Small Growth and Distress Returns: Two Sides of the Same Coin?

January 31, 2017

Abstract

We propose a unified-explanation for two seemingly disparate empirical findings: the negative abnormal returns of distressed stocks, and of small growth stocks. Based on a counterintuitive finding relating option prices to jump risk (Merton (1976)), we show via an investment valuation model that higher idiosyncratic risks of sudden corporate failure simultaneously generate lower expected returns and higher valuation ratios among smaller firms. Corroborating the model, high failure risk traits characterize small growth firms, and a failure risk factor subsumes small growth returns while explaining several asset pricing anomalies, indicating that anomalies are partial expressions of differences in failure risk across firms.

JEL Classification: G10, G12, G13, G19, G30, G32, D21, D24, D92.

Keywords: Distress, small, growth, failure risk, glamor, anomalies, cross section of stock returns, asset pricing, growth options, mixed jump-diffusion process.

I. Introduction

The empirical literature highlights the existence of cross-sectional patterns in stock returns (Fama and French (1993)). For example, smaller stocks earn higher average returns (the size effect hereafter), as do value stocks (the book-to-market effect or value premium hereafter).[1] Deviations from patterns exist, however. Fama and French (1996) document that the stocks of small growth firms tend to have negative abnormal returns. The pervasiveness of small growth returns presents a major challenge to asset pricing models. While Fama and French (2015) demonstrate their latest five-factor model outperforms other models capturing a battery of patterns in average stock returns, it still struggles to explain the returns of small growth stocks.

In a different strand of the literature, Dichev (1998) and Campbell, Hilscher, and Szilagyi (2008) document that distressed stocks also tend to have negative abnormal returns. Distress is commonly invoked to explain the size (Chan and Chen (1991)) or the book-to-market (Fama and French (1996); Vassalou and Xing (2004)) effect. The idea is that the stocks of distressed companies tend to move together, so their risk are not diversified away and investors require a premium for bearing such risk. The empirical findings on distressed returns, however, go in the opposite direction, posing another major challenge to asset pricing researchers.[2]

This paper investigates whether these seemingly disparate empirical regularities are related via a common risk embedded in the operating environment of the firms. Theoretically, we make three claims which are verified empirically. The first is that distress, as conventionally measured, captures idiosyncratic risk of negative jumps in the value of the assets of the firms. That is, investors of distressed firms are exposed to risks of experiencing sudden and large loses in investment value. The second claim is that a higher distress, counterintuitively, is associated with a lower risk premia and, simultaneously, a higher valuation ratio. This explains the seemingly persistent overvaluation and underperformance of distressed stocks. The third claim is that the return of small growth stocks is a manifestation of distress returns. Most of the small growth firms are precisely those most distressed among the firms sorted by size and book-to-market ratio.

Our argument hinges on a little-known and counterintuitive result first formerly introduced by Merton (1976). Ceteris paribus, the value of a call option is increasing with the idiosyncratic risk of downward jumps in the price of the underlying stock. Building on this result, it can be shown that a higher option value caused by an idiosyncratic risk source leads to a lower proportion of the option exposed to the systematic risk of the underlying stock. This translates to a lower systematic risk for the option itself if the jump risk is higher. In a similar vein, introducing business failure risk

[1]The size effect refers to the higher average return of smaller stocks, while the book-to-market effect refers to the higher average return of value stocks shown to exist in the cross-section of firms. Fama and French (1993) and Fama and French (1996) are excellent sources for a landscape view of patterns in average returns in the cross-section of firms.

[2]Campbell, Hilscher, and Szilagyi (2008) show that the distress anomaly does not reflect momentum in small loser stocks (Hong, Lim, and Stein (2000)), high idiosyncratic volatility stocks (Ang, Hodrick, Xing, and Zhang (2006)), or other phenomena already documented in the literature.

in the form of idiosyncratic jump risk in a firm valuation model with growth options simultaneously generates a higher option value, and hence a higher valuation ratio, and a lower risk premia for firms with higher failure risk. This in turn creates a cross-sectional relation between observable characteristics related to distress, growth, and low risk premiums for younger firms that possess growth options.

The paper is composed of two main parts. First, based on a simple model of corporate investments and idiosyncratic failure risk we formulate testable hypotheses that relate distress to small growth in the cross-section of firms. The salient points are made by augmenting the the growth option model of Carlson, Fisher, and Giammarino (2004) with idiosyncratic failure risk. The second part is empirical. Guided by the predictions of the model, we test the hypotheses and show empirical support for the model in the sample of US manufacturing firms.

In the model, each firm faces uncertainty driven by the price of the output they produce. Firms have growth opportunities modeled as timing options on expansion projects, which if undertaken, are irreversible. Firms also face an idiosyncratic risk of experiencing complete loss in timing options which concurs with a sudden loss in expansion projects. In line with our empirical findings, failure risk is assumed to be more prominent for younger and less mature firms. We derive closed-form expressions for firm value and expected return, and show that, similarly to Carlson, Fisher, and Giammarino (2004), the model is able to relate size and book-to-market effects to a single-factor model. That is, the model is able to generate the book-to-market effect, captured by the cross-sectional dispersion in operating leverage, and separately the size effect, captured by the cross-sectional dispersion in growth opportunities incorporated in the value of the firm.

Additionally, the model offers a new economic role for idiosyncratic failure risk in explaining expected returns in the cross-section of stocks. Although failure risk represents pure non-systematic risk, the prospect of a sudden loss in the value of the underlying assets affects the equilibrium value of the timing options, "i.e., one cannot 'act as if' the jump component was not there and compute the correct option price."(Merton (1976), p.134) The economic mechanism driving this result hinges on the advantage that options offer over owning the underlying assets. Intuitively, a higher failure risk leads to a lower benefit from physically owning an inactive project which is not obtained from owning the timing option. This leads to a lower convenience yield from owning expansionary projects, hence generating a greater divergence in the value of timing options and expansionary projects.

We also show, in the context of the model, that more valuable timing options have a lower elasticity with respect to the value of underlying projects, and therefore options have a lower exposure to the systematic risk of the underlying projects. In a cross-section of heterogeneous firms, the model proposes firms with higher failure risk to inherent growth traits and lower expected returns even if they possess growth opportunities facing greater risk of obsolescence. The model supposes that the market prices differentials in failure risk, and there is a direct cross-sectional relation between high failure risk and small growth firms in observed characteristics and returns.

We empirically tests the predictions of the model. We require an empirical measure that captures idiosyncratic risks of sudden losses in asset value in line with our model. Using O-Scores as ex-ante proxies for risk of failure (Griffin and Lemmon (2002); Dichev (1998)), our first empirical exercise confirms that O-Scores are strong predictors of exchange delistings and worse delisting returns. Corroborated by the findings that business failures are mostly idiosyncratic events (Opler and Titman (1994); Asquith, Gertner, and Sharfstein (1994)), and that investors suffer large and abrupt losses from exchange-delistings (Shumway (1997)), as required, O-Scores are appropriate ex-ante proxies for idiosyncratic failure risk for our study.[3]

Our second set of empirical tests investigates whether common traits exist between firms sorted by failure risk, size and book-to-market ratio in line with the predictions of the model. The findings confirm that the intersection of the smallest and the most growth firms resembles the most distressed firms along several characteristics; they share commonalities in average stock returns, distress measures, firm size, firm age, growth attributes, S&P credit ratings, and financial leverage, among others.

The next set of empirical tests investigates whether distress returns are related to financial leverage. This part of the study is important because it address whether the distress anomaly is exclusively related to financial distress. The results reveal that distress returns relate significantly to the operating components, as opposed to the financial components, of the O-Score measure.[4] The results support a novel explanation for distress anomaly predicated on *economic* distress, rather than *financial* distress, departing from the explanations proposed previously in the literature.[5]

The model supposes there is a direct cross-sectional relation between high failure risk and small growth in returns, and our empirical findings strongly support this prediction as well. A trading strategy constructed by buying high distress stocks and selling low distress stocks completely subsumes the abnormal returns of a small growth strategy.[6] The return relation is robust to calendar months, sample periods, business cycles, the exclusion of low-priced stocks, micro-cap stocks, and negative returns due to exchange-delistings.

Additional empirical results confirm that growth opportunities are the channel whereby failure risk operates on firm valuations and expected returns. Using four alternate empirical proxies for growth intensity, the return-relation between the failure risk strategy and the small growth strategy strengthens if the strategies are constructed from subsamples of firms with higher growth intensity.

Building on the evidence that idiosyncratic failure risk is reflected in firm valuations and returns,

[3]Exchange-delistings are almost always ex-ante unannounced and accompanied by trading halts. As a consequence, investors are unable to engage in timely trades to mitigate investment losses. See Shumway (1997), for example.

[4]The O-Score measure is composed of nine components: four are financial and the remaining five capture the operations of the firm (Ohlson (1980)).

[5]Garlappi and Yan (2011) and George and Hwang (2010) propose theoretical explanations for the distress anomaly which are based on the presence of corporate debt.

[6]Results using raw returns, risk-adjusted returns relative to the CAPM, Fama and French 3-factor model, or the four-factor model all offer qualitatively identical results.

we examine to what extent other existing asset pricing anomalies are reflections of differences in failure risk. Buying high and selling low failure risk stocks exhibits returns that relate to several asset pricing anomalies. And a 2-factor model composed of the market risk premium and a failure risk factor outperforms the 3-factor model (Fama and French (1993)) and the 4-factor model (Carhart (1997)) explaining several anomalies, confirming that the failure risk factor proxies for priced risk ingrained in several asset pricing anomalies. Our model, coupled with the empirical findings, suggests the inclusion of a failure risk factor when evaluating the performance of managed funds, particularly those running strategies formed on the basis of size, book-to-market ratio, and other existing anomalies.

On a more practical note, short-distress strategies are good hedges against small growth risks ingrained in other strategies while offering enhanced returns. An investor running joint short-distress/long-SMB or joint short-distress/long-HML strategies would capture at better risk-return tradeoff than running SMB or HML strategies independently.[7]

Relation to Literature. Several papers motivate our study. Berk, Green, and Naik (1999) were among the first to establish a correspondence between corporate investments and systematic risk to explain anomalous regularities in the cross-section of stocks.[8,9] Since then, the literature has been extended in many directions (Carlson, Fisher, and Giammarino (2004); Zhang (2005); Sagi and Seasholes (2007); Cooper (2007)). These papers demonstrate that firm value evolves in response to optimal corporate investment decisions, giving rise to observable characteristics that proxy for time-varying risk premia. A common feature of this literature focuses on the extent that growth options enhance systematic risk in relation to assets-in-place. We contribute to this literature by expanding the firms' operating environment in an important way to reconcile empirical regularities the extant literature has attributed to market mispricing (Griffin and Lemmon (2002)) and investors' cognitive biases (Conrad, Kapadia, and Xing (2012)).[10] In our model, while failure risk improves the relative importance of growth options, it nonetheless attenuates the risk premia of firms.

Our work is also motivated by a growing literature on the inverse cross-sectional relation between distress and risk premia.[11] Existing theoretical explanations are predicated either on the ability

[7] SMB refers to Small minus Big, or the size trading strategy return, and HML refers to High minus Low, or the book-to-market trading strategy.

[8] Fama and French (1992) provide evidence on the ability of a size factor and a book-to-market factor to explain stock returns in the cross-section. Fama and French (1996) provide a cross-sectional view of how average returns vary across stocks. Consistent with this literature, Anderson and Garcia-Feijóo (2006) show that growth in capital investment conditions assignments to size and book-to-market portfolios.

[9] Firm-level investment in a real option context was first pioneered by MacDonald and Siegel (1985), MacDonald and Siegel (1986) and Brennan and Schwartz (1985), and later adopted and extended by many others. Dixit and Pindyck (1994) is a standard reference for a detailed analysis of the literature.

[10] Griffin and Lemmon (2002) suggest distress returns are a result of market mispricing. Conrad, Kapadia, and Xing (2012) argue that lottery and glamor stocks, which also conform to high distress characteristics, earn abnormally low returns.

[11] Empirical evidences against the distress anomaly also exist. Using corporate yield spreads as the risk-

of shareholders to extract firm value through strategic default on corporate debt (Garlappi, Shu, and Yan (2008) and Garlappi and Yan (2011)) or on the choice of heavy borrowing by firms with low systematic risk (George and Hwang (2010)).[12] Our explanation relies on idiosyncratic failure risk and its ability to attenuate the risk of growth options. Distress in this context takes on a different meaning from financial distress.[13] Consequently, the underlying economics driving our results are distinct from those in the extant literature, permitting a novel channel between the operating environment faced by firms and expected returns.[14] The distinct features of the model yield novel testable predictions, such as the correspondence between distress and small growth, for which we find strong empirical support with extensive robustness checks.

