1-\tau)}_{\textit{American Put Option of Delaying Bankruptcy}}. \tag{9}$$

The optimal default threshold X_d is

$$X_d = \frac{c(r_f - \mu_H)\omega_{H,1}}{r_f(\omega_{H,1} - 1)}. \tag{10}$$

Equity value $E_{H,t}$ and $\omega_{H,1}(\mu_H, \sigma_H) < 0$ are given in Appendix A.

Proof: See Appendix A.1.

Equation (7) shows that the expected stock return is the sum of the risk-free rate and the product of the *systematic* risk premium, λ, and the sensitivity of stocks to underlying assets, $\gamma_{H,t}$. By its definition, $\lambda = \theta\rho_s\sigma_s$. We follow Garlappi and Yan (2011) and Gomes and Schmid (2010) in assuming that the systematic risk $\rho_s\sigma_s$ is the same across all firms. Given the constant θ, the systematic risk premium λ is constant as well. The only time-varying element for expected stock return is then $\gamma_{H,t}$. While Garlappi and Yan (2011) label $\gamma_{H,t}$ as the "beta",[10] we denote it the "stock-asset sensitivity" because, strictly speaking, it measures how much the stock value changes in response to changes in asset values.

[10]Garlappi and Yan (2011) 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.

Equation (9) 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 ϵ 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 (See Corollary 1 in Appendix A). 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, $\partial V_{H,d}/\partial \nu_H < 0$. Everything else being equal, the payoff of the put option $c/r - V_{H,d}$ increases with ν_H. 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 asset at default is only 66% (61.6%) of the face value of debt. This finding shows the importance of the option of delaying bankruptcy.

Taken together, idiosyncratic asset growth volatility, ν_H, lowers the stock-asset sensitivity, $\gamma_{H,t}$, and therefore the expected stock returns, $\mathbb{E}[r^s_{H,t}]$, for firms in the high-risk state. Next, we take a step further to understand why and 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 risk increment.

2.3 The Firm Prior to Risk-Shifting

In the low-risk state, the firm chooses to invest in assets that generate cash flows, characterized by a pair of growth rate and volatility ($\hat{\mu}_L$ and σ_L). Equity holders choose the optimal risk-shifting threshold X_r, where they optimally switch to a higher risk strategy, as well as the optimal excess idiosyncratic asset growth volatility ϵ^* from a *continuum* of ϵ. We impose two boundary conditions to determine the threshold X_r as follows:

$$E_{L,r} = E_{H,r} - \eta\epsilon^2 V_{H,r}(1-\tau), \tag{11}$$

$$E'_{L,r} = E'_{H,r} - \eta\epsilon^2(1-\tau)/(r-\mu_H). \tag{12}$$

The value matching condition in equation (11) 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 ν_L to ν_H at a cost of $\eta\epsilon^2 V_{H,r}(1-\tau)$. Equation (12) 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 ϵ^*. Unlike the exogenous risk increment in Leland (1998), we allow equity holders to choose the optimal increment ϵ^* to maximize the equity value $E_{H,r}$ at X_r after debt is in place,[11]

$$\epsilon^* = \underset{\epsilon}{argmax} \quad E_{H,r} - \eta\epsilon^2 V_{H,r}(1-\tau). \tag{13}$$

[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 (11).

On one hand, the excess risk ϵ 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 ϵ^* to maximize their own wealth at X_r. After obtaining a semi-closed-form solution for X_r as a function of ϵ^*, we solve for ϵ^* and X_r jointly. The next proposition gives the expected stock return 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 $\mathbb{E}[r^s_{L,t}]$ is*

$$\mathbb{E}[r^s_{L,t}] = r_f dt + \mathbb{E}[\gamma_{L,t}\lambda dt], \tag{14}$$

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

$$\gamma_{L,t} = \frac{\partial E_{L,t}/E_{L,t}}{\partial V_{L,t}/V_{L,t}} \tag{15}$$

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

$$- \underbrace{\frac{c/r_f - V_{H,d}}{E_{L,t}} \left(\frac{X_r}{X_d}\right)^{\omega_{H,1}} \left(\frac{X_t}{X_r}\right)^{\omega_{L,1}} (1-\tau)(1-\omega_{L,1})}_{Option\ of\ delaying\ bankruptcy\ (+)}. \tag{16}$$

The optimal risk-shifting threshold X_r is

$$X_r = \left[\frac{(c/r_f - V_{H,d})(\omega_{H,1} - \omega_{L,1})}{X_d^{\omega_{H,1}} \left(\frac{1}{r_f - \mu_L} - \frac{1-\eta\epsilon^2}{r_f - \mu_H}\right)(1-\omega_{L,1})}\right]^{\frac{1}{1-\omega_{H,1}}}. \tag{17}$$

Equity value $E_{L,t}$, $\omega_{L,1} < 0$ and $\omega_{H,1}(\epsilon^*) < 0$ are given in Appendix A. The optimal default threshold X_d is defined in equation (10) *and the optimal asset risk increment ϵ^* is defined in* *equation* (13).

Proof: See Appendix A.2.

Compared with the stock-asset sensitivity in equation (9) for the post-shifting firm, the option to increase asset risk in equation (16) is a new element for a pre-shifting firm. This option 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 ϵ^*. This contrast implies that equity holders gain by taking on high-risk investments and transfer wealth from debt holders to themselves. In addition, the option to delay bankruptcy in (16) is slightly different from the one in equation (9). 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 underperformed firm in the high-risk state.

Equation (17) indicates that the optimal risk-shifting threshold decreases with the proportional adjustment cost η, in line with our intuition that equity holders who face high costs are reluctant to increase asset risk. If $\eta = 0$ and $\mu_H = \mu_L$, equity holders opt to increase asset growth volatility immediately when they enter the market at time 0, because they can capture the upside profits from riskier projects with the same expected return on asset without any costs.

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 of exercising them. First, the potential increment in idiosyncratic volatility ϵ has a positive impact on the payoff for the option of increasing volatility. As shown in equation (16), given the constant cost η, the greater the risk increment ϵ, the greater the payoff $(V_{L,r} - V_{H,r} + \eta\epsilon^2 V_{H,r})$ is. Second, before the risk-shifting, the likelihood of going bankrupt and the expected value of the option of going bankrupt are small because the firms are still in a low-risk state.[12] Put together, the option of increasing idiosyncratic risk dominates the option of going into bankruptcy, and the potential increment of ϵ positively impacts the stock-asset sensitivity only among the pre-shifting firms.

Our model differs from Leland's model in three aspects. First and most importantly, unlike Leland (1998) who models the timing of risk-shifting only, we allow equity holders to endogenously determine the amount of excess risk, given their expected return on assets (RoA) when the firm is entering high-risk state. While it is empirically difficult to infer the timing of risk-shifting, we are able to directly test the relation between expected RoA and the amount of idiosyncratic risk. Second, Leland models debt endogenously in order to quantify agency costs, while we mainly focus on implications of risk-shifting for stock returns and we take debt as exogenously given. Third, Leland extends the one-shot game of Jensen and Meckling (1976) into a repeated game by allowing the firm to increase asset risk when the firm is entering high-risk state, and then costlessly decrease its risk back to its original level when the firm bounces back and refinances its debt. In contrast, in our model, the firm does not have such incentives because it does not need to refinance its debt. The two simplifications of exogenous debt financing and irreversible risk-shifting decisions allow us to obtain closed-form solutions for stock returns.

2.4 Testable Predictions

To generate the cross-sectional predictions for stock returns from our model, we follow Gomes and Schmid (2010) and perform comparative statics analysis across firms. Suppose that there

[12] Mathematically, the probability of exercising those two options can be approximated by the distance of X_t to 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 to increase 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 to delay bankruptcy.

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. When the cash flows decline to the threshold, e.g., $X_t \to X_r$, they have different $\hat{\mu}_H = 0.02$, 0.03, and 0.04 respectively for those three firms. We are interested in the optimal increment in idiosyncratic volatility, ϵ^*, at X_r, and the subsequent impacts from ϵ^* on expected stock returns after X_r.

We obtain the parameter values from the extant literature, such as Garlappi and Yan (2011) and Gomes and Schmid (2010), except for the proportional cost of excess risk η. We choose $\eta = 0.20$ to produce a reasonable value of ν_H. The specific choice of η has no material impact on the qualitative implications of the model. The parameter values are listed in Table 1.

The following two predictions summarize the way the firms increase their idiosyncratic volatilities and the resulting impacts on expected stock returns.

Prediction 1: *Equity holders of a firm with a lower $\hat{\mu}_H$ choose a greater increment ϵ^* and therefore have a higher idiosyncratic asset growth volatility ν_H.*

Figure 1 plots the optimal ϵ^* against the expected $\hat{\mu}_H$. For the firm with the lowest $\hat{\mu}_H$ = 0.02, the optimal increment ϵ^* is 0.751, while for the firm with the highest $\hat{\mu}_H = 0.04$, the optimal increment ϵ^* becomes 0.606. It is evident that 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.

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 follows our first prediction that ν_H increases endogenously in response to a lower value of $\hat{\mu}_H$ and shows the consequent effect on stock returns from the increased ν_H. Equations (7) and (14) state that the expected excess return is simply the *market* risk premium of assets λ scaled by the stock-asset sensitivity $\gamma_{s,t}$ for the pre- and post-shifting firms, respectively. We are interested in $\gamma_{s,t}$ that varies across firms with different levels of idiosyncratic volatility, ν_s.

To demonstrate that only the increased idiosyncratic volatility has a negative impact on stock returns, we plot the stock-asset sensitivity $\gamma_{s,t}$ against X_t in Figure 2.[13] We use equation (9) for $X_t < X_r$ and equation (16) for $X_t \geq X_r$.

For $X_t < X_r$, all the three firms have already increased their idiosyncratic risk by ϵ^* given a lower expected RoA, $\hat{\mu}_H$. It is evident that, given a certain level of cash flows X_t, firms that choose lower increment ϵ^* and $\nu_H = \sqrt{\nu_L^2 + (\epsilon^*)^2}$ have higher sensitivity $\gamma_{H,t}$. For instance, when $X_t = 0.2$, Firm 3 with a greater increment $\epsilon^* = 0.744$ has a lower sensitivity $\gamma_{H,t}$ than does Firm 1 with a smaller increment $\epsilon^* = 0.598$. Given the constant market risk premium λ across the three firms, the lower sensitivity $\gamma_{H,t}$ implies a lower expected stock return $\mathbb{E}[r^s_{H,t}]$ according to equation (7).

This observation is the opposite for the pre-shifting firms when $X_t \geq X_r$. For example, when $X_t = 0.55$, Firm 3 has a higher stock-asset sensitivity than Firm 1 because of the positive effect from the option of increasing asset growth volatility, as discussed for equation (16). Moreover, there is no monotonic increasing or decreasing relation between idiosyncratic volatility ν_s and the stock-asset sensitivity $\gamma_{s,t}$ for $0.349 \leq X_t < 0.499$.

Put together, Figure 2 shows that only the strategically increased idiosyncratic volatility by equity holders has a negative impact on stock returns, which supports for our second prediction. Our closed-form solutions for equity returns directly shows that stock return is negatively related to a firm's idiosyncratic risk, which is strategically chosen by equity

[13] The legend lists the exact values of the optimal ϵ^* and the optimal X_r for these three firms. Because risky assets with low $\hat{\mu}_H$ are less attractive, those firms are prone to delay taking on high-risk investments and therefore have the low threshold X_r.

holders in response to the declining RoA.

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 availability of quarterly ComputStat data, our sample period is from January 1975 to December 2011. We restrict the sample to firm-quarter observations with non-missing values for operating income and total assets, with positive total assets and with non-negative book values. We include common stocks listed on the NYSE, AMEX, and NASDAQ with CRSP share code 10 or 11, and we exclude firms from the financial and utility sectors. To ensure that monthly stock returns can be matched with fiscal-quarter operating incomes, we only include firms with fiscal year-ends of March, June, September and December. Our results are robust to the inclusion of data with other fiscal year-ends. 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 monthly stock return and idiosyncratic volatility to examine the second prediction.

Our measure of return on assets (RoA) closely follows our theoretical definition, $dV_t/V_t = X_t/V_t$. We calculate the RoA by dividing the sum of income before extraordinary items (or net income, compustat item IBQ) and interest (XINTQ) and depreciation (DPQ) over assets (ATQ) of the previous quarter. RoA values are truncated at the upper and lower onepercentiles in order to reduce the impact of the outliers and eradicate errors in calculating the volatility of RoA.

We compute three proxies for idiosyncratic risk for each firm i at quarter t. The first is Research & Development investments $R\&D_{i,t}$. To mitigate the potential seasonality problem from the quarterly data, we use the average of the ratio of R&D expenses (Item XRDQ) over the assets (ATQ) from quarter $t-3$ to t. Following Hirshleifer et al. (2012), we set negative values or missing values of R&D to zero. R&D investment is a good proxy for the *idiosyncratic* asset growth risk because research innovations are not recognized by the market before they are converted into production. Moreover, because of high failure probability of R&D projects, they are much riskier than capital investments.

The second measure 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,

$$RoA_{i,t} = a_i + b_i RoA_{M,t} + u_{i,t}^{RoA}, \tag{18}$$

where $RoA_{M,t}$ is the average of RoA across all the firms at quarter t, proxying for the movement of the whole production market. We compute $\nu_{i,t}^{RoA}$ as the standard deviation of the residual RoA from previous 12 quarters.

The third measure is idiosyncratic volatility of stock returns. The previous literature, such as 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, and Zhang (2006) and estimate the idiosyncratic volatility of stock returns as the standard deviation of the residuals of daily stock returns.

We estimate both the quarterly and monthly idiosyncratic volatilities.

We first estimate the daily stock return residuals from the Fama-French (1993) three-factor model for quarter or month t as follows:

$$r^s_{i,d} = \alpha_{i,t} + \beta^{MKT}_{i,t} r^{MKT}_d + \beta^{SMB}_{i,t} r^{SMB}_d + \beta^{HML}_{i,t} r^{HML}_d + u_{i,d}, \tag{19}$$

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

The three idiosyncratic risk proxies are closely related. Irvine and Pontiff (2009) argue that the increases in idiosyncratic volatility can be attributed to an increase in the idiosyncratic volatility of fundamental cash flows. Chun, Kim, Morck, and Yeung (2008) and Comin and Philippon (2006) link idiosyncratic volatility to research intensity and spending, arguing that a more intensive use of information technology leads to higher idiosyncratic volatility. Empirically, the three proxies are measured over different horizons, with $R\&D_{i,t}$ computed over one year, $\nu^{RoA}_{i,t}$ over three years, and $\nu^s_{i,t}$ over one quarter. 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.

In 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. In addition, we follow Hirshleifer et al. (2012) and use managerial stock-based compensation to control for their incentives of risk-taking. Using Standard and Poor's Execucomp database, we calculate delta and vega using the 1-year approximation method of Core and Guay (1999) and take the natural logarithms of these two variables. Delta is defined as a dollar change in a CEO's stock and option portfolio for a 1% change in stock price, which measures the managerial incentives to increase stock price. Vega is the dollar change in a CEO's option holdings in response to a 1% change in stock return volatility, which measures the risk-taking incentives generated by the managerial stock option holdings.

In 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 (19). Firm characteristics include size, book-to-market equity (BE/ME), market leverage (MktLev), and previous six-month cumulative stock return (PreRets). Size is the natural logarithm of market equity (ME). The book-to-market equity ratio, BE/ME, is the ratio of book equity over the market equity.[14] Observations with negative BE/ME are excluded. Market leverage, MktLev, is measured as a ratio of total debt over 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).

[14]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.

3.2 Summary Statistics

Table 2 presents summary statistics of both 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 order autocorrelation coefficients.

The quarterly data in Panel A are for testing the first prediction. On average, our sample includes 2300 – 2500 firms per quarter. As shown in the first row, the annualized return on asset RoA has a mean of 4.82% and a STD of 13.71%. RoA is also highly persistent with an autocorrelation of 0.68. For the three proxies of idiosyncratic risk, the R&D proxy has a mean of 4.48% with a STD of 1.97%, the volatility of 12-quarter RoAs has a mean of 9.32% with a STD of 4.09%, and the three-month idiosyncratic return volatility has a mean of 55.02% with a STD of 26.04%. All three proxies are highly persistent as indicated by their AR(1) coefficients, which are at least above 70%. 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, all three proxies are cross-sectionally correlated with a correlation coefficient of around 20% to 30%. The average logarithm of firm sales is 3.4 million dollars. Book-to-market ratio (BE/ME)and market leverage ($MktLev$) are both highly persistent and have a mean of 0.74 and 0.22 respectively.

Panel B presents the monthly data we use in testing the second prediction. The annualized monthly stock return has an average of 14.96% and is slightly negatively serially correlated. The average one-month idiosyncratic volatility has an average of 51.64%. The average size and book-to-market ratio in our monthly data are \$117.91 ($e^{4.77}$) million dollars and 0.76, respectively, both of which are about the same as those of a median firm in US stock markets. The average firm leverage ratio is 0.23. The average annualized lagged six-month cumulative returns after skipping a month ($PreRets$) is 12.99% with a standard deviation of 80.99%. The average firm-level betas on 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 our two theoretical predictions in this section. In section 4.1, we test the prediction that, in response to the decreased RoA, firms choose to increase idiosyncratic risk. In section 4.2, we examine the prediction that the component of idiosyncratic volatility predicted from previous RoA has a negative impact on future stock returns. We compare our findings with the existing literature in section 4.3.

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 investment with high idiosyncratic risk, particularly when their firm experiences negative cash flow shocks. Given that the $RoA_{i,t}$ is highly persistent in Table 2, we assume that the expected RoA of the next quarter, conditioning on that of the current quarter, 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. 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 inference 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:

$$y_{i,t} = a_t + b_t RoA_{i,t-1} + c_t RoA_{i,t-1} I(RoA_{i,t-1} < 0) + d_t control_{i,t-1} + e_{i,t}, \qquad (20)$$

where the dependent variable $y_{i,t}$ is our idiosyncratic volatility proxy. To examine the asymmetric impacts of negative shocks of asset returns on idiosyncratic risk-taking, we include a dummy variable, $I(RoA_{i,t-1} < 0)$, which takes the value of 1 when $RoA_{i,t-1}$ is negative, and 0 otherwise. That is, when RoA_{t-1} is positive, b_t captures how RoA_{t-1} affects future risk-taking; when RoA_{t-1} is negative, $b_t + c_t$ captures the impact of $RoA_{i,t-1}$ on future idiosyncratic volatility. Finally, we include various control variables, $control_{i,t-1}$.

We report Fama-MacBeth regression results in Table 3. In Panel A, we use $R\&D$ expenditure as a proxy for idiosyncratic volatility. In Panel B, the idiosyncratic volatility proxy becomes the volatility of RoA of the next 12 quarters, $\nu_{i,t}^{RoA}$. In Panel C, we use the idiosyncratic return volatility of the next quarter, $\nu_{i,t}^{s}$. 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 consider the asymmetric impact of negative RoA on future idiosyncratic volatility by including $I(RoA_{i,t-1} < 0)$. In the third regression (Reg III), we control for firm characteristics from the previous literature, such as industry averages, logarithmic values of sales, book-to-market equity, and market leverage ratio as well as delta and vega of managerial stock options. In addition, we include $RoA_{i,t-2}$ and lagged dependent variable $y_{i,t-1}$ to control for the persistence in the dependent variables.

In Panel A, we use $R\&D_{i,t}$ to proxy for idiosyncratic risk. From Reg I, the coefficient on $RoA_{i,t-1}$ is –0.14 (t = –7.41). The negative coefficient shows that when $RoA_{i,t-1}$ decreases by 1%, future idiosyncratic risk-taking increases by 0.14%. In the second regression with the dummy $I(RoA_{i,t-1}< 0)$, for the negative RoA shocks, the R&D expenses increase by 0.02% in response to a 1% decrease in $RoA_{i,t-1}$, while for the negative RoA shocks, they increase by 0.21% (= 0.02 + 0.19). Therefore, firms experiencing negative shocks significantly increase their idiosyncratic risk by investing more in R&D projects, and the impact of negative shocks is much larger than that of positive shocks. In Reg III where we include other control variables, the coefficient of $RoA_{i,t-1}I(RoA_{i,t-1}< 0)$ becomes –0.01 (t = –3.53), indicating that the increase in R&D expenditures is 0.01% for positive RoA and 0.02% (0.01% + 0.01%) for negative RoA. This indicates that the impact of negative RoA shocks on the idiosyncratic risk-taking doubles that positive RoA shocks. Consistent with existing literature, we also find that small firms, value firms and high-leverage firms take less risk than their counterparts do.

When we use the volatility of RoA in Panel B and daily return idiosyncratic volatility as proxies for idiosyncratic risk in Panel C, we obtain similar results. For instance, in the third regression in Panel B, the coefficient on $RoA_{i,t-1}$ is –0.03 (t= –5.60) and the coefficient on $RoA_{i,t-1}I(RoA_{i,t-1}< 0)$ is –0.08 (t= –3.61). That is, $\nu_{i,t}^{RoA}$ increases by 0.03% in response to a 1% *decrease* in positive RoA shocks, but it increases by 0.11% (0.03% + 0.08%) in response to a 1% *decrease* in negative RoA shocks. Hence, the increase in $\nu_{i,t}^{RoA}$ in response to negative RoA shocks is about three times that in response to positive shocks. For Reg III in Panel C, the coefficient on $RoA_{i,t-1}$ is –0.03 (t = –1.82) and the coefficient on $RoA_{i,t-1}I(RoA_{i,t-1}< 0)$ is –0.11 (t = –3.40), which indicates that the increase in $\nu_{i,t}^{s}$ in response to the negative RoA (–0.14) is about four times the response to the positive RoA (–0.03).