The rest of the paper is organized as follows. The next section builds the model and develops the main ideas and predictions. Section III discusses the calibration of the model and the numerical results. Section IV takes the predictions of the model and show empirical support in the data. The last section concludes. The Appendix contains all the proofs and derivations, and other technical details omitted in the main body of the paper.

II. Model and Testable Implications

In this section, we develop the model and discuss its properties. Its purpose is to illustrate the logic and intuition behind our hypotheses and empirical predictions in a simple and straightforward fashion.[15]

A. The Environment

The setup extends the growth option model of Carlson, Fisher, and Giammarino (2004) by introducing idiosyncratic risk of sudden loss in growth opportunity.

---

neutral measure for default probability, Anginer and Yildizhan (2010) find default risk is not priced in equity markets. Friewald, Wagner, and Zechner (2014), on the other hand, find stock returns increase with credit risk premia if credit risk is estimated from CDS spreads.

[12] Garlappi et al. (2008) show in generality default probability is not positively related to risk premia in the presence of bargaining between shareholders and creditors in the event of default. Garlappi and Yan (2011) extends this idea by explicitly accounting for financial leverage and allowing shareholders to strategically default on corporate debt in order to extract residual firm value upon the resolution of financial distress. Consistent with this literature, Favara, Schroth, and Valta (2012) find empirical evidence supporting an inverse relation between strategic default and equity return in countries where the bankruptcy code favors debt renegotiation and for firms with shareholders with more bargaining power over debt holders.

[13] Non-financial, non-debt, distress can take on many forms. Examples of economic distress unrelated to corporate debt include: defeat in a patent race, inability to make positive profits due to excessive regulation or competition, bad management, sudden technological or output obsolescence, inability to meet payments of operating liabilities such as payments to suppliers, governments (in the form of taxes), laborers and pensioners, and other non-debt liabilities.

[14] Our explanation is also consistent with Avramov, Cederburg, and Hore (2012a). They show empirically that high default risk firms have lower systematic risk and hence lower expected returns.

[15] A more general model capturing the same economic forces is possible but at a cost of analytical tractability.

Each Firm k, $k \in \{1, \ldots, K\}$, produces its own output which can be sold at time-t for price $P_{k,t}$. $P_{k,t}$ is composed of an idiosyncratic component $X_{k,t}$ and a systematic component Y_t, i.e.,

$$P_{k,t} = X_{k,t} Y_t, \tag{1}$$

with dynamics

$$\begin{aligned} \frac{dX_{k,t}}{X_{k,t}} &= \sigma_k^{id} dB_{k,t}^{id}, \\ \frac{dY_t}{Y_t} &= \mu dt + \sigma^{sys} dB_t^{sys}, \end{aligned} \tag{2}$$

where μ is a constant drift reflecting return for systematic volatility σ^{sys} in the product market, $\sigma_{k,t}^{id}$ denotes idiosyncratic volatility, and $dB_{k,t}^{id}$ and dB_t^{sys} are the increments of two independent Brownian motions. $dB_{k,t}^{id}$ is independent across firms.

The operating scale of a firm is determined by the number of expansion projects activated by time-t. At stage i, $1 \leq i < n$, firms have a finite number of sequential expansion projects each allowing an incremental increase in production scale from ξ_i to ξ_{i+1}, $\xi_{i+1} > \xi_i$. The lumpiness of production scale is motivated by fixed adjustment cost $I_i > 0$ which is incurred in order to launch a stage i project. At their most infant stage $i = 1$ firms have in total n sequential expansion projects until reaching full maturity.

Each firm has operating costs amounting to f,[16] hence the profit function for a stage i firm is

$$\pi_i(P) = \xi_i P - f. \tag{3}$$

The central feature of the model is an exogenous idiosyncratic shock variable $z_{k,i,t}^{id}$ that captures Firm-k's inability to exploit all future expansion opportunities.[17,18] This event can arise from a sudden switch in technology, output obsolescence, a preemptive move by a competitor, or shifts in consumer tastes. Such outcome arrives with probability $\lambda_{k,i}$ per unit of time (or failure risk hereafter). In the model, failure risk relates inversely with firm stage, i.e. $\lambda_i > \lambda_{i+1}$, in order to stay consistent with the empirical findings discussed in Section IV.[19] Conditional on no failure by date-t, i.e. $z_{k,i,t}^{id} = 0$, $z_{k,i,t}^{id}$ evolves as follows:

[16]This feature captures quasi-fixed operating costs and contribute to the value premium (see Carlson, Fisher, and Giammarino (2004), for example).

[17]We assume that previously deployed projects do not face this risk. An earlier version of the paper allowed complete business failure and produced qualitatively identical asset pricing results. The generalization precludes analytical tractability without adding to the underlying economics.

[18]We assume $z_{k,i,t}^{id}$ is non-systematic to stay consistent with the empirical findings that most business failures are non-systematic events. See Opler and Titman (1994) and Asquith, Gertner, and Sharfstein (1994), for example.

[19]Failure risk in reduced-form follows intensity-based models in the credit risk literature. See Duffie and Singleton (2003) for an excellent discussion of the topic.

$$dz^{id}_{k,i,t} = \begin{cases} 0 & \text{, with probability } (1-\lambda_i)dt \\ 1 & \text{, with probability } \lambda_i dt. \end{cases} \tag{4}$$

We carry out our valuations under the risk-neutral measure $\mathbb{Q}$. Following several papers investigating the cross-section of equity returns (Berk, Green, and Naik (1999), Carlson, Fisher, and Giammarino (2004), Zhang (2005) and Livdan, Sapriza, and Zhang (2009)), we assume a pricing kernel with the following process:

$$\frac{d\zeta_t}{\zeta_t} = -rdt - \Theta dB^{sys}_t \tag{5}$$

where $\Theta = \frac{\mu_S - r}{\sigma_S}$ is the constant market price of risk, and r, μ_S and σ_S denote respectively the risk-free rate, the market rate of return, and the market return volatility.[20,21]

Working under $\mathbb{Q}$ changes the dynamics of Y_t to

$$\frac{dY_t}{Y_t} = \hat{\mu}dt + \sigma^{sys} d\hat{B}^{sys}_t, \tag{6}$$

where the risk-neutral drift, $\hat{\mu} = \mu - \sigma^{sys}\Theta$, is by assumption strictly less than r and $d\hat{B}^{sys}_t = \Theta dt + dB^{sys}_t$ is the increment of a standard Brownian motion under $\mathbb{Q}$.

B. Value of Mature Firms

We derive the market value of mature firms. For convenience, we omit firm subscripts throughout the rest of the paper.[22]

The cash flows of a mature firm stem solely from the output produced by assets-in-place.[23] Denote $A_M(P_t)$ the value of assets-in-place that produce a unit of output per unit time for a mature firm. The cost of producing a unit of this output is $\frac{f}{\xi_M}$ and so the profit per unit time is $P_t - \frac{f}{\xi_M}$. Therefore,

$$A_{M,t} = A_M(P_t) = E^{\mathbb{Q}}_t \left[\int_t^{\infty} e^{-r(u-t)} \left(P_u - \frac{f}{\xi_M} \right) du \right] = \frac{P_t}{r - \hat{\mu}} - \frac{f}{\xi_M r}. \tag{7}$$

Since mature firms operate at scale ξ_M, their profit flow is $\pi_M(P_t) = \xi_M P_t - f$ and their market value is $V_{M,t} = V_M(P_t) = \xi_M\, A_{M,t} = \frac{\xi_M P_t}{r-\hat{\mu}} - \frac{f}{r}$.

[20] The existence of ζ_t implicitly assumes the existence of a financial market with a risk-free asset B_t and a risky security S_t with return processes $\frac{dB_t}{B_t} = rdt$ and $\frac{dS_t}{S_t} = \mu_S dt + \sigma_S dB^{sys}_t$ respectively.

[21] A constant risk-free rate and market price of risk is purely for clarity. Both the risk-free rate and market price of risk could be stochastic, but they are not central to the underlying economics discussed in the paper.

[22] All of the derived expressions that follow are invariant to k, $k \in \{1, \ldots, K\}$.

[23] Assets-in-place refer to assets currently generating revenues for the firm. Growth options, on the other hand, are non-producing assets that have the potential to earn additional revenues in the future.

C. Value of Premature Firm

Following the same steps, a stage $i < n$ firm has assets-in place with a market value of $\xi_i\, A_{i,t}$, where $A_{i,t} = A_i(P_t) = E_t^{\mathbb{Q}}\left[\int_t^{\infty} e^{-r(u-t)}\left(P_u - \frac{f}{\xi_i}\right) du\right] = \frac{P_t}{r-\hat{\mu}} - \frac{f}{\xi_i r}$.

In addition to assets-in-place, pre-mature firms have opportunities to expand operating scale in the future. At stage i, the deployment of an expansion project raises profits by $(\xi_{i+1} - \xi_i)P_t$ and, if $i < n-1$, the firm acquires an opportunity to adopt another expansion project in the future, which if activated, increases profits by $(\xi_{i+2} - \xi_{i+1})P_t$. Expansion opportunities, therefore, amount to sequential compound timing options that allow the firm to launch expansion projects in succession at discrete points in time.

In the Appendix we show the value $F_{i,t} = F_i(P_t, z_{i,t}^{id})$ of a stage i expansion project has the equilibrium return process

$$\frac{dF_{i,t}}{F_{i,t}} = (\mu + \lambda_i)dt + \sigma^{id} dB_t^{id} + \sigma^{sys} dB_t^{sys} - dz_{i,t}^{id}. \tag{8}$$

Equation (8) represents the evolution of $F_{i,t}$ prior to project launch, which is different from the evolution of $F_{i,t}$ after the project is activated. The investment decision, however, depends only on the dynamics of $F_{i,t}$ up to the time of project deployment.[24]

The drift of $F_{i,t}$ conditional on date-t when the current failure state is $z_{i,t}^{id} = 0$ includes failure risk $+\lambda_i$ which is a consequence of the asset pricing equilibrium result $E\left[\frac{dF_{i,t} + (\xi_{i+1} - \xi_i)P_t dt}{F_{i,t}} | z_{i,t}^{id} = 0\right] = \mu$, i.e. the expansion project does not offer a risk premia for idiosyncratic risk. The underlying economics for the drift hinge on the advantage an activated project has over an inactivate project due to exposure to failure risk. This leads to a negative convenience yield in stark contrast to a positive yield commonly seen in the real option literature. Looking ahead, λ_i will play a prominent role in our asset pricing results.

Given a market value of the timing option $G_{i,t} = G_i(F_i(P_t, z_{i,t}^{id}))$ (or growth option hereafter) and summing together, the total market value of a stage i firm is

$$V_{i,t} = \xi_i\, A_{i,t} + G_{i,t}. \tag{9}$$

At the moment the timing option is exercised, τ, the value of the firm's assets-in-place increases by $\xi_{i+1} A_{i+1,\tau} - \xi_i A_{i,\tau}$ and, if $i < n-1$, the firm acquires another timing option for the future. After exercising the option, $t > \tau$, the option value is merely the value of the incremental increase in assets-in-place plus the value of the new option. That is, $G_{i,t} = \xi_{i+1} A_{i+1,t} - \xi_i A_{i,t} + G_{i+1,t}$, and therefore $V_{i,t} = \xi_i\, A_{i,t} + (\xi_{i+1}\, A_{i+1,t} - \xi_i\, A_{i,t}) + G_{i+1,t} = \xi_{i+1}\, A_{i+1,t} + G_{i+1,t} = V_{i+1,t}$.

Prior to exercise, $t < \tau$, the expected present-value of the payoff $\xi_{i+1} A_{i+1,\tau} - \xi_i A_{i,\tau} + G_{i+1,t} - I_i$

[24] This argument follows from Majd and Pindyck (1987) pages 11-13.

gives the value of the timing option

$$G_{i,t} = G_i(F_i(P_t, z^{id}_{i,t})) = G_i(P_t, z^{id}_{i,t}) = E^{\mathbb{Q}}_t\big[e^{-r(\tau-t)}(\xi_{i+1}A_{i+1,\tau} - \xi_i A_{i,\tau} + G_{i+1,t} - I_i)|z^{id}_{i,t} = 0\big],\ t \leq \tau, \tag{10}$$

which is dependent on $z^{id}_{i,t} = 0$. This is indicated by $E^{\mathbb{Q}}_t\big[\cdot|z^{id}_{i,t} = 0\big]$, the expectation operator under $\mathbb{Q}$ conditional on date-t when the current failure state is $z^{id}_{i,t} = 0$. If $z^{id}_{i,t} = 1$, then the expansion project has become obsolete and hence the option value is zero.