Overall, we find strong support for our first prediction that the firms take on riskier investments given the low RoA, particularly for negative RoA shocks. Our results are robust across three proxies for idiosyncratic risk and over different horizons. Our results are also robust to the inclusion of lagged dependent variables and other lagged firm characteristics.

4.2 Negative Relation between Idiosyncratic Volatility and Stock Returns

We proceed to examine our second prediction that the strategic risk-shifting behavior adversely impacts stock returns. We first decompose idiosyncratic return volatility into two components, one related to previous RoA, and one unrelated. Then, we show that it is the strategic component predicted from the past RoA that negatively impacts the future stock returns. We further use the decomposition method of Hou and Loh (2012) to quantify the magnitude of this risk-shifting effect from the strategic component.

4.2.1 Decomposing the Negative Impacts of Risk-Shifting on Stock Returns

Our model states that when the asset values decrease, firms choose to increase idiosyncratic risk, which in turn results in lower stock-asset sensitivity and stock returns. Hence, we decompose the idiosyncratic volatility of stock returns $\nu^s_{i,t}$ into the predicted and residual components in response to RoA. The idiosyncratic volatility at month t is computed using current one-month daily returns and three-month daily returns up to the end of current month, respectively. To decompose the monthly and quarterly idiosyncratic volatility, we estimate the following cross-sectional regression at month t,

$$\nu^s_{i,t} = a_t + b_t RoA_{i,t} + c_t RoA_{i,t} I(RoA_{i,t} < 0) + u_{i,t}, \tag{21}$$

where $u_{i,t}$ is the error term. To be consistent with the decomposition method proposed by Hou et al. (2012), we use the contemporaneous $RoA_{i,t}$ to decompose $\nu^s_{i,t}$. The results using $RoA_{i,t-1}$ are very similar and are available upon request. Based on the estimated coefficients at each month, we then have the following decomposition,

$$\begin{aligned} \nu^s_{i,t} &= \nu^{Pred}_{i,t} + \nu^{Rsd}_{i,t} \\ &= (\hat{b}_t RoA_{i,t} + \hat{c}_t RoA_{i,t} I(RoA_{i,t} < 0)) + (\hat{a}_t + u_{i,t}). \end{aligned} \tag{22}$$

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

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

$$r_{i,t} = a_t + b_t \nu^s_{i,t-1} + c_t control_{i,t-1} + u_{i,t}, \tag{23}$$

where control variables, $control_{i,t-1}$, include size, book to market ratio, previous returns, market leverage and factor loadings on market, size and value factors. We conduct statistical inference 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.

Table 4 reports the estimation results. For robustness, we present two sets of results. In Panel A, $\nu^s_{i,t-1}$ is computed using previous one-month daily returns, while in Panel B, $\nu^s_{i,t-1}$ is computed using previous three-month daily returns.

Within each panel, we investigate which component, $\nu_{i,t-1}^{Pred}$ or $\nu_{i,t-1}^{Res}$, has a significant negative relation with future returns. For the first regression in Panel A, the coefficient on $\nu_{i,t-1}^{s}$ is –0.13 (t = –4.13). That is, if annualized volatility increases by 10%, then the stock return for next month decreases by 1.3%, which confirms the finding in Ang et al. (2006) that idiosyncratic volatility $\nu_{i,t-1}^{s}$ has a negative impact on future stock returns $r_{i,t}$. We replace $\nu_{i,t-1}^{s}$ with the predicted component, $\nu_{i,t-1}^{Pred}$, in the second regression and with the residual component, $\nu_{i,t-1}^{Res}$, in the third regression to examine their separate effects on the future stock returns. We include both components in the fourth regression. In the second regression, the negative impact of the predicted component, $\nu_{i,t-1}^{Pred}$, on stock returns is economically and statistically significant, with a coefficient of –1.41 (t = –11.42). In sharp contrast, the estimated coefficient of residual component $\nu_{i,t-1}^{Rsd}$ is nearly zero and statistically insignificant in Reg III. This sharp contrast indicates that the firm's risk-shifting behavior, captured by $\nu_{i,t}^{Pred}$, is the driving force behind the negative relation between idiosyncratic volatility and future stock returns. When including both components in Reg IV, the estimated coefficients on $\nu_{i,t-1}^{Pred}$ and $\nu_{i,t-1}^{Rsd}$ remain very similar in terms of magnitude.

Among the control variables, size and market leverage are negatively associated with future stock returns, book-to-market ratio is positively associated with future returns, and lagged six-month cumulative stock return is positively related to future returns. Consistent with the findings in the literature, all these characteristics are highly statistically significant. Additionally, contemporaneous loading on the market factor carries a significant positive coefficient while 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 $\nu_{i,t-1}^{s}$ is computed using three-month daily returns. To save space, we focus our future discussion on the one-month horizon, which is consistent with most of the existing literature.

To summarize, by decomposing the idiosyncratic volatility into the predicted and residual components, we have shown that the predictive power of idiosyncratic volatility for subsequent returns comes primarily from the strategic component that is predicted from $RoA_{i,t-1}$ and $RoA_{i,t-1}I(RoA_{i,t-1} < 0)$.

4.2.2 Quantifying the Negative Impacts of Risk-Shifting on Stock Returns in Hou et al. (2012) Decomposition

In a recent paper, Hou et al. (2012) evaluate a large number of existing explanations for the negative relation between idiosyncratic volatility and subsequent stock returns. They propose a methodology to decompose 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 magnitude of impacts from candidate variables. Hou et al. (2012) show 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 et al. (2012) is as follows. First, for each month t, stock returns are regressed on lagged idiosyncratic volatility cross-sectionally,

$$r^s_{i,t} = \alpha_t + \gamma_t \nu^s_{i,t-1} + u_{i,t}. \tag{24}$$

Next, idiosyncratic volatility is regressed on a candidate variable,

$$\nu^s_{i,t-1} = a_{t-1} + \delta_{t-1} Candidate_{i,t-1} + u_{i,t-1}. \tag{25}$$

The component $\delta_{t-1} Candidate_{i,t-1}$ is essentially the same as our predicted component $\nu^{Pred}_{i,t}$ in equation (22). Lastly, γ_t is decomposed into two components, γ^c_t, explained by the candidate and γ^r_t, explained by the residual,

$$\gamma_t = \frac{Cov\left(r^s_{i,t}, \nu^s_{i,t-1}\right)}{Var\left(\nu^s_{i,t-1}\right)} = \frac{Cov\left(r^s_{i,t}, \delta_{t-1} Candidate_{i,t-1}\right)}{Var\left(\nu^s_{i,t-1}\right)} + \frac{Cov\left(r^s_{i,t}, a_{t-1} + u_{i,t-1}\right)}{Var\left(\nu^s_{i,t-1}\right)} = \gamma^c_t + \gamma^r_t. \tag{26}$$

To be consistent with Hou et al. (2012), we exclude observations with a stock price lower than one dollar.

Table 5 shows the results from the Hou-Loh decomposition. As in Table 4, 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 estimation results for the three steps of the Hou-Loh decomposition, respectively. For the one-month idiosyncratic volatility, for the first step in Panel A, the coefficient of $\nu^s_{i,t-1}$ is –0.15 (t = –3.34), confirming the negative relation between idiosyncratic volatility and future stock return. In the second step in Panel B, we regress idiosyncratic volatility on $RoA_{i,t-1}$ and $RoA_{i,t-1} I(RoA_{i,t-1} < 0)$. Both variables are significantly negatively related to idiosyncratic volatility, especially the asymmetric part, $RoA_{i,t-1} I(RoA_{i,t-1} < 0)$, which is consistent with our findings in previous section. In the last step of decomposition in Panel C, the predicted component γ^c_t, using $RoA_{i,t-1}$ and $RoA_{i,t-1} I(RoA_{i,t-1} < 0)$, explains 77.21% (= –0.11/–0.15) of the negative impact of idiosyncratic volatility on stock returns, while the residual component, γ^r_t, suggests that a proportion of 22.79% (= –0.03/–0.15) remains unexplained. In addition, the t-statistic of γ_t^c is -9.81, which is highly significant, while the t-statistic of γ_t^r is –0.93, which is insignificant. We report the decomposition of Hou et al. (2012) using three-month idiosyncratic volatility in the right panel. The results are similar to the left panel.

In Hou et al. (2012), the most promising variable is maximum daily return, and it can explain about 53.8% of the volatility puzzle. Many existing explanations examined in Hou et al. (2012) explain less than 10% of the idiosyncratic volatility puzzle. In sharp contrast, our results in Table 4 show that the risk-shifting mechanism alone can explain a striking 77.21% of the idiosyncratic volatility puzzle.

4.3 Alternative Explanations

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

4.3.1 Summary of Alternative Explanations for the Idiosyncratic Volatility Puzzle

Bekaert, Hodrick, and Zhang (2010) provide a summary of existing studies of how firm fundamentals affect idiosyncratic risk, and thus possibly affect stock returns. Cao, Simin, and 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 asset over book assets ($MABA$) as a proxy. Irvine and Pontiff (2009) and Gaspar and 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 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 first order difference in EPS to proxy for innovations in earnings, and then compute a cross-sectional variance of the earnings innovations for each of the 48 industries and assign this earning dispersion measure to each individual firm.

In addition, we include all alternatives cited in Hou et al. (2012). First, Jiang et al. (2009) show that high idiosyncratic volatility stocks have negative earnings shocks both before and after portfolio formation, and argue that 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 an candidate. It is also possible that the negative association between idiosyncratic volatility and stock returns is a reflection of illiquidity. For this concern, we adopt a transaction cost/liquidity measure developed in Lesmond, Ogden, and 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 and 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 forecast on earnings to proxy for the uncertainty of volatility parameter. Using a similar approach, we follow Diether, Malloy, and Scherbina (2002) and use the number of analysts ($Analysts$) to proxy for the dispersion of earning forecasts, the analysts who provide current fiscal year annual earnings estimates in the I/B/E/S database. 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 in the past month, proposed by Bali et al. (2011). We exclude the maximum daily return because the maximum daily return, proposed as an indicator for stocks preferred by lottery-seeking investors, has a high collinearity with idiosyncratic volatility. Hou et al. (2012) report a 89% correlation between the maximum daily return and the idiosyncratic volatility measure. 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.