The second equality in equation (10) makes it explicit that once we know the value $F_{i,t}$ of the expansion project as a function of the current output price P_t and failure risk $z^{id}_{i,t}$, we can obtain the diffusion process of $F_{i,t}$ from that of P_t and $z^{id}_{i,t}$ by using Itô's Lemma. This allow us to find the value $G_{i,t}$ of the timing option as a function of $F_{i,t}$. An alternative to this approach is to find the value $G_{i,t}$ as a function of price P_t and $z^{id}_{i,t}$ using the value $F_{i,t}$ and the boundary condition that holds at the optimal timing decision τ.[25] We prove the following in the Appendix:

PROPOSITION 1: *Conditional on $z^{id}_{i,t} = 0$, the value of a stage $i < n$ timing option is*

$$G_{i,t} = \left(\frac{P_t}{P^*_i}\right)^{\phi_i}[V_{i+1}(P^*_i) - \xi_i A_i(P^*_i) - I_i] = \delta_i P^{\phi_i}_t, \qquad P^{\max}_t < P^*_i \tag{11}$$

where $P^{\max}_t = \sup_{t\geq 0}\{P_u : u \in [0, t)\}$ is the firm's maximum output price, $\phi_i > 0$ is the positive root of the quadratic equation

$$q_i(\phi) = \frac{1}{2}\left((\sigma^{id})^2 + (\sigma^{sys})^2\right)\phi(\phi - 1) + (\hat{\mu} + \lambda_i)\phi - (r + \lambda_i) = 0, \tag{12}$$

and P^*_i is the optimal threshold for P_t where the advancement to the next stage $i+1$ occurs. For a stage $1 \leq i < n-1$ firm, P^*_i is the solution to the following equation:

$$\phi_i\delta_i\big(P^*_i\big)^{\phi_i - 1} = \frac{\xi_{i+1} - \xi_i}{r - \hat{\mu}} + \phi_{i+1}\delta_{i+1}\big(P^*_i\big)^{\phi_{i+1}-1} \tag{13}$$

where δ_i takes on the recursive expression

$$\delta_i\big(P^*_i\big)^{\phi_i} = \frac{(\xi_{i+1} - \xi_{i+1})P^*_i}{r - \hat{\mu}} + \delta_{i+1}\big(P^*_i\big)^{\phi_{i+1}} - I_i. \tag{14}$$

For a stage $i = n-1$ firm, P^*_i takes on a closed-form solution

$$P^*_i = \frac{\phi_i}{\phi_i - 1} \times \frac{\hat{\mu} - r}{r} \times \frac{-I_i r}{\xi_{i+1} - \xi_i}. \tag{15}$$

Proof: *See Appendix.* □

Proposition 1 states the market value of timing options in the model. The solution is expressed

[25] See Dixit and Pindyck (1994) page 182 for an explanation of both solution approaches.

in closed-form up to at most one constant which is identifiable by a simple algebraic equation. Although the expansion opportunities are compound options – for $1 \leq i < n-1$, activating an expansion project grants the firm another expansion opportunity in future – the model remains tractable when generalized to any i and n.

The model shares similarities with Carlson, Fisher, and Giammarino (2004) in that firms are portfolios of two assets with market values $\xi_i A_{i,t}$ and $G_{i,t}$. Each asset responds differently to shocks X_t, Y_t, and $z_{i,t}$. Looking ahead to this, our model is similarly able to produce the size effect and, *separately*, the book-to-market effect.[26]

What is novel to our model is failure risk λ_i and its ability to explain additional relations between observable firm-characteristics and average returns such as the *joint effects* of size and book-to-market ratio, and distress returns. We explore these features below.

D. *Implications for Growth Characteristics*

We now investigate how failure risk affects growth characteristics. We prove the following in the Appendix:

PROPOSITION 2: *The value of a timing option is rising in failure risk, i.e.,*

$$\frac{\partial G_{i,t}}{\partial \lambda_i} > 0. \tag{16}$$

As such, firms have growth characteristics that become more prominent with failure risk, i.e.,

$$\frac{\partial}{\partial \lambda_i}\left[\frac{V_{i,t}}{F}\right] > 0, \tag{17}$$

where $F = \frac{f}{r}$ denotes the capitalized value of quasi-fixed operating costs.

Proof: *See Appendix.* □

Because inactive expansion projects become worthless with the arrival of failure, i.e. $dz_{i,t} = 1$, conventional wisdom suggests the market value of timing options should be lower if the risk of failure is higher. Proposition 2, however, says otherwise.

To understand this counterintuitive result, consider the value of a standard call option on a stock that exhibits jumps. Merton (1976) shows, ceteris paribus, the value of the call option is increasing in the idiosyncratic risk of downward jumps in the price of the stock. The economic mechanism driving this result hinges on the advantage that the option offers over owning the underlying stock. Intuitively, a higher jump risk leads to a lower benefit from physically holding the stock which is not obtained from holding the call option. This in turn, leads to a lower convenience yield of

[26] The size effect refers to the higher average return of smaller stocks, while the book-to-market effect refers to the higher average return of value stocks shown to exist in the cross-section of firms. Fama and French (1993) and Fama and French (1996) are excellent sources for a landscape view of patterns in average returns present in the cross-section of firms.

owning the stock, and hence a greater difference in the market value of the two securities in favor of the option.

In similar fashion, introducing non-systematic failure risk to assets from which timing options derive value increases the value of the options. Given a cross-section of heterogeneous firms, the first statement of the proposition asserts that firms with higher idiosyncratic failure risk have more valuable timing options even if their projects face greater risk of obsolescence.

An immediate consequence of this result is growth characteristics that become more prominent with failure risk, i.e. $\frac{\partial}{\partial \lambda_i}\left[\frac{V_{i,t}}{F}\right] > 0$, the second statement of the proposition. F, the capitalized value of fixed costs, represents the fixed assets of the firm, and hence $\frac{V_{i,t}}{F}$ proxies for the market-to-book ratio (see Carlson, Fisher, and Giammarino (2004)). The proposition suggests that firms with higher failure risk should have more prominent growth characteristics stemming from more valuable timing options. An inverse relation between failure risk and firm maturity, i.e. $\lambda_i > \lambda_{i+1}$, additionally establishes a relation between growth characteristics and failure risk that concentrates more strongly among smaller and younger firms. As such, the model reconciles seemingly disparate empirical findings the extant literature has attributed to market mispricing with an explanation fully predicated on rational pricing.[27] Corroborating Proposition 1, our empirical findings reported below reveal that small-sized growth firms are precisely those most likely to face failure risk in the cross-section.

Proposition 2 also differentiates our model from that of Garlappi and Yan (2011). Garlappi and Yan develop a model of firms whose equity holders extract firm value through strategic default on corporate debt. The mechanism driving a higher equity value in their model is an inverse relation between the likelihood of default and the duration of the residual value extracted by the equity holders upon default.

The underlying mechanism in our model, on the other hand, is not related to debt or the duration of the residual terminal value. Instead, it relies on the advantage of having timing options as opposed to owning the underlying assets if the assets are prone to failure; an advantage which becomes more prominent with failure risk. The plausibility of this result is confirmed empirically in a section below where we report that firms with high failure risk, as conventionally measured, are among those with the highest growth characteristics, but are also among those that choose the lowest financial leverage.

E. Implications for Returns

Having discussed the valuation, we turn our attention to the model-implied returns. The return on a mature firm is independent of the production scale because the value of the firm exhibits constant returns with respect to production scale. The assets-in-place of a stage $i < n$ firm exhibits

[27] The empirical literature has attributed the seemingly overvaluation of higher distress and small growth firms to investors' cognitive biases and market mispricings (see Griffin and Lemmon (2002) and Conrad, Kapadia, and Xing (2012), for example).

the same property, therefore it makes more sense to refer to the return on assets-in-place $dR_{A,t}$, where

$$dR_{A_i,t} = \Big[r + \big(1 + L(P_t)\big)\Theta\sigma^{sys}\Big]dt + \big(1 + L(P_t)\big)\sigma^{sys}dB_t^{sys} + \big(1 + L(P_t)\big)\sigma^{id}dB_t^{id}, \tag{18}$$

and $L(P_t) = \frac{\frac{f}{r}}{\frac{P_t}{r-\hat{\mu}} - \frac{f}{r}}$.

Equation (18) is intuitive. σ^{sys} denotes the systematic risk of the product market, a constant by assumption, which multiplied by the market price of risk Θ gives the product market risk premia. Operating leverage arises as a consequence of quasi-fixed costs. Profits are net of fixed costs, hence operating leverage, denoted by $L(P_t)$, amplifies return volatility and the risk premia of assets-in-place.

We now look at the return of a pre-mature firm $dR_{i,t}$, which is a weighted average of the return on assets-in-place $dR_{A_i,t}$ and the return on the timing option $dR_{G_i,t}$, i.e.

$$dR_{i,t} = \left(1 - \frac{G_{i,t}}{V_{i,t}}\right) dR_{A_i,t} + \frac{G_{i,t}}{V_{i,t}} dR_{G_i,t}, \tag{19}$$

We prove the following in the Appendix:

PROPOSITION 3: *The growth option return is given by*

$$dR_{G_i,t} = \frac{dG_{i,t}}{G_{i,t}} = \mu_{G_{i,t}}dt + \Omega_{i,t}\big(\sigma^{sys}dB_t^{sys} + \sigma^{id}dB_t^{id}\big) - dZ_{i,t}^{id}, \tag{20}$$

where

$$\mu_{G_{i,t}} = \Omega_{i,t}(\hat{\mu} + \lambda_i) - \lambda_i + \frac{1}{2}\frac{P_t^2}{G_{i,t}}\frac{\partial^2 G_{i,t}}{\partial P_t^2}\left((\sigma^{sys})^2 + (\sigma^{id})^2\right), \tag{21}$$

$\Omega_{i,t} = \frac{P_t}{G_{i,t}}\frac{\partial G_{i,t}}{\partial P_t}$ *is the elasticity of the growth option with respect to the output price, and*

$$dZ_{i,t}^{id} = dz_{i,t}^{id} - \lambda_i dt \tag{22}$$

is a compensated Poisson process, and hence a discontinuous martingale, driven by $dz_{i,t}^{id}$.

Proof: *See Appendix.* □

Proposition 3 shows that timing options have a more complicated return structure than assets-in-place. The first two terms of (20) correspond to the drift and diffusion terms common in standard diffusion processes representing the states where the option has a positive value. The third term captures the possibility of a jump in the value of the option which concurs with the sudden arrival of loss in expansion projects.

Importantly, $\Omega_{i,t}$, the output price elasticity of the growth option, is a common component of both the drift and diffusion terms. As a measure of sensitivity, $\Omega_{i,t}$ additionally captures the exposure of the timing option to the systematic risk of the underlying assets. The sensitivity $\Omega_{i,t}$

to λ_i has important implications for the relationship between risk premia and failure risk in the cross-section of firms. We prove the following in the Appendix:

PROPOSITION 4: *A firm's conditional systematic return volatility is given by*

$$\sigma_{R_{i,t}}^{sys} = \left[\left(1 - \frac{G_{i,t}}{V_{i,t}}\right)(1 + L(P_t)) + \frac{G_{i,t}}{V_{i,t}}\Omega_{i,t}\right]\sigma^{sys} \tag{23}$$

and it relates inversely with failure risk, i.e.

$$\frac{\partial \sigma_{R_{i,t}}^{sys}}{\partial \lambda_i} < 0. \tag{24}$$

Proof: *See Appendix.* □

The proposition states the systematic risk of the firms in the model. Applying the basic asset pricing equation, the proposition extends to risk premia as $\sigma_{R_{i,t}}^{sys}\Theta$ or to expected return as follows:

$$E_t[dR_{i,t}] = \left(r + \sigma_{R_{i,t}}^{sys}\Theta\right)dt. \tag{25}$$

As a portfolio of two assets, a firm's conditional systematic risk is a weighted average of the systematic risk of assets-in-place and a timing option. The expected return on assets-in-place is amplified by operating leverage, which is captured by $L(P_t)$; a consequence of the quasi-fixed operating costs. $L(P_t)$ relates inversely to P_t and becomes more prominent for firms that derive a greater proportion of firm value from assets-in-place. Operating leverage contributes to the value premium, or the book-to-market effect.

Timing options also play an amplifying role on the systematic risk of firms. As levered positions in underlying assets, options are riskier than revenues, i.e. $\Omega_{i,t} > 1$. Finite opportunities to expand adds to the importance of timing options for pre-mature firms, separately, contributing to the size effect. Younger and less mature firms proportionately derive a greater value from timing options and hence they are more sensitive to the risk of options.[28]

The novel feature of the model is the dependence of the firms' expected return on failure risk λ_i. Although the possibility of a sudden loss in the value to expand operating scale represents pure non-systematic risk, it nonetheless affects the expected return on growth options. As stated in the proposition, a firm's systematic risk, and hence risk premia, is lower the greater the λ_i. This result hinges on the property that the output price elasticity of the timing option itself is decreasing with failure risk, i.e. $\frac{\partial \Omega_{i,t}}{\partial \lambda_i} < 0$, which is proven in the Appendix.

Intuitively, a higher value stemming from a higher non-systematic risk factor makes a timing option less sensitivity to the underlying asset, which in turn, lowers the option's exposure to the systematic risk of the underlying assets. Two effects occur simultaneously in relation to a lower

[28]See Carlson et al. (2004) for a thorough explanation of how the book-to-market effect, and separately, the size effect arise in the context of the model.

risk premia. The first is a greater option value making the option's systematic risk proportionately more relevant for the systematic risk of the firm. The second is a lower systematic risk exposure of the option itself, which coupled with a greater option weight, establishes a negative relation between $E_t[dR_{i,t}]$ and λ_i.

In summary, the model simultaneously generates stronger growth traits and a lower risk premia, and hence lower expected return, for smaller and younger firms exposed to higher failure risk. To the extent that conventional measures for distress capture non-systematic risks of business failure, and firm valuations incorporate timing options on revenue-increasing projects, firms with higher distress should have lower risk premiums and higher valuation ratios. The model hypothesizes that the market prices differentials in failure risk, and there is a direct cross-sectional association between high distress and small growth firms in both return and observable characteristics. Since failure risk operates through timing expansionary options, the model also supposes the empirical relation between distress, valuation ratios and risk premiums to strengthen in empirical proxies for growth option intensity. This forms the basis for some of our empirical tests. We discuss the empirical results supporting the plausibility of the model below.[29]

III. Model Calibration and Numerical Results

Section II discussed the model results from an analytical and theoretical standpoint. This section describes the calibration of the model and discuss the numerical results. The purpose of this section is to solve the model with realistic parameters and investigate the implications of the model numerically.

A. Model Calibration

We describe the choice of parameters used to solve the model developed in Section II of the paper.

Without loss of generality, we assume that there are three stages to firms, i.e. $n = 3$. From this, there is a total of fifteen additional parameters in the model: three are economy wide (i.e., r, μ_S, and σ_S); three refer to the firms' output price process (i.e., μ, σ^{id} and σ^{sys}); and nine refer to the firms' operating environment (i.e., ξ_i, λ_i, for $i \in \{1, 3\}$, and f, I_1 and I_2). To solve the model we need to select a set of parameter combinations characterizing a representative firm. Below we

[29]The linearity between systematic risk and expected return means that we can relate failure risk, size and book-to-market to the cross-section of returns. In the model, risk premium differ only because systematic risks differ in the cross-section. Absent a proper empirical proxy for the systematic risk factor to risk-adjust portfolio returns, lower average returns appear in the puzzling guise of negative abnormal returns. This view of abnormal returns follows several recent papers that study the risk premia implications of product market competition (Aguerrevere (2009)), of corporate investments (Carlson, Fisher, and Giammarino (2004)), of seasoned equity offerings (Carlson, Fisher, and Giammarino (2006)), of mergers and acquisitions (Hackbarth and Morellec (2008)), and of financial distress (Garlappi and Yan (2011) and Favara, Schroth, and Valta (2012)).

provide a description of our choice of parameters. A summary of the parameters is reported in Table I.

Insert Table I Here

The most important parameter of the model is the idiosyncratic risk of encountering sudden loss in investment value λ_i. Empirical studies demonstrate that business failures are unexpected idiosyncratic events (see Opler and Titman (1994) and Asquith, Gertner, and Sharfstein (1994), for example), and that investors suffer large – and in many instances complete – abrupt losses from exchange-delistings (see Shumway (1997), for example).[30] In light of these findings, each month in our data sample, we identify exchange delisted stocks and match them with their O-Score decile group one year prior to the month of delisting. Then, we compute the proportion of stock delistings for each O-Score rank. The results reported in Table III reveals that the mean proportion of delistings ranges from 0.69% to 16.53% from the lowest to the highest O-Score decile. Hence, for comparative analysis, we set λ_1 equal to alternate values ranging from 0 to 17% to roughly match the empirical proportion of delistings. λ_2 and λ_3 are set to 1.35% and 0.69% to match the mean proportion of delistings for the 5th O-Score decile and the lowest O-Score decile, respectively.

In the model, the ratio of a firm's idiosyncratic cash flow volatility to systematic volatility equates to the corresponding return volatility ratio. This means that we can rely on equity returns to approximate σ^{id} and σ^{sys}. To this end, we estimate monthly idiosyncratic return volatility $IVol$ for each stock in our sample following the approach used in Ang, Hodrick, Xing, and Zhang (2006). Then, we take the annualized sample mean of the 50th $IVol$ percentile to approximate a value for σ^{id}. The sample mean is 0.4312, so we set σ^{id} to 0.4. And, without loss of generality, we set σ^{sys} to 16%.

The financial market variables r, μ_S, and σ_S are set to 4%, 12% and 20%, respectively, to roughly match empirical estimates of the short rate, equity market return and equity market return volatility (see Campbell (2003), for example). The capitalization rate $\delta = r + \hat{\mu}$ is commonly treated as a 'free' parameter in real option models. We choose δ to be 3.60%, which implies a μ value of 6% given the other parameters.

As for the operating variables, ξ_i and f are scale parameters and, similarly to I_i, are not the main focus of the paper. We treat these as free parameters as reported in Table I so that firms have options with positive time value.

B. Numerical Results

Given the realistic set of parameters, we solve the model using alternate values of λ_1 in order to investigate the role that the idiosyncratic risk of sudden loss in investment value plays in the

[30] Exchange-delistings are almost always ex-ante unannounced and accompanied by trading halts. As a consequence, investors are unable to engage in timely trades to mitigate investment losses (Shumway (1997)).

growth and return characteristics of the firms in the model.

Insert Table II Here

Table II summarizes the results. As discussed in Proposition 2, ceteris paribus, δ_i, the constant of integration that determines the value of growth options, is increasing with λ_i values which coincides with a higher exercise threshold P_i^*.[31] The operating leverage ratio $\frac{F}{V_i}$ relates inversely with growth characteristics $\frac{V_i}{F}$. As shown in the table, $\frac{V_i}{F}$ is higher for higher values of λ_i. The effect of λ_i is quite strong. Increasing λ_i from 0.0189 to 0.17 – this is equivalent to going from the middle O-Score decile to the top O-Score decile – increases $\frac{V_i}{F}$ by about 85%.[32] Hence λ_i has important consequences for growth characteristics in the model.

The risk premia is also dependent on λ_i. As levered positions on underlying assets, i.e. $\Omega_1 > 1$, in theory a higher growth option value steaming from a higher λ_i could enhance the systematic risk of the firm. However, as discussed in Proposition 4, the table confirms the opposite is true since the option's own risk, Ω_i, decreases in λ_i. In conjunction with a lower operating leverage, the effect of a higher λ_i is to further reduce the systematic risk of the firm through a greater prominence of the growth option and a reduction in the systematic risk of the growth option. The spread between extreme λ_i values corresponds to a -12.132% difference in expected returns which roughly matches the difference in average returns between extreme portfolios sorted on distress measures (see Table VIII, for example).

IV. Empirical Analysis

In this section, we test the predictions of the model and show empirical support in the data.

A. Data Source

All our accounting and market-related variables are from the annual COMPUSTAT and the CRSP monthly return files, respectively, with the exception of monthly factor returns and risk-free rates which are from Ken French's website.[33] We consider only ordinary shares traded on the NYSE, AMEX and Nasdaq with primary link to companies on COMPUSTAT with US domestic data source. Following the literature, we drop from our sample stocks of firms with a negative book-to-market ratio. It is common in the empirical literature to also exclude stocks with prices below

[31] Intuitively, a higher option value caused by a larger λ_i implies a higher opportunity cost of exercising the option since the action would entail forfeiting a higher valued asset in exchange for the net value of an incremental increase in assets-in-place. This leads to a higher investment threshold P_i^* (Dixit and Pindyck (1994)).

[32] Alternatively, this is equivalent to going from an expected time to failure $E[T] = \frac{1}{\lambda_i}$ of 52.9 years to 5.88 years.

[33] http:// mba.tuck.dartmouth.edu/ pages/faculty/ken.french/data library.html

$1 to remove the effects of illiquidity. Low-priced stocks on average have greater risk of distress (Garlappi and Yan (2011)), consequently are likely to experience greater failure risk. Therefore, the reported results are based on the full sample without a minimum price filter. However, we show in our robustness checks that our main results are robust to the exclusion of stocks with price below $3. Our baseline sample contains 1,026,726 firm-month stock return observations with non-missing observations of the distress variable and spans from July 1981 to December, 2010.[34]

B. Variable Description

We require several firm characteristics to investigate the predictions of the model. Following many in the literature, we rely on the firms' market equity capitalization to proxy for size, and the firms' book-to-market ratio to proxy for value or growth.[35] We assume in our model that failure risk relates inversely with firm maturity. To verify this assumption, we rely on the age of firms as a measure of maturity. Age is defined as the number of years since the firms' first stock return observation in CRSP.

We also require an empirical proxy for failure risk λ_i. To this end, we follow Dichev (1998), Griffin and Lemmon (2002) and George and Hwang (2010), among many others, and rely on O-Score as a measure for the likelihood of failure (Ohlson (1980)). In our own empirical verification discussed below, we confirm O-Score to be a reliable measure for idiosyncratic risk of failure.

[34]Pre-1980 COMPUSTAT variables are not reliable for the construction of the O-Score measures. See Dichev (1998), for example.

[35]Following Fama and French (1993), market value of equity is defined as the share price at the end of June times the number of shares outstanding. Book equity is defined as stockholders' equity minus preferred stock plus balance sheet deferred taxes and investment tax credit if available, minus post-retirement benefit asset if available. If missing, stockholders' equity is defined as common equity plus preferred stock par value. If these variables are missing, we use book assets less liabilities. Preferred stock, in order of availability, is preferred stock liquidating value, or preferred stock redemption value, or preferred stock par value. The denominator of the book-to-market ratio is defined as the end of December closing stock price times the number of shares outstanding.

Following Dichev (1998), O-Scores are computed according to the following formula:

$$
\begin{aligned}
O - Score_t = & - 1.32 + 6.03 \times \frac{TotalLiabilities_t}{TotalAssets_t} - 1.43 \times \frac{WorkingCapital_t}{TotalAssets_t} \\
& + 0.076 \times \frac{CurrentLiabilities_t}{CurrentAssets_t} \\
& - 1.72 \times (1 \text{ if } TotalLiabilities_t > TotalAssets_t, \text{ 0 otherwise}) \\
& - 0.407 \times log(TotalAssets_t) - 2.37 \times \frac{NetIncome_t}{TotalAssets_t} \\
& - 1.83 \times \frac{FundsFromOperations_t}{TotalLiabilities_t} \\
& + 0.285 \times (1 \text{ if Net Loss for the last 2 yrs, 0 otherwise}) \\
& - 0.521 \times \frac{NetIncome_t - NetIncome_{t-1}}{|NetIncome_t| + |NetIncome_{t-1}|}
\end{aligned}
$$

The first four inputs to the O-Score measure are financial variables, while the remaining five capture operating performance (Ohlson (1980)). Using the O-Score as our measure of failure risk will prove useful when investigating whether the distress anomaly relates to economic distress or financial distress.