4.3.2 The Significance of the Risk-Shifting Proxy in Presence of Alternatives

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

$$r_{i,t} = a_t + b_t \nu_{i,t-1}^{Pred} + c_t \nu_{i,t-1}^{Rsd} + d_t Alternative_{i,t-1} + e_t control_{i,t-1} + u_{i,t}, \tag{27}$$

where $Alternative_{i,t-1}$ stands for an alternative variable. If the risk-shifting story is robust to alternative explanations, we expect that the coefficient b_t remains significantly negative.

Table 6 presents the results of nine regressions with different alternatives. We include the alternatives one by one for regressions I to VIII. In the final regression, we include all alternatives together. Across all nine regressions, the coefficients on $\nu_{i,t-1}^{Pred}$ range between

–1.12 and –1.41, with t-statistics at least greater than 11.01 in absolute term. 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 other alternative explanations. Meanwhile, the coefficient on $\nu^{Rsd}_{i,t-1}$ range between –0.07 and 0.00, with t-statistics insignificant in six out of nine 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 and insignificant, possibly because $MABA$ is usually highly correlated with the book to market ratio. Next are the two competition proxies, $IndTurn$ and $Dispers$. The coefficient on $IndTurn$ is statistically insignificant, while the coefficient on $Dispers$ is significant and negative, which is consistent with previous literature. 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 coefficients on $Reversal$ and $ESkew$ are both negative and significant, indicating that firms with strong return reversal effect and high idiosyncratic skewness tend to have lower future stock returns. Finally, the number of analysts and the indicator for missing records of analysts are both insignificant.

To summarize, in the presence of all the alternative explanations, the strategic component of idiosyncratic volatility predicted by $RoA_{i,t-1}$ and $RoA_{i,t-1}I(RoA_{i,t-1} < 0)$ 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.

4.3.3 Contribution of Risk-Shifting Explanation in Hou et al. (2012) Decomposition

In the previous section, we show that alternative explanations cannot attenuate the significance or explanatory power of risk-shifting behavior, proxied by RoA. 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 other competing variables. We adopt the Hou-Loh decomposition introduced in Section 4.2.2. In this section where the Hou-Loh decomposition include all alternative variables, we expect that the best explanation variable should account for the highest proportion of γ_t.

Table 7 presents the results for the multivariable decomposition. The left panel contains the results for idiosyncratic volatility computed from one-month daily stock return, and the right panel contains results for idiosyncratic volatility computed from three-month daily stock returns. From the left panel, the risk-shifting variable, proxied by $RoA_{i,t-1}$ and $RoA_{i,t-1}I(RoA_{i,t-1} < 0)$, alone captures 41.15% (= –0.05/–0.12) of the puzzle. Compared to Table 5, 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 alternative explanations.

The time-series average γ_t^j divided by γ_t measures the fraction of the negative idiosyncratic volatility-return explained by any other candidate variable j. MABA, industry turnover, earnings dispersion, SUE, short-term reversal, expected idiosyncratic skewness and the number of analysts each explain 6.77%, 1.07%, 1.09%, 9.56%, 0.43%, 29.84%, 19.16% and 2.77%, respectively. Among all the competing explanations, reversal has the highest contribution.

Lastly, γ_t^r for the residual component is 0.01 with a t-statistic of 0.49. Therefore, this low statistic power indicates that the point estimation of the negative contribution from the residual component does not have sufficient economic meaning.

The right panel presents results using three-month idiosyncratic volatility. It shows a very similar pattern to the left panel. The risk-shifting variable itself explains 59.88% of the negative relation between idiosyncratic volatility and stock returns. In this decomposition, $ESkew$ explains a large proportion of 18.65% and $Reversal$ significantly declines to 16.09%. In addition, SUE is highly significant, but it only explains 8.94% of the negative relation between idiosyncratic volatility and future stock returns.

In short, the results in Table 7 strongly demonstrate that, compared to other explanations, the risk-shifting variable explains 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

We examine a prominent agency conflict problem between equity and debt holders and its implication for cross-sectional stock returns. Due to limited liability, equity holders have incentives to take on more high-risk projects because they capture upside profits but have limited downside exposure. The debt-in-place, as an embedded put option, provides downside protection for equity holders, particularly for firms with increased high idiosyncratic volatility.

We conduct thorough and solid tests for our two predictions. In testing our first prediction on the negative association between RoA and subsequent idiosyncratic risk-taking, we carefully use the R&D investments, volatility of RoA and idiosyncratic volatility of stock returns as our risk-taking proxies. Our three proxies uniformly and consistently suggest that the negative relation between profitability and risk-shifting behavior is amplified in firms experiencing negative cash flow shocks.

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 less risk premiums and receiving lower stock returns. We empirically confirm that only the component of idiosyncratic volatility predicted from the past profitability variable, RoA, has an adverse impact on stock returns. Specifically, the strategic component alone can explain 77.21% and 94.33% of the negative impact of idiosyncratic volatility on monthly stock returns when the volatility is computed using one- and three-month daily stock returns, respectively. 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.

The limitation of our model is that we assume that the firms change their risk profile by taking on projects with high idiosyncratic risk, while keeping asset beta and market volatility constant. In other words, the counter-cyclical time variation of asset risk is mainly driven by its idiosyncratic component. However, it is well known that market risk is counter-cyclical, which has been studied in a macroeconomic framework (Chen (2009) and Bhamra et al. (2010)). It will be fruitful to extend our model in this direction.

References

Albuquerue, Rui, and Neng Wang, 2008, Agency conflicts, investment, and asset pricing, *Journal of Finance* 63, 1–40.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2009, High idiosyncratic volatility and low returns: International and further U.S. evidence, *Journal of Financial Economics* 91, 1–23.

Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2013, Anomalies and financial distress, *Journal of Financial Economics* 108, 139–159.

Babenko, Ilona, Oliver Boguth, and Yuri Tserlukevich, 2013, Idiosyncratic cash flows and systematic risk, *ASU Working Paper* .

Bali, Turan G., Nusret Cakici, and Robert F. Whitelaw, 2011, Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99, 427–446.

Barberis, Nicholas, and Ming Huang, 2008, Stocks as lotteries: The implications of probability weighting for security prices, *American Economic Review* 98, 2066–2100.

Bekaert, Geert, Robert J Hodrick, and Xiaoyan Zhang, 2010, Aggregate idiosyncratic volatility, *Journal of Financial and Quantitative Analysis* 1, 1–62.

Berk, Jonathan B., Richard C. Green, and Vasant Naik, 1999, Optimal investment, growth options and security returns, *Journal of Finance* 54, 1553 – 1607.

Bhamra, Harjoat, and Kyung Shim, 2013, Stochastic idiosyncratic operating risk and real options: Implications for stock returns, *Working Paper, Available at SSRN 2199749* .

Bhamra, Harjoat S., Lars-Alexander Kuehn, and Ilya A. Strebulaev, 2010, The levered equity risk premium and credit spreads: A unified framework, *Review of Financial Studies* 23, 645–703.

Boehme, Rodney D, Bartley R Danielsen, Praveen Kumar, and Sorin M Sorescu, 2009, Idiosyncratic risk and the cross-section of stock returns: Merton (1987) meets miller (1977), *Journal of Financial Markets* 12, 438–468.

Boyer, Brian, Todd Mitton, and Keith Vorkink, 2010, Expected idiosyncratic skewness, *Review of Financial Studies* 23, 169–202.

Cao, Charles, Timothy Simin, and Jing Zhao, 2008, Can growth options explain the trend in idiosyncratic risk?, *Review of Financial Studies* 21, 2599–2633.

Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross-section of returns, *Journal of Finance* 59, 2577–2603.

Carlson, Murray, and Ali Lazrak, 2010, Leverage choice and credit spreads when managers risk shift, *Journal of Finance* 65, 2323–2362.

Chen, Hui, 2009, Macroeconomic conditions and the puzzles of credit spreads and capital structure, *Journal of Finance, forthcoming* .

Chun, Hyunbae, Jung-Wook Kim, Randall Morck, and Bernard Yeung, 2008, Creative destruction and firm-specific performance heterogeneity, *Journal of Financial Economics* 89, 109–135.

Comin, Diego A, and Thomas Philippon, 2006, *The rise in firm-level volatility: Causes and consequences*, 167–228 (MIT Press).

Core, John, and Wayne Guay, 1999, The use of equity grants to manage optimal equity incentive levels, *Journal of Accounting and Economics* 28, 151–184.

Davydenko, Sergei A., 2008, When do firms default? a study of the default boundary, *Working paper* .

Davydenko, Sergei A., and Ilya A. Strebulaev, 2007, Strategic actions and credit spreads: An empirical investigation, *Journal of Finance* 62, 2633–2671.

Diether, Karl B, Christopher J Malloy, and Anna Scherbina, 2002, Differences of opinion and the cross section of stock returns, *Journal of Finance* 57, 2113–2141.

Eisdorfer, Assaf, 2008, Empirical evidence of risk shifting in financially distressed firms, *Journal of Finance* 63, 609–637.

Fama, Eugene F, and Kenneth R French, 2013, A five-factor asset pricing model, *Fama-Miller Working Paper* .

Fan, Hua, and Suresh M. Sundaresan, 2000, Debt valuation, renegotiation, and optimal dividend policy, *Review of Financial Studies* 13, 1057–1099.

Favara, Giovanni, Erique Schroth, and Philp Valta, 2011, Strategic default and equity risk across countries, *Journal of Finance, Forthcoming* .

Fu, Fangjian, 2009, Idiosyncratic risk and the cross-section of expected stock returns, *Journal of Financial Economics* 91, 24–37.

Galai, Dan, and Ronald W. Masulis, 1976, The option pricing model and the risk factor of stock, *Journal of Financial Economics* 3, 53–81.

Garlappi, Lorenzo, and Hong Yan, 2011, Financial distress and the cross section of equity returns, *Journal of Finance* 66, 789 – 822.

Gaspar, Jos Miguel, and Massimo Massa, 2006, Idiosyncratic volatility and product market competition, *Journal of Business* 79, 3125–3152.

Gomes, João F., Leonid Kogan, and Lu Zhang, 2003, Equilibrium cross section of returns, *Journal of Political Economy* 111, 693–732.

Gomes, João F., and Lukas Schmid, 2010, Levered returns, *Journal of Finance* 65, 467–494.

Han, Yufeng, and David Lesmond, 2011, Liquidity biases and the pricing of cross-sectional idiosyncratic volatility, *Review of Financial Studies* 24, 1590–1629.

Hennessy, Christopher A., and Yuri Tserlukevich, 2008, Taxation, agency conflicts, and the choice between callable and convertible debt, *Journal of Economic Theory* 143, 374–404.

Hirshleifer, David, Angie Low, and Siew Hong Teoh, 2012, Are overconfident ceos better innovators?, *Journal of Finance* 67, 1457–1498.

Hou, Kewei, and Roger Loh, 2012, Have we solved the idiosyncratic volatility puzzle?, *Fisher College of Business Working Paper* 028.

Hou, Kewei, and Tobias J Moskowitz, 2005, Market frictions, price delay, and the cross-section of expected returns, *Review of Financial Studies* 18, 981–1020.

Hou, Kewei, Chen Xue, and Lu Zhang, 2012, Digesting anomalies: An investment approach, Technical report, National Bureau of Economic Research.

Huang, Alan Guoming, 2009, The cross section of cashflow volatility and expected stock returns, *Journal of Empirical Finance* 16, 409–429.

Huang, Wei, Qianqiu Liu, S Ghon Rhee, and Liang Zhang, 2010, Return reversals, idiosyncratic risk, and expected returns, *Review of Financial Studies* 23, 147–168.

Irvine, Paul J, and Jeffrey Pontiff, 2009, Idiosyncratic return volatility, cash flows, and product market competition, *Review of Financial Studies* 22, 1149–1177.

Jensen, Michael C., and William H. Meckling, 1976, Theory of the firm: Managerial behavior, agency costs and ownership structure, *Journal of Financial Economics* 3, 305–360.

Jiang, George J., Danielle Xu, and Tong Yao, 2009, The information content of idiosyncratic volatility, *Journal of Financial and Quantitative Analysis* 44, 1–28.

Johnson, Timothy C., 2004, Forecast dispersion and the cross section of expected returns, *Journal of Finance* 59, 1957–1978.

Leland, Hayne E., 1994, Corporate debt value, bond covenants, and optimal capital structure, *Journal of Finance* 49, 1213–1252.

Leland, Hayne E., 1998, Agency costs, risk management, and capital structure, *Journal of Finance* 53, 1213–1243.

Lesmond, David A, Joseph P Ogden, and Charles A Trzcinka, 1999, A new estimate of transaction costs, *Review of Financial Studies* 12, 1113–1141.

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

Panageas, Stavros, 2010, Bailouts, the incentive to manage risk, and financial crises, *Journal of Financial Economics* 95, 296–311.

Titman, Sheridan, 1984, The effect of capital structure on a firm's liquidation decision, *Journal of Financial Economics* 13, 137–151.

Zhang, Lu, 2005, The value premium, *Journal of Finance* 60, 67–103.

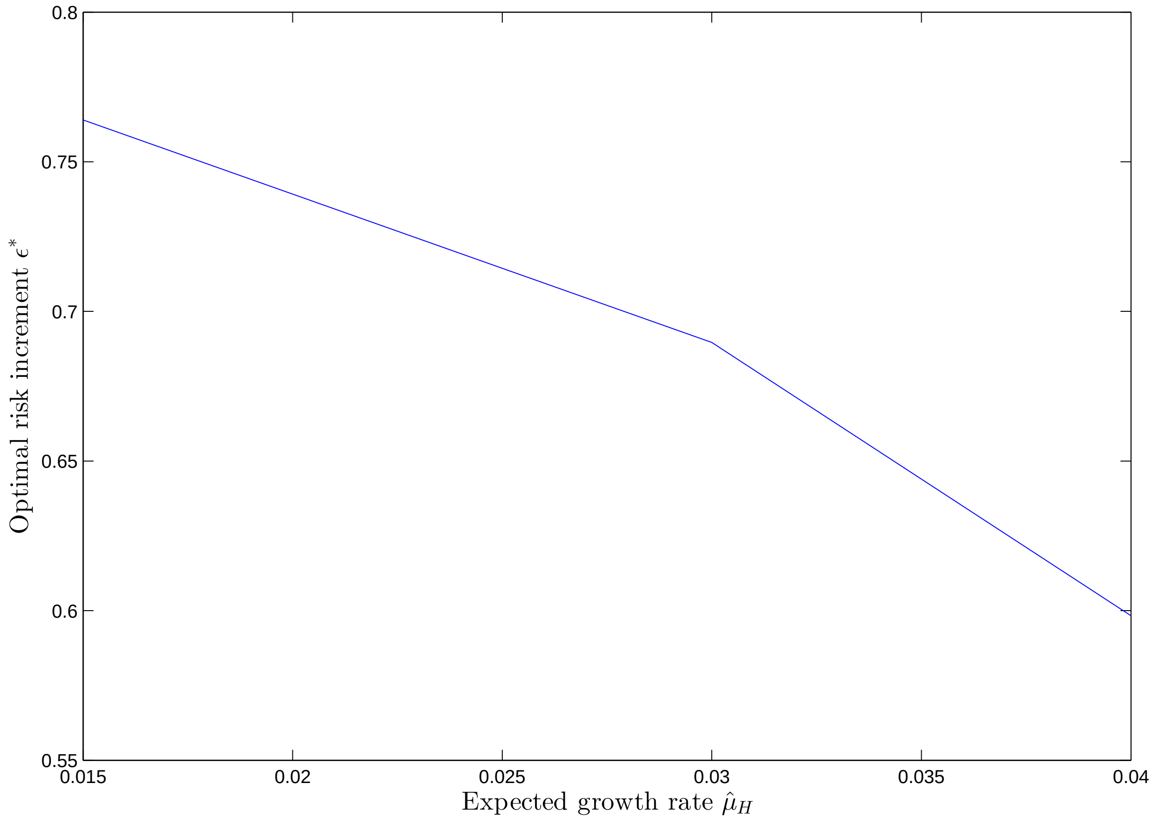

Figure 1: **Expected Growth Rate vs. Optimal Risk Increment.**
This figure plots the optimal risk increment ϵ^* against the expected growth rate $\hat{\mu}_H$ for three firms that are entering a high-risk state. These three firms start with the same $\hat{\mu}_L = 0.05$ and $\hat{\nu}_L = 0.1$ at $X_0 = 1$ 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 ϵ^*'s.

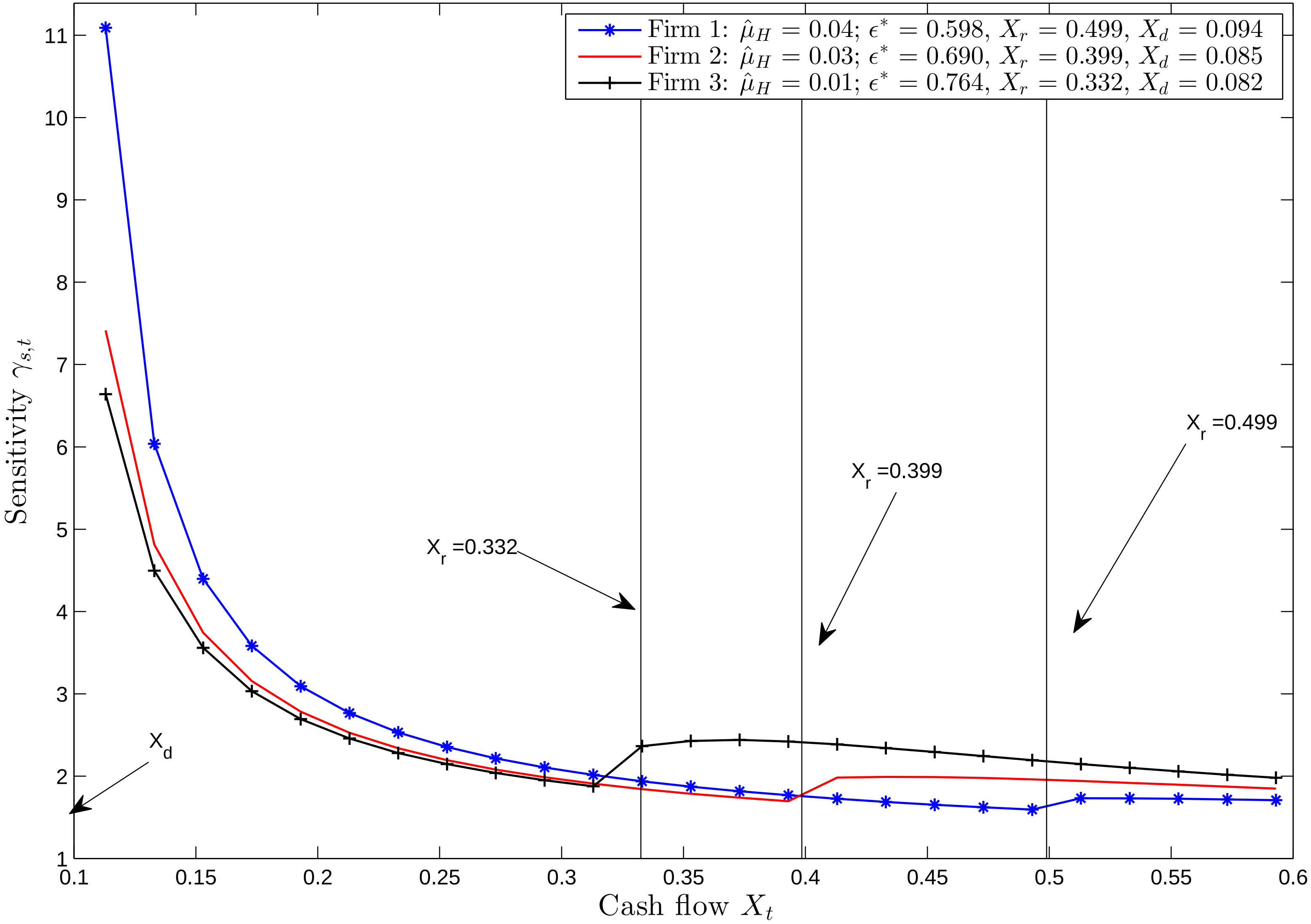

Figure 2: **Stock-Asset Sensitivity**

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 ϵ^*, X_r and X_d. We calculate $\gamma_{s,t}$ according to equation (9) for $X_t < X_r$ and equation (16) 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 η.