We also compute a credit risk measure for descriptive purposes. Following Avramov, Chordia, Jostova, and Philipov (2007), we transform COMPUSTAT S&P issuer ratings into numerical values as follows: $AAA = 1, AA+ = 2, AA = 3, AA- = 4, A+ = 5, A = 6, A- = 7, BBB+ = 8, BBB = 9, BBB- = 10, BB+ = 11, BB = 12, BB- = 13, B+ = 14, B = 15, B- = 16, CCC+ = 17, CCC = 18, CCC- = 19, CC = 20, C = 21, D = 22$. A greater value corresponds to a higher credit risk.

We also require empirical measures for growth option intensity when investigating the strength of the cross sectional relation between failure risk and small growth. The most common type of real options comes in the form of future growth opportunities (Grullon, Lyandres, and Zhdanov (2010); Brennan and Schwartz (1985); MacDonald and Siegel (1986); Majd and Pindyck (1987); Pindyck (1988)). Therefore, we rely on ready-made measures of growth opportunities from the literature.

We consider the market-to-book ratio as an alternate measure for growth intensity. Higher market-to-book ratio firms tend to derive value from future growth opportunities while lower market-to-book ratio firms tend to derive value from assets-in-place (Carlson, Fisher, and Giammarino (2004)).

Our second (inverse) proxy for growth intensity is firm size. Larger firms tend to be mature and derive more value from assets-in-place, while smaller firms tend to be younger and derive more value from future growth opportunities (Brown and Kapadia (2007); Carlson, Fisher, and Giammarino (2004)). Firm size is defined by the book value of the assets of the firm.

Growth opportunities are revealed in growth capitalized in the future in the form of increased sales. Following Grullon, Lyandres, and Zhdanov (2010), as our third growth intensity measure we define sales growth as the sum of the sales growth rates starting 2 years and ending 5 years after the stock return observation.[36] We alleviate concerns of spurious correlations between contemporaneous surprises in sales growth and returns by merging month t returns with sales growth measures starting from two years after the return observation.

The fourth and last growth option measure is R&D intensity. Research and development generates investment opportunities. Therefore, the greater a firm's R&D intensity the more growth options the firm is expected to have. R&D intensity is defined as the ratio of R&D capital to total assets where we follow Chan, Lakonishok, and Sougiannis (2001) in the definition of R&D capital.

We match returns from January to June of year t with year $t-2$ accounting variables from COMPUSTAT, while the returns from July to December are matched with COMPUSTAT variables of year $t-1$. This matching scheme is conservative and ensures that the accounting variables are contained in the information set of the investors prior to the realization of the market-based variables. We employ the same matching scheme in all our matches involving accounting and CRSP variables except when matching future sales growth with returns, as explained earlier.

C. Distress and Non-Systematic Risk of Failure

The model developed in Section II relies on non-systematic failure risk to capture the likelihood of sudden losses in asset value. Does the O-Score measure capture non-systematic risk of sizeable and sudden losses in asset value? Since O-Score is the sort variable for failure risk in our empirical implementations, it is crucial for our study to address this question.

Empirical studies demonstrate that business failures are unexpected idiosyncratic events (see Opler and Titman (1994) and Asquith, Gertner, and Sharfstein (1994), for example), and that investors suffer large – and in many instances complete – abrupt losses from exchange-delistings (see Shumway (1997), for example). In light of these findings, we investigate if the proportion of exchange delistings relate O-Score measures. To this end, each month we match exchange delisted stocks with O-Score rankings up to six years prior to the month of delisting, then compute the proportion of delistings for each O-Score group and each year.

Insert Table III Here

Table III reports the results. As shown, the proportion of firm delisted from exchanges is increasing in the O-Score ranking. The pattern holds at least up to 6 years prior to the month of delisting. Delistings caused by bankruptcy or liquidation offer inconclusive relation with O-Scores (Panel A) due to their sparsity in occurrence across O-Score rankings. However, Panel B reveals that performance-related delistings are increasing with O-Score ranking. From this, we conclude

[36] One caveat with this growth variable is the possibility of look-ahead bias. As in Grullon, Lyandres, and Zhdanov (2010), we are not concerned with potential issues related to look-ahead bias since the focus of our paper is on investigating the relation between failure risk and small growth returns, as opposed to predicting future stock returns.

that, as required, the O-Score measure captures idiosyncratic risk of sudden and sizeable losses in asset value which relate more strongly with economic failure than financial distress.

Exchange-delistings are almost always ex-ante unannounced and accompanied by trading halts. As a consequence, investors are unable to engage in timely trades to mitigate investment losses (Shumway (1997)). To further explore if O-Scores capture features of failure risk from the model, we investigate whether high O-Scores relate to worse returns during the month of delisting. Each month, we sort delisted stocks into five equal-sized groups based on their returns in the month of delisting and compute the mean O-Score for each group and each year up to six years prior to the month of delisting.

Insert Table IV Here

Table IV reports the results. The worst delisting returns are associated with the highest mean O-Score prior to delisting. This holds at least up to six years prior to the month of delisting. Panel A reports the results based on CRSP delisting returns, and Panel B reports the results based on Shumway (1997) delisting returns.[37] As shown, our finding is robust to the way delisting returns are calculated.

To summarize, these results confirm that the O-Score measure captures idiosyncratic risk of sudden and sizeable losses in asset value, and hence it is a suitable measure of failure risk for the empirical tests.

D. Descriptive Analysis

Having established the correspondence between O-Scores and idiosyncratic failure risk, this section reports some descriptive statistics across groups of firms sorted by O-Scores, and groups of firms sorted by size and book-to-market ratio (BM). The purpose of this section is to highlight commonalities in observable characteristics between high failure risk firms and small growth firms in line with the predictions of the model in Section II.

D.1. Characteristics of Firms Across Size $\times$ BM and Failure Risk

At the end of each June, we sort the stocks in our sample evenly into deciles by O-Scores, and independently, we sort the stocks into 25 5×5 groups by size and book-to-market ratio (BM). Following most in the literature, the quintile cutoff values for size and BM are determined by NYSE stocks. Then for each O-Score group, and for each of the 5×5 size and BM groups, we compute the sample mean of the following variables: O-Scores, credit risk, age, market equity, BM, book leverage, market leverage, number of stock-month observations (N) with non-missing O-Scores, the

[37]Shumway (1997) shows that missing delisting returns in CRSP data files can lead to biases in portfolio returns and proposes a way to calculate delisting returns.

percentage of firms with book and market financial leverage ratio lower than 0.3, and the percentage of firms with book and market financial leverage ratio greater than 0.7.

Insert Table V Here

Tables V and VI summarize the results. Panel A of Table V reveals that the highest O-Score decile has the lowest mean market equity value. It also has among the lowest mean BM, highlighting the correspondence between high failure risk and growth characteristics. This also demonstrates that high failure risk firms tend to be small growth, a finding that departs from existing views that value characteristics capture distress risk.[38] Furthermore, the highest failure risk decile also has the lowest average age and the worst average credit risk, corroborating the assumed inverse relation between λ_i and firm maturity in the model.

Insert Table VI Here

Table VI reports summary statistics for each of the 5×5 size and BM groups. The group which intersects between the smallest and the lowest BM (small growth) shares similar firm characteristics as the top O-Score decile. It has the highest mean O-Score, the worst mean credit risk, and the lowest mean age among all the 5×5 size and BM groups, offering further verification that failure risk relates inversely with firm size and firm maturity. These results confirm that small growth relates to high failure risk; results that agree with Proposition 2 of our model, but defy existing views about failure risk and value characteristics.

D.2. Financial Leverage Across Size $\times$ BM and Failure Risk

Now we investigate the financial leverage ratio of the firms sorted by size $\times$ BM and failure risk. The extant literature has relied on the presence of high financial leverage, or financial distress, to explain the abnormal return of high failure risk stocks. We demonstrate in this section that there is an additional dimension to failure risk that is orthogonal to financial distress.

Table V reveals that the highest O-Score decile has a mean book financial leverage ratio slightly above the full sample mean and a mean market financial leverage ratio significantly below the full sample mean. This highlights that the most failure prone firms have financial leverage comparable with those that are operationally and financially sound. Since these firms are unlikely to suffer from high financial distress, the evidence suggests that high failure risk is not an artifact of financial distress.

The same findings are present for the intersection between the smallest and the lowest BM firms. This group has a mean book financial leverage ratio slightly below the full sample mean and a mean market financial leverage significantly below the full sample mean. Similar to high

[38] A part of the literature views the value premium as compensation for distress risk (Fama and French (1996); Vassalou and Xing (2004)).

failure risk firms, small growth firms have mean financial leverage comparable with those firms that are financially sound even though they have the highest mean O-Score. This suggests that small growth firms are prone to failure due to reasons that are orthogonal to financial distress.

To further explore the degree of financial distress of these firms, we investigate the proportion of firms with financial leverage ratio lower than 0.3 and the proportion of firms with financial leverage ratio greater than 0.7 across O-Score and size × BM classifications. Panels B and C of Table V report the results for book leverage and market leverage respectively across O-Score deciles, and Panels I to L of Table VI report the results across size × BM groups.

A mean 15% (32%) of the highest failure risk decile firms have market (book) leverage ratios greater than 0.7, but a mean 56% (32%) of these firms have market (book) leverage ratios lower than 0.3. While some high failure risk firms have exposure to heavy borrowing, the lion's share rely on very low corporate borrowing.

The intersection of the smallest and the lowest BM firms have proportions similar to the most failure risk firms. A mean of only 3% (19%) of the lowest size and BM firms have market (book) leverage ratios greater than 0.7, while 80% (37%) have market (book) leverage ratios lower than 0.3. These findings also support the notion that financial distress is the unlikely contributor to the high O-Scores of small growth firms.

Taken together, these findings depart from the commonly held view that distress, as conventionally measured, captures financial distress. Our empirical findings support explanations for high failure risk that hinges on economic distress, as opposed to financial distress, in similar fashion to the model in Section II of the paper.

E. Small Growth and High Failure Risk Portfolio Returns

In this section, we rely on portfolio approach to show that low returns concentrate among firms with high failure risk and small firms with low book-to-market ratio. The next section discusses the empirical link between the two anomalies in line with the predictions of our model.

The model in Section II predicts that differences in failure risk combine with growth options to determine market valuation ratios and stock returns in the cross-section. If the differential in failure risk is priced but not completely captured by the existing pricing factors, then we should expect significant pricing errors captured by the intercepts (Jensen's alphas) from portfolio return regressions. This should translate to portfolios of small growth firms and high failure risk firms to have significant and negative intercept estimates.

To verify this prediction, at the end of each June, we rank NYSE stocks into 5 groups by size and, separately, into 5 groups by BM to determine quintile cutoff values, then we compute value-weighted monthly portfolio returns for each of the 5 × 5 size and BM rank classifications using the full sample. Separately, we group stocks evenly into 10 groups by O-Scores, then we compute monthly value-weighted portfolio returns for each decile. We also compute the returns of the zero-cost portfolios that take a long position in the highest quintile, or decile, portfolio funded from a short position in the lowest quintile, or decile, portfolio for each rank classification of size, BM and O-Score. Then, we find the portfolio alphas by estimating the pricing errors relative to the Fama French three factor model (FF-3):

$$r_t - r_{f,t} = \alpha + \gamma_1 SMB_t + \gamma_2 HML_t + \gamma_3 MKTRF_t + \epsilon_t \quad (26)$$

where r_t denotes the portfolio return, $r_{f,t}$ is the monthly riskless rate, SMB, HML and $MKTRF$ are the Fama and French (1993) factors that proxy for size, book-to-market and the market risk premium respectively.[39]

Insert Table VII Here

Table VII reports the estimated pricing errors for the size × BM portfolios. Granulating the full sample by double sorting reveals some very interesting patterns in returns. It shows that the value premium is only present in the smallest size group while relying more strongly on the short leg than on the long leg of the trading strategy. Among the smallest stocks, the positive abnormal returns of value stocks is less than half as large as the negative abnormal returns of the growth stocks (2.48% vs. -5.56%). This demonstrates that the famed value premium is an artifact of the negative abnormal returns of small growth stocks, underscoring the importance of these stocks – a main focus of this paper – for a better understanding of the value premium itself.

The table also reveals that the commonly held view that larger stocks earn lower average returns than smaller stocks, the size effect, does not apply to the stocks in the lowest BM quintile. This reverse size effect is attributed, again, to the abnormal returns of the smallest stocks in the lowest book-to-market quintile.