Parameters	Symbols	Values
Risk-free rate	r_f	0.06
Effective tax rate	τ	0.15
Market return volatility	σ_M	0.2
Market price of risk	θ	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)	ν_L	0.1
Total Vol. (Low-risk state)	σ_L	0.2059
Correlation coefficient	ρ_L	0.8742
Cost of excess volatility	η	0.20

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

This table reports the number of observations, mean, 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 RoAs ($\nu_{i,t}^{RoA}$), idiosyncratic stock return volatility ($\nu_{i,t}^{s}$), the natural logarithm of sales ($log(sales)_{i,t}$), book-to-market equity ($BE/ME_{i,t}$), market leverage ($MktLev_{i,t}$) and natural logarithm of delta and vega of managerial stock options. The monthly variables include stock return ($r_{i,t}^{s}$), monthly idiosyncratic stock return volatility ($\nu_{i,t}^{s}$), 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 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)
$RoA_{i,t}$	2435	4.82	13.71	0.68
$R\&D_{i,t}$	2435	4.48	1.97	0.97
$\nu_{i,t}^{RoA}$	2381	9.32	4.09	0.96
$\nu_{i,t}^{s}$	2396	55.02	26.04	0.70
$log(sales)_{i,t}$	2397	3.40	0.55	0.99
$BE/ME_{i,t}$	2320	0.74	0.37	0.88
$MktLev_{i,t}$	2400	0.22	0.10	0.96
$log(1+Delta)_{i,t}$	2435	0.85	0.41	0.96
$log(1+Vega)_{i,t}$	2435	0.61	0.29	0.97

Panel B. Monthly Data				
	Obs./Month	Mean	STD	AR(1)
$r_{i,t}^{s}$	2822	14.96	71.88	−0.04
$\nu_{i,t}^{s}$	2822	51.64	31.68	0.64
$Size_{i,t}$	2822	4.77	0.64	1.00
$BE/ME_{i,t}$	2746	0.76	0.39	0.96
$PreRets_{i,t}$	2764	12.99	80.99	0.81
$MktLev_{i,t}$	2822	0.23	0.10	0.98
$\beta_{i,t}^{mkt}$	2821	0.90	2.35	0.10
$\beta_{i,t}^{SMB}$	2821	0.77	3.18	0.06
$\beta_{i,t}^{HML}$	2821	0.15	3.93	0.03

Table 3: **Asymmetric Impacts of Return on Assets (RoA) on Subsequent Risk-Taking**

This table reports the results from the quarter-by-quarter Fama-MacBeth regressions at the firm level. We regress subsequent risk measures on a constant, lagged quarterly return on assets (RoA), and lagged firm characteristics quarter-by-quarter as follows:

$y_{i,t} = a_t + b_t RoA_{i,t-1} + c_t RoA_{i,t-1} I(RoA_{i,t-1} < 0) + d_t control_{i,t-1} + e_{i,t},$

where the dependent variable, $y_{i,t}$, is research and development expenditure $R\&D_{i,t}$ in Panel A, idiosyncratic volatility of RoAs $\nu^{RoA}_{i,t}$ in Panel B and quarterly idiosyncratic stock return volatility $\nu^{s}_{i,t}$ 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, $log(sales)_{i,t-1}$, book-to-market equity $BE/ME_{i,t-1}$, and market leverage $MktLev_{i,t-1}$ as well as the natural logarithm of delta and vega of managerial stock options. If the delta and vega from ExecuComp are missing, they are replaced with zero and indicator $I_{missingExec}$ is set to one. We also include $RoA_{i,t-2}$ and 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. $y_{i,t} = R\&D_{i,t}$			Panel B. $y_{i,t} = \nu^{RoA}_{i,t}$			Panel C. $y_{i,t} = \nu^{s}_{i,t}$		
	Reg I	Reg II	Reg III	Reg I	Reg II	Reg III	Reg I	Reg II	Reg III
Intercept	4.26	2.64	0.68	9.32	8.27	7.78	54.95	55.41	25.72
(t)	(7.84)	(7.37)	(5.67)	(23.68)	(21.37)	(20.62)	(25.49)	(22.50)	(16.00)
$RoA_{i,t-1}$	−0.14	−0.02	−0.01	−0.15	−0.07	−0.03	−0.57	−0.61	−0.03
(t)	(−7.41)	(−1.60)	(−3.59)	(−17.02)	(−8.25)	(−5.60)	(−23.10)	(−12.73)	(−1.82)
$RoA_{i,t-1} * I(RoA_{i,t-1} < 0)$		−0.19	−0.01		−0.22	−0.08		−0.16	−0.11
(t)		(−7.20)	(−3.53)		(−6.71)	(−3.61)		(−1.53)	(−3.40)
$R\&D^{Ind}_{i,t-1}$			0.15			0.08			0.05
(t)			(5.57)			(5.32)			(2.09)
$log(sales)_{i,t-1}$			−0.08			−0.65			−2.70
(t)			(−5.77)			(−21.74)			(−18.20)
$BE/ME_{i,t-1}$			−0.09			0.35			1.17
(t)			(−4.63)			(2.82)			(4.08)
$MktLev_{i,t-1}$			−0.59			−1.42			12.08
(t)			(−5.04)			(−6.31)			(12.83)
$log(1 + Delta)_{i,t-1}$			−0.02			−0.09			0.08
(t)			(−2.12)			(−4.77)			(2.19)
$log(1 + Vega)_{i,t-1}$			0.05			0.13			−0.07
(t)			(3.74)			(4.43)			(−1.17)
$I_{MissingExec}$			−1.20			0.41			−1.54
(t)			(−1.90)			(1.27)			(−1.71)
$RoA_{i,t-2}$			0.00			−0.03			−0.05
(t)			(−0.58)			(−10.36)			(−6.71)
$y_{i,t-1}$			0.51			0.35			0.60
(t)			(7.69)			(25.84)			(34.29)
$Adj.R^2$	0.18	0.21	0.79	0.12	0.14	0.32	0.09	0.09	0.54
Total N. of Obs.	322091			315647			322640		

Table 4: **Decomposing the Impact of Idiosyncratic Volatility on Stock Returns**
This table reports the results from the month-by-month Fama-MacBeth regressions at the firm level. We regress the monthly raw stock return in annual percent ($r^s_{i,t}$) on a constant, lagged return on assets ($RoA_{i,t-1}$), lagged idiosyncratic volatility ($\nu^s_{i,t-1}$), 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 return ($PreRets_{i,t-1}$) as well as the factor loadings on market factor ($\beta^{mkt}_{i,t}$), size factor ($\beta^{SMB}_{i,t}$) and value factor ($\beta^{HML}_{i,t}$). To decompose $\nu^s_{i,t-1}$ 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:
$\nu^s_{i,t-1} = a_{t-1} + b_{t-1}RoA_{i,t-1} + c_{t-1}RoA_{i,t-1}I(RoA_{i,t-1} < 0) + u_{i,t-1}$
where $u_{i,t-1}$ is the error term. The predicted component is calculated as $\nu^{Pred}_{i,t-1} = \hat{b}_{t-1}RoA_{i,t-1} + \hat{c}_{t-1}RoA_{i,t-1}I(RoA_{i,t-1} < 0)$ and the residual component as $\nu^{Rsd}_{i,t-1} = \nu^s_{i,t-1} - \nu^{Pred}_{i,t-1}$. 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 $\nu^s_{i,t-1}$				Panel B. Three-month $\nu^s_{i,t-1}$			
	Reg I	Reg II	Reg III	Reg IV	Reg I	Reg II	Reg III	Reg IV
Intercept	20.05	16.67	9.49	19.18	22.29	16.75	6.88	18.66
(t)	(3.89)	(3.05)	(1.67)	(4.03)	(4.50)	(3.08)	(1.26)	(4.06)
$\nu^s_{i,t-1}$	−0.13				−0.15			
(t)	(−4.13)				(−3.89)			
$\nu^{Pred}_{i,t-1}$		−1.41		−1.44		−1.23		−1.26
(t)		(−11.42)		(−10.94)		(−11.29)		(−10.69)
$\nu^{Rsd}_{i,t-1}$			0.00	−0.07			0.02	−0.06
(t)			(−0.05)	(−2.28)			(0.60)	(−1.77)
$size_{i,t-1}$	−2.84	−3.81	−1.85	−3.97	−3.04	−3.79	−1.59	−3.87
(t)	(−4.71)	(−6.46)	(−2.85)	(−7.21)	(−5.34)	(−6.43)	(−2.56)	(−7.26)
$BE/ME_{i,t-1}$	15.21	14.51	15.64	14.13	15.07	14.50	15.70	14.11
(t)	(9.16)	(9.05)	(9.30)	(8.92)	(9.16)	(9.03)	(9.44)	(8.99)
$MktLev_{i,t-1}$	−15.42	−19.80	−16.36	−19.03	−15.39	−19.80	−16.72	−19.17
(t)	(−4.16)	(−5.30)	(−4.31)	(−5.15)	(−4.20)	(−5.31)	(−4.41)	(−5.23)
$\beta^{mkt}_{i,t}$	6.40	6.09	6.05	6.47	6.47	6.09	6.02	6.48
(t)	(5.46)	(5.22)	(5.06)	(5.65)	(5.65)	(5.22)	(5.11)	(5.77)
$\beta^{SMB}_{i,t}$	0.47	0.47	0.45	0.49	0.46	0.47	0.44	0.48
(t)	(1.10)	(1.09)	(1.06)	(1.12)	(1.08)	(1.08)	(1.05)	(1.10)
$\beta^{HML}_{i,t}$	−0.97	−0.85	−0.85	−1.01	−1.03	−0.86	−0.86	−1.04
(t)	(−1.74)	(−1.53)	(−1.52)	(−1.81)	(−1.88)	(−1.54)	(−1.56)	(−1.91)
$PreRets_{i,t-1}$	0.04	0.02	0.05	0.02	0.04	0.02	0.05	0.02
(t)	(2.76)	(1.11)	(3.10)	(1.11)	(2.97)	(1.13)	(3.11)	(1.24)
$Adj.R^2$	0.05	0.05	0.05	0.06	0.05	0.05	0.05	0.06

Table 5: **Quantifying the Impact of Strategic Component of Idiosyncratic Volatility of on Stock Returns**

This table reports the impact of the strategic component of idiosyncratic volatility on stock returns. We follow Hou and Loh(2012) and decompose a negative coefficient obtained from the Fama-MacBeth regression of stock returns on past idiosyncratic volatility $\nu^s_{i,t-1}$. The past idiosyncratic volatility is computed using previous one-month and three-month daily returns, respectively. The negative coefficient is decomposed into a strategic component that is related to $RoA_{i,t-1}$ and $RoA_{i,t-1}I(RoA_{i,t-1} < 0)$, 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., $r^s_{i,t} = \alpha_t + \gamma_t \nu^s_{i,t-1} + u_{i,t}$. Second, idiosyncratic volatility is regressed on a candidate variable, i.e., $\nu^s_{i,t-1} = a_{t-1} + \delta_{t-1} Candidate_{i,t-1} + u_{i,t-1}$. We obtain two orthogonal components, such as $\delta_{t-1}Candidate_{i,t-1}$ and $a_{t-1} + \varepsilon_{i,t-1}$. Lastly, γ_t is decomposed into two components. Specifically, $\gamma_t = \frac{Cov(r^s_{i,t}, \nu^s_{i,t-1})}{Var(\nu^s_{i,t-1})} = \frac{Cov(r^s_{i,t}, \delta_{t-1}Candidate_{i,t-1})}{Var(\nu^s_{i,t-1})} + \frac{Cov(r^s_{i,t}, a_{t-1}+u_{i,t-1})}{Var(\nu^s_{i,t-1})} = \gamma^c_t + \gamma^r_t$. The time-series average γ^c_t divided by γ_t measures the fraction of the negative idiosyncratic volatility-return explained by the candidate variable. Our candidate variable is the combination of $RoA_{i,t-1}$ and $RoA_{i,t-1}I(RoA_{i,t-1} < 0)$. The t-statistics in parentheses are adjusted using the Newey-West method with 12 lags.

Panel A. Regression of monthly stock returns $r^s_{i,t}$ on $\nu^s_{i,t-1}$				
	One-month $\nu^s_{i,t-1}$		Three-month $\nu^s_{i,t-1}$	
	γ_t		γ_t	
Intercept	21.91		22.09	
(t)	(7.53)		(8.07)	
$\nu^s_{i,t-1}$	-0.15		-0.14	
(t)	(-3.34)		(-2.69)	
Panel B. Regression of $\nu^s_{i,t-1}$ on $RoA_{i,t-1}$ and $RoA_{i,t-1}I(RoA_{i,t-1} < 0)$				
	One-month $\nu^s_{i,t-1}$		Three-month $\nu^s_{i,t-1}$	
	δ_t		δ_t	
Intercept	47.38		51.73	
(t)	(41.82)		(42.31)	
$RoA_{i,t-1}$	-0.43		-0.45	
(t)	(-23.82)		(-23.56)	
$RoA_{i,t-1}I(RoA_{i,t-1} < 0)$	-0.61		-0.73	
(t)	(-2.33)		(-2.25)	
Adj. R^2	0.09		0.11	
Panel C. Decomposition of the $\nu^s_{i,t-1}$ coefficient				
	One-month $\nu^s_{i,t-1}$		Three-month $\nu^s_{i,t-1}$	
	γ^c_t	$\gamma^c_t/\gamma_t(\%)$	$\gamma^c_{i,t}$	$\gamma^c_t/\gamma_t(\%)$
$RoA_{i,t-1} + RoA_{i,t-1}I(RoA_{i,t-1} < 0)$	-0.11	77.21	-0.13	94.33
(t)	(-9.81)		(-9.55)	
	γ^r_t	$\gamma^r_t/\gamma_t(\%)$	γ^r_t	$\gamma^r_{i,t}/\gamma_t(\%)$
Residuals $\varepsilon_{i,t-1}$	-0.03	22.79	-0.01	5.66
(t)	(-0.93)		(-0.19)	

Table 6: **Alternative Explanations**

This table presents the results from month-by-month Fama-MacBeth regressions at the firm level and controls for alternative explanations. $MABA_{i,t-1}$ is the ratio of market assets over 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 equal to zero each month (Lesmond, Ogden, and Trzcinka, 1999), $Reversal_{i,t-1}$ is the lagged monthly return in annual percent proxing for the return reversal effect (Huang, Liu, Rhee and Zhang, 2010), $ESkew_{i,t-1}$ denotes the monthly expected stock return skewness obtain 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 definitions of the other control variables are the same as in Table 4. The t-statistics in parentheses are adjusted using the Newey-West method with 12 lags.

	I	II	III	IV	V	VI	VII	VIII	XI
Intercept	21.47	21.85	24.62	21.51	18.39	18.12	43.48	27.37	49.39
(t)	(3.17)	(3.27)	(3.67)	(3.21)	(2.59)	(2.69)	(5.50)	(3.76)	(5.14)
$\nu_{i,t-1}^{Pred}$	−1.39	−1.38	−1.37	−1.13	−1.37	−1.41	−1.35	−1.38	−1.12
(t)	(−11.57)	(−11.30)	(−11.25)	(−9.64)	(−11.18)	(−11.25)	(−11.01)	(−11.28)	(−9.45)
$\nu_{i,t-1}^{Rsd}$	−0.06	−0.06	−0.06	−0.07	−0.06	0.00	−0.06	−0.07	0.02
(t)	(−2.06)	(−2.11)	(−2.05)	(−2.45)	(−1.83)	(0.14)	(−1.94)	(−2.38)	(0.58)
$size_{i,t-1}$	−4.48	−4.53	−4.55	−4.79	−4.15	−3.97	−6.69	−5.80	−7.11
(t)	(−4.28)	(−4.32)	(−4.33)	(−4.58)	(−3.90)	(−3.80)	(−6.28)	(−5.42)	(−6.30)
$BE/ME_{i,t-1}$	12.75	12.83	13.09	13.90	12.68	10.87	13.33	12.52	11.32
(t)	(5.39)	(5.49)	(5.56)	(5.86)	(5.37)	(4.68)	(5.55)	(5.34)	(4.84)
$MktLev_{i,t-1}$	−15.48	−15.37	−15.29	−12.33	−15.57	−14.98	−14.81	−15.42	−11.83
(t)	(−3.38)	(−3.22)	(−3.23)	(−2.64)	(−3.26)	(−3.09)	(−3.10)	(−3.24)	(−2.53)
$\beta_{i,t}^{mkt}$	5.90	5.89	5.86	5.83	5.96	5.54	5.51	5.87	5.25
(t)	(5.69)	(5.65)	(5.68)	(5.60)	(5.70)	(5.18)	(5.20)	(5.66)	(4.94)
$\beta_{i,t}^{SMB}$	0.45	0.45	0.44	0.48	0.48	0.44	0.37	0.50	0.50
(t)	(1.07)	(1.07)	(1.06)	(1.12)	(1.14)	(1.03)	(0.87)	(1.17)	(1.16)
$\beta_{i,t}^{HML}$	−0.94	−0.92	−0.91	−0.87	−0.92	−0.85	−0.87	−0.91	−0.83
(t)	(−1.74)	(−1.70)	(−1.69)	(−1.59)	(−1.69)	(−1.59)	(−1.62)	(−1.68)	(−1.58)
$PreRets_{i,t-1}$	0.02	0.03	0.03	0.01	0.03	0.02	0.02	0.03	0.00
(t)	(2.09)	(2.24)	(2.27)	(0.89)	(2.39)	(1.50)	(1.65)	(2.74)	(−0.14)
$MABA_{i,t-1}$	−0.03								−2.07
(t)	(−0.04)								(−2.26)
$IndTurn_{i,t-1}$		−209.34							−123.13
(t)		(−0.90)							(−0.79)
$Dispers_{i,t-1}$			−55.47						−87.27
(t)			(−3.09)						(−2.19)
$SUE_{i,t-1}$				6.93					7.06
(t)				(13.67)					(13.41)
$Zeros_{i,t-1}$					11.51				14.53
(t)					(2.47)				(3.08)
$Reversal_{i,t-1}$						−64.54			−69.37
(t)						(−12.37)			(−12.72)
$ESkew_{i,t-1}$							−11.47		−13.82
(t)							(−3.93)		(−4.51)
$Analysts_{i,t-1}$								−0.21	−0.51
(t)								(−0.17)	(−0.41)
$I_{MissAnalyst}$								0.51	−6.65
(t)								0.10	−1.30
$Adj.R^2$	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.07

Table 7: **Comparing the Impact of Strategic Component of Idiosyncratic Volatility on Stock Returns with Other Explanations**

This table reports the comparison between the impact of the strategic component of idiosyncratic volatility on stock returns with those of other explanatory variables. We follow Hou and Loh(2012) and decompose a negative coefficient obtained from the Fama-MacBeth regression of stock returns on past idiosyncratic volatility $\nu^s_{i,t-1}$. The past idiosyncratic volatility is computed using previous one-month and three-month 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., $r^s_{i,t} = \alpha_t + \gamma_t \nu^s_{i,t-1} + u_{i,t}$. Second, idiosyncratic volatility is regressed on n candidate variables indexed by j, i.e., $\nu^s_{i,t-1} = a_{t-1} + \sum_1^n \delta^j_{t-1} Candidate^j_{i,t-1} + u_{i,t-1}$. We obtain orthogonal components, such as $\delta^j_{t-1} Candidate^j_{i,t-1}$ and $a_{t-1} + \varepsilon_{i,t-1}$. Lastly, we decompose γ_t. Specifically, $\gamma_{i,t} = \frac{Cov(r^s_{i,t}, \nu^s_{i,t-1})}{Var(\nu^s_{i,t-1})} = \sum_1^n \frac{Cov(r^s_{i,t}, \delta^j_{t-1} Candidate^j_{i,t-1})}{Var(\nu^s_{,t-1})} + \frac{Cov(r^s_{i,t}, a_{i,t-1} + \varepsilon_{i,t-1})}{Var(\nu^s_{i,t-1})} = \sum_1^n \gamma^j_t + \gamma^r_{i,t}$. The time-series average γ^j_t divided by γ_t measures the fraction of the negative idiosyncratic volatility-return explained by the candidate variable j. Our candidate variable is the combination of $RoA_{i,t-1}$ and $RoA_{i,t-1} I(RoA_{i,t-1} < 0)$ that proxies for risk-shifting behavior. Other 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 $r^s_{i,t}$ on $\nu^s_{i,t-1}$				
	One-month $\nu^s_{i,t-1}$		Three-month $\nu^s_{i,t-1}$	
	γ_t		γ_t	
ν^s_{t-1}	−0.12		−0.12	
(t)	(−2.38)		(−2.25)	
Panel B. Decomposition of the $\nu^s_{i,t-1}$ coefficient				
	One-month $\nu^s_{i,t-1}$		Three-month $\nu^s_{i,t-1}$	
	γ^j_t	$\gamma^j_t/\gamma_t(\%)$	γ^j_t	$\gamma^j_t/\gamma_t(\%)$
$RoA_{i,t-1} + RoA_{i,t-1} * \mathbf{1}_{RoA_{i,t-1}<0}$	−0.05	41.15	−0.07	59.88
(t)	(−1.70)		(−4.70)	
$MABA_{i,t-1}$	−0.01	6.77	−0.01	9.69
(t)	(−1.81)		(−2.09)	
$IndTurn_{i,t-1}$	−0.00	1.07	−0.00	1.02
(t)	(−1.81)		(−1.51)	
$Dispers_{i,t-1}$	−0.00	1.09	−0.00	1.27
(t)	(−1.03)		(−1.09)	
$SUE_{i,t-1}$	−0.01	9.56	−0.01	8.94
(t)	(−3.59)		(−3.16)	
$Zeros_{i,t-1}$	−0.00	0.43	0.01	−6.02
(t)	(−0.07)		(1.12)	
$Reversal_{i,t-1}$	−0.04	29.84	−0.02	16.09
(t)	(−3.33)		(−3.11)	
$ESkew_{i,t-1}$	−0.02	19.16	−0.02	18.65
(t)	(−1.98)		(−1.60)	
$Analysts_{i,t-1}$	−0.00	2.77	−0.00	3.83
(t)	(−0.96)		(−1.24)	
	γ^r_t	$\gamma^r_t/\gamma_t(\%)$	γ^r_t	$\gamma^r_t/\gamma_t(\%)$
Residuals $\varepsilon_{i,t-1}$	0.01	−11.85	0.02	−13.34
(t)	(0.49)		(0.49)	

A Proofs

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

$$G(s, X_t) = H_t dt + e^{-r_f dt}\mathbb{E}^Q(G(s, X_t + dX_t)), \tag{28}$$

where $H_{s,t}$ denotes cash flows accruing to claim holders.