Insert Table VIII Here

Panel A of table VIII reports the annualized mean returns across O-Score decile portfolios. The three highest failure risk decile portfolios exhibit an inverse relation between O-Score and average return. This pattern is made worse by risk-adjusting relative to the CAPM, the Fama the French 3-factor or the Carhart 4-factor models. Relative to the Fama and French 3-factor model, the highest failure risk portfolio earns on average an annualized risk-adjusted return of -9.27% contributing to a mean risk-adjusted return of -12.95% in excess of the other extreme portfolio. The spread in return is mainly attributed to the long leg of the strategy, since it has a mean return substantially lower than the lowest failure risk portfolio (3.68%).

Does the distress anomaly bear a strong relation with financial distress? Answering this question helps address whether the distress anomaly is a financial one. Panels B and C of the table report the performance (relative to the 3-factor model) of the O-Score portfolios constructed from each financial leverage ratio tercile group. As shown, the distress anomaly does not appear to bear a

[39] For zero-cost portfolios, we use portfolio returns instead of excess returns on the left size of (26).

relation with financial leverage. The anomaly is present across all the book leverage ratio terciles, while is it significant only in the lowest market leverage ratio tercile. These findings conflict with the premise that financial distress is the root cause of the distress anomaly.

Overall, the results demonstrate that small growth stocks, and high O-Score stocks have negative abnormal returns that go in the direction of the predictions of our model.

F. Does Financial Distress Drive Distress Returns?

Existing explanations for the distress anomaly hinge on financial distress (Garlappi and Yan (2011) and George and Hwang (2010)). This section reports further evidence supporting alternative explanations predicated on operating distress.

A salient feature of the O-Score is its nine components: the first four which are financial, and the remaining five related to operations (see Ohlson (1980)). In contrast to other measures for distress, the O-Score measure allows us to distinguish the reliance of stock returns on the performance components of the O-Score measure from the financial components. Hence, the O-Score measure helps address the question whether the distress anomaly is a financial one. To this end, at the end of each June, we separately sort the stocks in the sample into ten equally-sized groups by each one of the continuous components of the O-Score measure $lt2at = \frac{TotalLiabilities_t}{TotalAssets_t}$, $wc2at = -\frac{WorkingCapital_t}{TotalAssets_t}$, $lc2ac = \frac{CurrentLiabilities_t}{CurrentAssets_t}$, $logat = -log(TotalAssets_t)$, $ni2at = -\frac{NetIncome_t}{TotalAssets_t}$, $fo2lt = -\frac{FundsFromOperations_t}{TotalLiabilities_t}$, $\Delta ni = -\frac{NetIncome_t - NetIncome_{t-1}}{|NetIncome_t| + |NetIncome_{t-1}|}$, and into two groups based on the value of the dummy components $ltatdummy$= (1 if $TotalLiabilities_t > TotalAssets_t$, 0 otherwise) and $nidummy$ = (1 if Net Loss for the last 2 yrs, 0 otherwise), and compute monthly value-weighted portfolio returns for each group.[40] Then we investigate the portfolio alphas relative to the FF-3 model as discussed earlier.

Insert Table IX Here

Table IX reports the results. As show, Δni, $fo2lt$, $logat$ and $ni2at$, all of which are operating components of the O-Score, generate the same return pattern as the O-Score measure itself across deciles. The financial components, by contrast, do not yield the same pattern. These results corroborate alternatives to debt-based explanations for the distress anomaly, such as the model developed in Section II.

G. Small Growth and Distress Returns. Two Sides of the Same Coin.

In line with model of Section II, commonalities in return and characteristics exist among high distress and small growth firms. This section examines the empirical relation between high failure risk returns and the returns of small growth firms.

[40] We multiply each continuous component of the O-Score with the sign of the coefficient estimate, therefore a higher component value contributes to a higher O-Score.

To this end, we construct a trading strategy, $FAIL$ as a zero-cost portfolio invested in the highest O-Score portfolio funded from a short position in the lowest O-Score portfolio. Similarly, the size growth strategy, SG, holds a long position in the smallest and the lowest BM portfolio funded from a short position in the middle size and the middle BM portfolio after the stocks in our sample are sorted in to 5×5 groups by size and BM.[41] All the portfolios used in the construction of these strategies are value-weighted and rebalanced monthly. Following the construction of the strategies, we estimate the following regression:

$$Y_t = \alpha + \gamma_1 SMB_t + \gamma_2 HML_t + \gamma_3 MKTRF_t + \gamma_4 X_t + \epsilon_t \tag{27}$$

where SMB, HML and $MKTRF$ are the Fama and French (1993) factors as described earlier, and Y and X serve as placeholders for SG or $FAIL$. The predictions translate to a positive and statistically significant γ_4 estimate.

Insert Table X Here

Table X reports the results. The first row reports the results from regressing SG on the FF factors SMB, HML and $MKTRF$. As expected, the estimated loadings on SMB and HML are significantly positive and negative, respectively. The loading on $MKTRF$ is comparatively smaller suggesting that SG hedges out a large portion of market risk. The results show that, consistent with our earlier portfolio results, the SG strategy yields an unexplained return of -5.5974% per annum with a t-statistic of -2.4671 which is highly significant.

The second row of the table reports the results with $FAIL$ added as an explanatory variable. The loading on $FAIL$ is positive and highly significant, establishing a positive correspondence between high failure risk and small growth returns. Hence, small growth and distress exhibit correlations in characteristics as well as in stock return in line with Proposition 4 of the model. More importantly, the results reveal that the abnormal returns of SG is completely subsumed by $FAIL$. Including $FAIL$ in the regression reduces the pricing error from -5.5974% to an insignificant annualized return of -0.8528%. The inclusion of $FAIL$ reduces the explanatory power of SMB by more than a half and slightly increases the explanatory power of HML. This suggests that $FAIL$ captures small growth risks embedded in SMB and HML on top of the additional explanatory power it offers on its own.

The results from regressing $FAIL$ on SMB, HML and $MKTRF$ are reported in the third row of the table. In line with our earlier portfolio results reported in Table VIII, $FAIL$ has an unexplained average return of -12.9519% per annum with a t-statistic of -4.4784. SMB has strong explanatory power as expected from our earlier results relating failure risk to firm characteristics. SMB has a coefficient estimate of 1.3994 with a t-statistic of 11.2867. Interestingly, the same is not true for HML. HML has a coefficient estimate of 0.166 with a t-statistic of 1.4110, defying

[41] Our results are robust to different short portfolios in the SG strategy.

existing claims that value premium reflects compensation for distress risk (Fama and French (1996); Vassalou and Xing (2004)) as suggested earlier.

The fourth row of the table reports the regression results with SG as an added explanatory variable. The estimated loading on SG is positive and highly significant, consistent with a positive correspondence between high failure risk returns and small growth returns. Including SG in the regression reduces the pricing error from -12.9519% to -9.3967%, which is an improvement of about 30%. While the $FAIL$ factor subsumes small growth abnormal returns, the converse is not true. This suggests that high failure risk is not exclusively concentrated among small growth stocks.

Interestingly, including SG reverses our earlier findings about the explanatory power of HML on $FAIL$. The loading on HML increases from an insignificant value of 0.166 to a highly significant value of 0.7704, which economically is also very significant. This suggests that a positive correspondence between $FAIL$ and HML, in line with a relation with the value premium (Fama and French (1996); Vassalou and Xing (2004)), is evident *only after* high failure risk present in small growth returns are properly neutralized in time series regressions. This finding raises the complex nature of high failure risk returns and suggests that distress does not have a uniform effects on risk premiums across firms. A possible reason for this is the large variation of the extent that firms incorporate growth options. The next section further investigates this possibility.

In sum, the empirical findings strongly support failure risk as the main contributor to the abnormal returns of small growth stocks in line with the predictions of the model in Section II.

H. *The Role of Growth Options on the Failure Risk Small Growth Return-Relation*

The reliance on growth options through which the failure risk channel operates on growth characteristics and risk premia is another crucial feature of our model. Hence, the model supposes the relation between small growth and distress to strengthen in growth option intensity. To test this prediction, we compare the strength of the empirical relation between SG and $FAIL$ constructed from subgroups of firms sorted by alternate measures of growth option intensity (market-to-book ratio, firm size by total assets, future sales growth and R&D intensity).

At the end of each June, after the independent sorts based on size $\times$ book-to-market and O-Scores discussed earlier, we evenly distribute the stocks in each of the size $\times$ book-to-market and each of the O-Score groups into terciles on the basis of the growth option criterions and construct the SG and $FAIL$ strategy returns repeating the entire process for each alternate measure of growth option intensity. Then we estimate regression (27) for each growth intensity subgroup with SG as the dependent variable and $FAIL$ as an explanatory variable along with the FF-3 factors.

Insert Table XI Here

Table XI reports the results. As shown, the loadings on $FAIL$ is significant for all growth option terciles, with loadings that increase from low growth intensity to high growth intensity. This pattern is present for all growth option intensity criterions.

These results demonstrate that the return-relation between failure risk and small growth is driven by a common underlying force that strengthens with the extent that firm valuations incorporate growth options. The results lend strong support for growth options as the channel whereby failure risk operates on returns.

I. Robustness Checks

In this section we conduct numerous checks to verify that the return-relation between failure risk and small growth is robust to different sub-samples and other potential explanations.

I.1. Failure Risk Small Growth Return Relation Across Months of the Year

The results of our model are independent of time, therefore we should observe the return-relation between failure risk and small growth to persist across months of the year. To establish robustness, we verify the strength of the return-relation across months of the year by running separate SG regressions on $FAIL$ for each month of the year.

Table XII summarizes the results. As shown, the loadings on $FAIL$ is positive for all the months of the year most of which are statistically highly significant. These results confirm that the return-relation between failure risk and small growth persists across months of the year.

I.2. Failure Risk Small Growth Return Relation by Time Periods

A concern is that the relation between failure risk and small growth could be sporadic or sample dependent invalidating the prediction of a persistent relation. To show additional robustness, we verify the strength of the return-relation between failure risk and small growth over separate non-overlapping sample periods and during recessionary and expansionary months.[42]

Panel A of Table XIII summarizes the results. As shown, the relation persists across time periods and economic conditions. These results further verify the robustness of the relation between SG and $FAIL$.

I.3. Failure Risk Small Growth Return Relation Excluding Low Price Stocks

Our main empirical analysis includes low-priced stocks. The empirical literature views low-priced stocks as highly illiquid and subject to misvaluations. If a low stock price characterizes both high failure risk and small growth firms, then illiquidity or misvaluation could be the root cause for a return-relation between the two trading strategies. For robustness checks, we construct the

[42]NBER recession month indicators are available from FRED.

$FAIL$ and SG trading strategies after excluding stocks with price below $3, and then we evaluate the strength of the return-relation between the strategies.

Panel B of Table XIII summarizes the results. As shown, the return-relation continues to hold even after excluding low-priced stocks. Hence, illiquidity or misvaluation is unlikely to be the reason for the relation between $FAIL$ and SG.

I.4. Failure Risk Small Growth Return Relation Excluding Micro Cap Firms

Our main empirical analysis does not exclude micro cap firms. A considerable literature argues that mispricing is more pronounced among stocks associated with high information uncertainty, and firm size is commonly used as a proxy for information uncertainty (Jiang, Lee, and Zhang (2005), Zhang (2006)). For robustness checks, we construct the $FAIL$ and SG trading strategies after excluding stocks of firms in the bottom size decile where size is measured by market equity capitalization, then we evaluate the strength of the return-relation between the strategies.

Panel B of Table XIII summarizes the results. As shown, the return relation continues to hold even after micro cap firms are excluded in the construction of the trading strategies.

I.5. Failure Risk Small Growth Return Relation Excluding Delisting Returns

Shumway (1997) demonstrates that exchange delistings concur with unexpected trading halts leading to large drops in stock prices. A concern is that the return-relation discussed thus far could be influenced by the price drops caused by the exchange-delistings. This is a valid concern because, as reported earlier, small growth and high failure risk firms tend to have the highest O-Scores, and O-Scores correlate with incidences of exchange-delistings and the severity of delisting returns. As our last robustness check, we construct the $FAIL$ and SG trading strategies after excluding exchange-delisted return observations up to one year prior to the month of delisting for all delisted stocks, and then we evaluate the strength of the return-relation between the strategies.

Panel B of Table XIII summarizes the results. As shown, the return-relation between $FAIL$ and SG continues to hold even after excluding drops in stock price drops caused by exchange-delistings in the construction of the trading strategies.