Standard dynamic programming suggests that $G(s, X_t)$ must satisfy the ordinary differential equation

$$\mu_s X G'_{s,t} + \frac{\sigma_s^2}{2} X^2 G''_{s,t} - r_f G_{s,t} + H_{s,t} = 0, \tag{29}$$

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.

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

$$E(s, X_t) = (1-\tau)\left(\frac{X_t}{r_f - \mu_s} - \frac{c}{r_f}\right) + e_{s,1}X_t^{\omega_{s,1}} + e_{s,2}X_t^{\omega_2}, \tag{30}$$

$$= (1-\tau)\left(V_{s,t} - \frac{c}{r_f}\right) + e_{s,1}X_t^{\omega_{s,1}} + e_{s,2}X_t^{\omega_2} \tag{31}$$

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

$$\frac{1}{2}\sigma_s^2\omega_s(\omega_s - 1) + \mu_s\omega_s - r_f = 0. \tag{32}$$

Given equation (2), Ito's lemma implies that the equity value $E(s, X_t) \equiv E_{s,t}$ satisfies

$$\frac{dE_{s,t}}{E_{s,t}} = \frac{1}{E_{s,t}}\left(\frac{\partial E_{s,t}}{\partial t} + \hat{\mu}_s X_t \frac{\partial E_{s,t}}{\partial X_t} + \frac{\sigma_s}{2} X_t^2 \frac{\partial^2 E_{s,t}}{\partial X_t^2}\right) dt + \frac{1}{E_{s,t}} X_t \sigma_s \frac{\partial E_{s,t}}{\partial X_t}. \tag{33}$$

The standard no-arbitrage argument gives us the following partial differential equation (PDE)

$$\frac{\partial E_{s,t}}{\partial t} + \mu_s X_t \frac{\partial E_{s,t}}{\partial X_t} + \frac{\sigma_s^2}{2} X_t^2 \frac{\partial^2 E_{s,t}}{\partial X_t^2} - r_f E_{s,t} + D_t = 0. \tag{34}$$

Substituting the above equation into equation (33), we obtain

$$\frac{dE_{s,t}}{E_{s,t}} = \frac{1}{E_{s,t}}\left[(\hat{\mu}_s - \mu_s)X_t\frac{\partial E_{s,t}}{\partial X_t} + r_f E_{s,t} - D_t\right]dt + \frac{1}{E_{s,t}}X_t\sigma_s\frac{\partial E_{s,t}}{\partial X_t}dW. \tag{35}$$

Simple algebraic manipulation yields

$$\frac{dE_{s,t} + D_t dt}{E_{s,t}} - r_f dt = \frac{1}{E_{s,t}}(\hat{\mu}_s - \mu_s)X_t\frac{\partial E_{s,t}}{\partial X_t}dt + \frac{1}{E_{s,t}}X_t\sigma_s\frac{\partial E_{s,t}}{\partial X_t}dW. \tag{36}$$

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

$$r^s_{s,t} - r_f dt = \gamma_{s,t}(\hat{\mu}_s dt + \sigma_s dW - \mu_s dt). \tag{37}$$

Since $\hat{\mu}_s dt - \mu_s dt = \lambda dt$, taking expectation on both sides yields

$$\mathbb{E}[r^s_{s,t}] = r_f dt + \mathbb{E}[\gamma_{s,t}\lambda dt]. \tag{38}$$

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

$$\begin{aligned}
\gamma_{s,t} =& \frac{X_t\partial E_{s,t}}{E_{s,t}\partial X_t} = \frac{V_{s,t}\partial E_{s,t}}{E_{s,t}\partial V_{s,t}} \\
=& \frac{1}{E_{s,t}}(X_t(1-\tau) + e_{s,1}\omega_{s,1}X_t^{\omega_{s,1}} + e_{s,2}\omega_{s,2}X_t^{\omega_{s,2}}) \\
=& \frac{1}{E_{s,t}}\left(E_{s,t} + \frac{c(1-\tau)}{r} - e_{s,1}X_t^{\omega_{s,1}} + e_{s,1}\omega_{s,1}X_t^{\omega_{s,1}} - e_{s,2}X_t^{\omega_{s,2}} + e_{s,2}\omega_{s,2}X_t^{\omega_{s,2}}\right) \\
=& 1 + \frac{c(1-\tau)}{rE_{s,t}} + \frac{(\omega_{s,1}-1)}{E_{s,t}}e_{s,1}X_t^{\omega_{s,1}} + \frac{(\omega_{s,2}-1)}{E_{s,t}}e_{s,2}X_t^{\omega_{s,2}}
\end{aligned} \tag{39}$$

A.1 Proposition 1 for the Firm after Risk-Shifting

To solve $e_{H,1}$ and $e_{H,2}$ for equation (31), we need boundary conditions. While the no-bubble condition implies $e_{H,2} = 0$, the value matching condition of equation (5) gives $e_{H,1} = -(V_H - c/r_f)(1-\tau)/X_d^{\omega_{H,1}}$. Hence, before bankruptcy $X_d \leq X_t < X_r$, the equity value function is

$$E_{H,t} = \left[\underbrace{\left(V_{H,t} - \frac{c}{r_f} \right)}_{\text{Equity-In-Place}} + \underbrace{\left(\frac{c}{r_f} - V_{H,d} \right) \left(\frac{X_t}{X_d} \right)^{\omega_{H,1}}}_{\text{Option of Delaying Bankruptcy}} \right] (1-\tau). \tag{40}$$

The equity value characterized by equation (40) consists of equity-in-place and the option of delaying bankruptcy. The equity-in-place is simply the assets-in-place minus debt, and the default option can be regarded as an American put option. Simply Substituting $e_{H,1}$ and $e_{H,2}$ into equation (39) , we obtain equation (9).

From the condition in equation (6), the optimal bankruptcy threshold X_d is given by

$$X_d = \frac{c(r_f - \mu_H)\omega_{H,1}}{r_f(\omega_{H,1} - 1)}. \tag{41}$$

Corollary 1 *The asset value is less than the value of the risk-free equivalent debt at bankruptcy and the bankruptcy threshold X_d decreases with asset idiosyncratic volatility.*

$$V_{H,d} \leq \frac{c}{r_f}; \tag{42}$$

$$\frac{\partial V_{H,d}}{\partial \nu_H} < 0. \tag{43}$$

From equation (41), we have

$$\frac{X_d}{(r_f - \mu_H)} = \frac{c\omega_{H,1}}{r_f(\omega_{H,1} - 1)}. \tag{44}$$

Because $X_d/(r_f - \mu_H) = V_{H,d}$ and $c\omega_{H,1}/(r_f(\omega_{H,1} - 1)) \leq c/r_f$, $V_{H,d} \leq c/r_f$. Additionally, because $\partial\omega_{H,1}/\partial\nu_H > 0$, $\partial X_d/\partial\nu_H < 0$ and therefore $\partial V_{H,d}/\partial\nu_H < 0$.

A.2 Proposition 2 for the Firm prior to Risk-Shifting

Similarly, the no bubble condition implies $e_{L,2} = 0$ for equation (31). The value matching condition of equation (11) suggests

$$\left(V_{L,r} - \frac{c}{r_f}\right)(1-\tau) + e_{L,1}X_r^{\omega_{L,1}} = \left(V_{H,r} - \frac{c}{r_f}\right)(1-\tau) + \left(\frac{c}{r_f} - V_{H,d}\right)\left(\frac{X_r}{X_d}\right)^{\omega_{H,1}}(1-\tau) - \eta\epsilon^2 V_{H,r}(1-\tau). \tag{45}$$

Hence,

$$e_{L,1} = \frac{(1-\tau)}{X_r^{\omega_{L,1}}}\left[(V_{H,r}(1-\eta\epsilon^2) - V_{L,r}) + \left(\frac{c}{r_f} - V_{H,d}\right)\left(\frac{X_r}{X_d}\right)^{\omega_{H,1}}\right]. \tag{46}$$

Substituting $e_{L,1}$ into equation (31) yields the equity valuation in the low-risk state

$$E_{L,t} = \left[\left(V_{L,t} - \frac{c}{r_f}\right) + (V_{H,r}(1-\eta\epsilon^2) - V_{L,r})\left(\frac{X_t}{X_r}\right)^{\omega_{L,1}} + (\frac{c}{r_f} - V_{H,d})\left(\frac{X_r}{X_d}\right)^{\omega_{H,1}}\left(\frac{X_t}{X_r}\right)^{\omega_{L,1}}\right](1-\tau). \tag{47}$$

The stock-asset sensitivity of equation (16) is obtained by substituting $e_{L,1}$ and $e_{L,2}$ into equation (39).

We use the smooth-pasting condition to derive the optimal risk-shifting threshold X_r. Multiplying equation (12) by X_r, its left-hand side becomes

$$X_r E'_{L,t} = \left[\frac{X_r}{r_f - \mu_L} + \left(\frac{X_r(1-\eta\epsilon^2)}{r_f - \mu_H} - \frac{X_r}{r_f - \mu_L}\right)\omega_{L,1} + \left(\frac{c}{r_f} - \frac{X_d}{r_f - \mu_H}\right)\left(\frac{X_r}{X_d}\right)^{\omega_{H,1}}\omega_{L,1}\right](1-\tau), \tag{48}$$

and its right-hand side is

$$X_r\left(E'_{H,t} - \frac{\eta\epsilon^2}{(r-\mu_H)}(1-\tau)\right) = \left[\frac{X_r}{r_f - \mu_H} + \left(\frac{c}{r_f} - \frac{X_d}{r_f - \mu_H}\right)\left(\frac{X_r}{X_d}\right)^{\omega_{H,1}}\omega_{H,1} - \frac{\eta\epsilon^2 X_r}{(r-\mu_H)}\right](1-\tau). \tag{49}$$

By equating equation (48) with (49), we obtain

$$X_r\left(\frac{1-\eta\epsilon^2}{r_f - \mu_H} - \frac{1}{r_f - \mu_L}\right)(1-\omega_{L,1}) = \left(\frac{c}{r_f} - V_{H,d}\right)(\omega_{L,1} - \omega_{H,1})\left(\frac{X_r}{X_d}\right)^{\omega_{H,1}}. \tag{50}$$

It follows

$$X_r = \left[\frac{(c/r_f - V_{H,d})(\omega_{L,1} - \omega_{H,1})}{X_d^{\omega_{H,1}} \left(\frac{1-\eta\epsilon^2}{r_f-\mu_H} - \frac{1}{r_f-\mu_L} \right) (1-\omega_{L,1})} \right]^{\frac{1}{1-\omega_{H,1}}}. \tag{51}$$