J. Distress and Asset Pricing Anomalies

Thus far we presented empirical evidence consistent with the notion that failure risk is priced in line with the predictions of the model of Section II. This section investigates whether failure risk relates to a wide range of seemingly unrelated asset pricing anomalies proposed previously in the literature. The purpose of this exercise is to investigate to what extent they may be expressions of failure risk disguised as anomalies, and potentially offering further evidence that failure risk is priced.

The anomaly strategies we consider are as follows (in alphabetical order): return on asset (Chen, Novy-Marx, and Zhang (2010)), asset turnover (Novy-Marx (2013)), return on book equity (Chen et al. (2010)), Piotroski's F-Score (Piotroski (2000)), gross margin (Novy-Marx (2013)), gross profitability (Novy-Marx (2013)), idiosyncratic volatility (Ang et al. (2006)), industry momemntum (Moskowitz and Grinblatt (1999)), industry relative reversals (Da, Liu, and Schaumurg (2014)), investments (Lyandres, Sun, and Zhang (2008)), return on market equity (Chen et al. (2010)), momentum (Jegadeesh and Titman (1993)), monthly net issuance (Fama and French (2008)), short-term reversals (Jegadeesh and Titman (1993)), seasonality (Heston and Sadka (2011)), value (Fama and French (1993)) and size (Fama and French (1993)). The anomaly strategy returns are constructed by Robert Novy-Marx and conveniently made available from his personal webpage.[43] The strategies are rebalanced either monthly or annually with long and short portfolios constructed by sorting stocks into deciles on the basis of the anomaly variables. The decile breakpoint values are based on NYSE firms, while the portfolios are constructed from the full sample of NYSE, NASDAQ and AMMEX traded firms excluding utilities and financials. Novy-Marx and Velikov (2014) contains a full description of the construction of the anomaly strategies.

We regress each anomaly strategy returns on the market risk premium and a factor constructed from a long position in the top failure risk portfolio funded from a short position in the bottom failure risk portfolio. In light of our earlier findings that the relation between SG and $FAIL$ is increasing in growth option intensity, we also run separate 2-factor regressions with the $FAIL$ factor constructed from the sample of the most growth intensive firms for each of the four alternate measures of growth option intensity. More specifically, we fit the following regression:

$$r_t = \gamma_0 + \gamma_1 MKTRF_t + \gamma_2 FAIL \tag{28}$$

where r_t, $MKTRF_t$ and $FAIL$ are the time t anomaly strategy return, market excess return and the distress strategy return, respectively. We repeat the regression separately for each anomaly and each growth intensity criterion (market-to-book ratio, size, future sales growth and R& D capital), and benchmark the pricing errors against the the 3-factor (FF-3) model of Fama and French (1996) and the 4-factor (FF-4) model of Carhart (1997).[44] The estimated pricing errors and loadings on $FAIL$ are reported in Table XIV.

Insert Table XIV here

The first two columns of the left size panel of Table XIV report the abnormal returns of the anomalies relative to the FF-3 and FF-4 models. The remaining columns report the abnormal returns of the anomalies relative to the 2-factor model. Judging by the pricing errors, at least one of the two factor models outperform the FF-3 and FF-4 models explaining return on asset, asset

[43] http://rnm.simon.rochester.edu/. We thank Robert Novy-Marx for making this data available.

[44] An overwhelming share of the literature investigates asset pricing anomalies in relation to FF-3 and FF-4 models.

turnover, return on book equity, F-Score, gross margin, gross profitability, industry momentum, industry relative reversals and seasonality anomalies. The 2-factor models partly explain most of these anomalies primarily through the loadings on the $FAIL$ factor as reported in the right panel of Table XIV. The loadings agree with the notion that long portfolios in anomaly strategies resemble low failure risk stocks, and short anomaly portfolios resemble high failure risk stocks in return characteristics.

The bottom row of the table reports the relative performance of each model pricing all the anomaly strategies collectively based on the size of the root mean squared pricing error. As shown, the 2-factor models fare better than the FF-3 model while performing remarkably well against the FF-4 model. The main challenges to the 2 factor models are the momentum, value and size anomalies. The 2 factor models unsurprisingly underperform the FF-4 model pricing these three anomalies since the FF-4 model was designed with these anomalies in mind.

In sum, the results agree with the notion that seemingly unrelated asset pricing anomalies exhibit commonalities which relate to failure risk, further suggesting that idiosyncratic failure risk is priced in line with the predictions of our model.

On a practical note, the findings also suggest that a failure risk factor should be taken into account when evaluating the performance of managed funds, particularly those running strategies formed on the basis of size, book-to-market ratio, and other exising anomalies. Absent a proper adjustment for failure risk, managed funds could be assess incorrectly.

K. Trading Strategies Based on SML, HML and $FAIL$

As shown, high failure risk firms are correlated with small growth firms in characteristics and returns. Trading strategies formulated on the basis of size and book-to-market ratio implicitly are exposed to small growth-related risks. A trading strategy that sells short high failure risk stocks should be a good hedge against small growth-related risks. With that in mind, this section investigates the improvement in investment performance of SMB and HML strategies when combined with a short-$FAIL$ position.

Insert Figure 1 Here

Figure 1 shows the performance of the $FAIL$, SMB, HML, $SMB - FAIL$, $HML - FAIL$ trading strategies overtime. The performance of the trading strategies are measured as the realized annualized Sharpe ratio over the preceding year at the end of each year during the sample period (1980 to 2010). Panel (a) of the figure shows that while both the $FAIL$ and SMB strategies performed well over sub-periods, both had significant periods in which they lost money. This was particularly the case for $FAIL$. The figure also reveals that generally the performance of the two strategies are highly correlated. The sample Spearman correlation between the two strategies was 0.586%. SMB on its own had a realized Sharpe ratio of 0.13407 from 1980 to 2010. A joint short-

$FAIL$ and long-SMB strategy in the same period had a realized Sharpe ratio of 0.5896, which is greater than a four fold improvement from the sole SMB strategy, and better than the realized market portfolio Sharpe ratio of 0.4173. The improved performance of the joint trading strategy over the sole SMB strategy is illustrated in panel (a) of the figure (solid line vs. dashed line).

While not as large in magnitude, similar results apply to value strategies. The in-sample Spearman correlation between $FAIL$ and HML was a paltry -0.037 during the sample period. However, from our earlier discussion of the regression results, controlling for SG reveals the presence of a significant correlation between $FAIL$ and HML. Consistent with these findings, panel (b) of the figure shows sub-periods of strong covariation in returns between the two strategies. As for performance, the realized Sharpe ratio of HML was 0.4224 during the sample period. A joint short-$FAIL$ and long-HML strategy had a realized Sharpe ratio of 0.4854, which is an improvement of almost 15% over the sole HML trading strategy, and better than the realized market portfolio Sharpe ratio of 0.4173. The improved performance of the joint trading strategy over the HML strategy is illustrated in panel (b) of the figure (solid line vs. dashed line).

Our results establish that trading strategies that short high failure risk stocks are good hedges against small growth-risks ingrained in trading strategies while offering enhanced returns. An investor running a joint short-distressed and long-SMB or a joint short-distress and long-HML strategy would capture a better risk-return tradeoff than running SMB or HML strategies independently.

V. Conclusion

Based on a simple model of corporate investments, we develop testable hypotheses connecting small growth traits to distress in characteristics and returns, and show empirical support for the hypotheses.

In the model, firms face stochastic output price driven by a lognormal diffusion. Growth options are modeled as future opportunities to irreversibly expand the scale of operations. At any instance, firms are exposed to an idiosyncratic risk of encountering complete loss in the value of growth opportunities (failure risk), which as motivated empirically, is assumed to be greater for younger and less mature firms. We derive closed-form expressions for valuations and expected returns, and show that, similarly to Carlson, Fisher, and Giammarino (2004), the model is able to relate size and book-to-market effects to a single-factor model.

The novel feature of the model is the dependence of the systematic risk of the firms on failure risk. A higher failure risk leads to a lower benefit from physically holding the underlying assets which is not obtained from holding growth options. This leads to a lower "convenience yield", which is a condition for higher option values. The model simultaneously generates higher valuation ratios and lower systematic risk, and hence lower expected returns, for younger firms exposed to higher failure risk. The model supposes that the market prices differentials in failure risk, and there is a direct relation between high distress and small growth firms in average returns and firm-characteristics.

Consistent with the model, the empirical findings reveal that distress, as conventionally measured, captures idiosyncratic risk of sudden loss in asset value, and small growth firms resemble high distress firms along several characteristics. Small growth stocks resemble high distress stocks in return characteristics as well. A trading strategy constructed by buying high distress stocks and selling low distress stocks explains and completely subsumes the abnormal returns of a small growth strategy. The return relation between these strategies is stronger if the strategies are constructed from stocks that share stronger growth traits, suggesting that, in line with the model, the effects of failure risk on valuation and risk premia operate through growth options.

Several asset pricing anomalies previously discovered in the literature are partial expressions of distress, offering further evidence that idiosyncratic failure risk proxy for priced risk. From a practical standpoint, short-distress strategies are good hedges against small growth-related risks ingrained in other strategies. An investor running joint short-distress/long-SMB or joint short-distress/long-HML strategies would capture a better risk-return tradeoff than running SMB or HML strategies independently.

The existing literature has attributed returns related to distress and small growth to persistent market mispricings and to cognitive biases. The explanation in this paper is risk-based and entirely predicated on rational pricing. Our work is part of a growing literature that recognizes the importance of the operating environment of the firms in order to attain a better understanding of the main determinants of returns in the cross section.

Appendix A. Proof of Equation (8)

The value $F_i(P_t, z_{i,t}^{id})$ of a stage i project is a function of output price P_t and failure risk $z_{i,t}^{id}$. Since the incremental profit from an expansion $(\xi_{i+1} - \xi_{i+1})P_t$ is homogeneous in P_t, so is $F_i(P_t, z_{i,t}^{id})$. Applying Itô's Lemma to $F_{i,t} = F_i(P_t, z_{i,t}^{id})$ with P_t and $z_{i,t}$ following the processes (1) and (4), and substituting the drift $\mu_{F_{i,t}}$ we obtain

$$\frac{dF_{i,t}}{F_{i,t}} = \mu_{F_{i,t}} dt + \sigma^{id} dB_t^{id} + \sigma^{sys} dB_t^{sys} - dz_{i,t}^{id} \tag{A1}$$

where $\mu_{F_{i,t}}$ must be determined in equilibrium. From the basic asset pricing equation $E_t^{\mathbb{Q}}[dF_{i,t} + (\xi_{i+1} - \xi_i)P_t dt - rF_{i,t}dt | z_{i,t}^{id} = 0] = 0$ and applying Itô's Lemma we have

$$\frac{1}{2}\sigma^2 P_t^2 \partial_{P_t}^2 F_{i,t} + \hat{\mu}_{F,i} P_t \partial_{P_t} F_{i,t} - (r + \lambda_i) F_{i,t} + (\xi_{i+1} - \xi_i) P_t dt = 0 \tag{A2}$$

where $\partial_{P_t} = \frac{\partial}{\partial P_t}$.

The instantaneous conditional expected return of $F_{i,t}$ under the physical measure is

$$E[R_{F_{i,t}}|z_{i,t}^{id}=0]=(\mu_{F_{i,t}}-\lambda_i)dt=E\left[\frac{dF_{i,t}+(\xi_{i+1}-\xi_i)P_t dt}{F_{i,t}}|z_{i,t}^{id}=0\right]. \tag{A3}$$

Applying Itô's Lemma to the right side and using the valuation equation (A2) to express $\frac{1}{2}\sigma^2 P_t^2 \partial_{P_t}^2 F_{i,t}$, we obtain

$$\mu_{F_{i,t}}-\lambda_i=\frac{\partial_{P_t}F_{i,t}P_t}{F_{i,t}}(\mu-\hat{\mu})+r=\mu-\hat{\mu}+r \tag{A4}$$

where the last equality follows from $\frac{\partial_{P_t}F_{i,t}P_t}{F_{i,t}}=1$ due to the homogeneity of $F_{i,t}$.

Since $Cov\left(\frac{dP_t}{P_t},\frac{dS_t}{S_t}\right)=\sigma^{sys}\sigma_S dt$, under the CAPM the equilibrium drift of P_t is $\mu=r+\frac{\sigma^{sys}\sigma_S}{\sigma_S}\Theta$. Since $\hat{\mu}=\mu-\sigma^{sys}\Theta$, equation (A4) reduces to

$$\mu_{F_{i,t}}=\mu+\lambda_i. \tag{A5}$$

Hence we obtain (8).

Appendix B. Proof of Proposition 1

Up to the exercise decision, $t\leq\tau$, the basic asset pricing equation for the timing option states that

$$E_t^{\mathbb{Q}}\big[dG_{i,t}-G_{i,t}r dt|z_t=0\big]=0, t\leq\tau. \tag{B1}$$

We have under $\mathbb{Q}$,

$$\frac{dF_{i,t}}{F_{i,t}}=\hat{\mu}_{F,i}dt+\sigma d\hat{B}_t-dz_{i,t}^{id}, \tag{B2}$$

where

$$\hat{\mu}_{F,i}=\hat{\mu}+\lambda_i \tag{B3}$$

$$\sigma=\sqrt{(\sigma^{id})^2+(\sigma^{sys})^2} \tag{B4}$$

$$d\hat{B}_t=\frac{\sigma^{id}}{\sigma}dB_t^{id}+\frac{\sigma^{sys}}{\sigma}d\hat{B}_t^{sys}. \tag{B5}$$

Applying Itô's Lemma to $G_{i,t}=G_i(F_{i,t})$, we obtain

$$\frac{dG_{i,t}}{G_{i,t}}=\mu_{G_{i,t}}dt+\Omega_{i,t}\big(\sigma^{sys}dB_t^{sys}+\sigma^{id}dB_t^{id}\big)-dZ_{i,t}^{id}, \tag{B6}$$

where

$$\mu_{G_{i,t}}=\Omega_{i,t}\hat{\mu}_{F,i}-\lambda_i+\frac{1}{2}\frac{P_t^2}{G_{i,t}}\frac{\partial^2 G_{i,t}}{\partial P_t^2}\left((\sigma^{sys})^2+(\sigma^{id})^2\right), \tag{B7}$$

$\Omega_{i,t} = \frac{P_t}{G_{i,t}} \frac{\partial G_{i,t}}{\partial P_t}$, and

$$dZ_{i,t}^{id} = dz_{i,t}^{id} - \lambda_i dt \tag{B8}$$

is a compensated Poisson process, and hence a discontinuous martingale, driven by $dz_{i,t}^{id}$. From the fundamental pricing equation (B1) we obtain the ordinary differential equation

$$\frac{1}{2}\sigma^2 P^2 \partial_{P_t}^2 G_{i,t} + \hat{\mu}_{F,i} P \partial_{P_t} G_{i,t} - (r + \lambda_i) G_{i,t} = 0,\ t \leq \tau, \tag{B9}$$

where $\partial_{P_t} = \frac{\partial}{\partial P_t}$.

Using $p_t = \ln P_t$ as the state variable, when $p < p_i^*$, $t \leq \tau$, and (B9) holds, the general solution is given by

$$G_i = \sum_{m=1}^{2} \delta_{i,m} e^{\phi_{i,m} p}, \tag{B10}$$

where $\phi_{i,1} > 1 > 0 > \phi_{i,2}$ are the roots of the quadratic equation

$$q_i(\phi) = \frac{1}{2}\left((\sigma^{id})^2 + (\sigma^{sys})^2\right)\phi(\phi - 1) + \hat{\mu}_{F,i}\phi - (r + \lambda_i) = 0 \tag{B11}$$

To ensure that G_i is finite as $p \to -\infty$, $\delta_{i,2} = 0$ and hence

$$G_i = \delta_i e^{\phi_i p}, \tag{B12}$$

where $\phi_i = \phi_{i,1}$ and $\delta_i = \delta_{i,1}$.

In the region $p \geq p_i^*$, investment will have occurred, and so

$$G_{i,t} = V_{i+1,t} - \xi_i A_{i,t}, \tag{B13}$$

while at the time of investment the above expression needs to be adjusted downward by subtracting the one-off investment cost of I_i.

Value matching and smooth pasting at $p = p_i^*$ for G_i implies that

$$\lim_{p \uparrow p_i^*} G_i = \lim_{p \downarrow p_i^*} G_i, \tag{B14}$$

$$\lim_{p \uparrow p_i^*} \frac{\partial G_i}{\partial p} = \lim_{p \downarrow p_i^*} \frac{\partial G_i}{\partial p}, \tag{B15}$$

which translate to the following systems of equations:

$$\delta_i \left(P_i^*\right)^{\phi_i} = \frac{(\xi_{i+1} - \xi_i) P_i^*}{r - \hat{\mu}} + \delta_{i+1}\left(P_i^*\right)^{\phi_{i+1}} - I_i, \tag{B16}$$

$$\phi_i \delta_i \left(P_i^*\right)^{\phi_i - 1} = \frac{\xi_{i+1} - \xi_i}{r - \hat{\mu}} + \phi_{i+1}\delta_{i+1}\left(P_i^*\right)^{\phi_{i+1} - 1} \tag{B17}$$

Taking (B16), solving for δ_i, and substituting δ_i into (B12) results in equation (11) of the proposition. (B17) is an algebraic expression of P_i^* that can be solved recursively and then used to find δ_i from (B16).

For $i = n-1$, it is possible to solve for P_i^* (and hence δ_i) in closed-form, which is (15) in the proposition. This completes the proof of the proposition.

Appendix C. Proof of Proposition 2

First, we prove that $\frac{\partial G_{i,t}}{\partial \lambda_i} > 0$. Proposition 1 states that

$$G_{i,t} = \delta_i P^{\phi_i} = a_i \left(\frac{P}{P_i^*} \right)^{\phi_i}, \tag{C1}$$

where $a_i, \delta_i, \phi_i > 0$. Taking the partial derivative gives

$$\frac{\partial G_{i,t}}{\partial \lambda_i} = \frac{\partial G_{i,t}}{\partial \phi_i} \frac{\partial \phi_i}{\partial \lambda_i}, \tag{C2}$$

Taking the partial derivative of $G_{i,t}$ with respect to ϕ_i reveals that

$$\frac{\partial G_{i,t}}{\partial \phi_i} = log \left(\frac{P_t}{P_i^*} \right) G_{i,t} < 0 \tag{C3}$$

since $P_t < P_i^*$. To figure out the sign of $\frac{\partial \phi_i}{\partial \lambda_i}$, take the quadratic equation $q_i(\phi_i) = \frac{1}{2}\sigma^2 \phi_i(\phi_i - 1) + \hat{\mu}_{F,i}\phi_i - (r + \lambda_i) = 0$, and differentiate it totally where the derivatives are evaluated at ϕ_i

$$\frac{\partial q_i(\phi_i)}{\partial \phi_i} \frac{\partial \phi_i}{\partial \lambda_i} + \frac{\partial q_i(\phi_i)}{\partial \lambda_i} = 0. \tag{C4}$$

Since $\frac{\partial q_i(\phi_i)}{\partial \phi_i}$ and $\frac{\partial q_i(\phi_i)}{\partial \lambda_i} > 0$, $\frac{\partial \phi_i}{\partial \lambda_i}$ must be negative, and thus $\frac{\partial G_{i,t}}{\partial \lambda_i} > 0$. This completes the proof of the first statement of the proposition.

Now to prove that $\frac{\partial}{\partial \lambda_i} \left[\frac{V_{i,t}}{F} \right] > 0$, consider the value of the firm $V_{i,t} = \xi_i A_{i,t} + G_{i,t}$. Taking the derivative gives

$$\frac{\partial}{\partial \lambda_i} \left[\frac{V_{i,t}}{F} \right] = \frac{\partial}{\partial \lambda_i} \left[\frac{G_{i,t}}{F} \right] > 0 \tag{C5}$$

since $\frac{\partial F}{\partial \lambda_i} = 0$ and $\frac{\partial G_{i,t}}{\partial \lambda_i} > 0$ as shown earlier. This completes the proof of the proposition.

Appendix D. Proof of Proposition 3

The proof follows from applying Itô's Lemma to $G_{i,t}$, which results in (20).

Appendix E. Proof of Proposition 4

Taking derivatives gives

$$\frac{\partial \sigma^{sys}_{R_{i,t}}}{\partial \lambda_i} = \frac{\partial}{\partial \lambda_i}\left[\frac{G_{i,t}}{V_{i,t}}\right](\Omega_{i,t} - 1 - L(P_t)) + \frac{G_{i,t}}{V_{i,t}}\frac{\partial \Omega_{i,t}}{\partial \lambda_i} \tag{E1}$$

Note that $\Omega_{i,t} = \frac{P_i}{G_{i,t}}\frac{\partial G_{i,t}}{\partial P_t} = \frac{P_t}{G_{i,t}}\delta_i \phi_i P_t^{\phi_i - 1} = \phi_i$. Hence, the second term of the right side of (E1) is negative since $\frac{\partial \Omega_{i,t}}{\partial \lambda_i} = \frac{\partial \phi_i}{\partial \lambda_i} < 0$ as proven in proposition 2.

The first term of the right side of (E1), on the other hand, can take on positive values for some values of P_t since $\frac{\partial}{\partial \lambda_i}\left[\frac{G_{i,t}}{V_{i,t}}\right] > 0$.[45] So it is not immediately clear that $\frac{\partial \sigma^{sys}_{R_{i,t}}}{\partial \lambda_i} < 0$. Our proposition is that after netting out with the second term, $\frac{\partial \sigma^{sys}_{R_{i,t}}}{\partial \lambda_i}$ is negative. To see this, consider first low values of P_t. If P_t is low, $L(P_t)$ will take on a high value and $(\Omega_{i,t} - 1 - L(P_t))$ will be negative making $\frac{\partial \sigma^{sys}_{R_{i,t}}}{\partial \lambda_i}$ negative as well. If P_t is high, on the other hand, $(\Omega_{i,t} - 1 - L(P_t))$ may become marginally positive, but $\frac{G_{i,t}}{V_{i,t}} \approx 1$ and $\frac{\partial \Omega_{i,t}}{\partial \lambda_i} < 0$ will receive a greater weight making $\frac{\partial \sigma^{sys}_{R_{i,t}}}{\partial \lambda_i}$ negative. This completes the proof.

[45] $\frac{\partial}{\partial \lambda_i}\left[\frac{G_{i,t}}{V_{i,t}}\right] = \frac{V_{i,t}\frac{\partial G_{i,t}}{\partial \lambda_i} - G_{i,t}\frac{\partial V_{i,t}}{\partial \lambda_i}}{V_{i,t}^2} = \frac{V_{i,t}\frac{\partial G_{i,t}}{\partial \lambda_i} - G_{i,t}\frac{\partial G_{i,t}}{\partial \lambda_i}}{V_{i,t}^2} > 0$ since $V_{i,t} > G_{i,t}$ and $\frac{\partial G_{i,t}}{\partial \lambda_i} > 0$ from Proposition 2.

REFERENCES

Aguerrevere, Felipe, 2009, Real options, product market competition, and asset returns, *Journal of Finance* 64, 957–983.

Anderson, Christopher, and Luis Garcia-Feijóo, 2006, Empirical evidence on capital investment, growth options, and security returns, *Journal of Finance* 171–194.

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

Anginer, Deniz, and Celim Yildizhan, 2010, Is there a distress risk anomaly? corporate bond spread as a proxy for default risk., *Working Paper* .

Asquith, Paul, Robert Gertner, and David Sharfstein, 1994, Anatomy of financial distress: An examination of junk-bond issuers., *Quarterly Journal of Economics* 109, 625–658.

Avramov, Doron, Scott Cederburg, and Satadru Hore, 2012a, Cross-sectional asset pricing puzzles: An equilibrium perspective., *Working Paper* .

Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2007, Momentum and credit rating, *Journal of Finance* .

Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2012b, Credit ratings and the cross-section of stock returns, *Working Paper* .

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

Brennan, Michael, and Eduardo Schwartz, 1985, Evaluating nature resource investments., *Journal of Business* 58, 135–157.

Brown, Gregory, and Nishad Kapadia, 2007, Firm-specific risk and equity market development., *Journal of Financial Economics* 84, 358–388.

Campbell, John Y., 2003, Consumption based asset pricing, *George Constantinides, Milton Harris, and Renee Stulz, eds. Handbook of the Economics of Finance* .

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *Journal of Finance* 63, 2899–2939.

Carhart, Mark, 1997, On persistence in mutual fund performance?, *Journal of Finance* 52, 57–82.

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, Adlai Fisher, and Ron Giammarino, 2006, Corporate investment and asset price dynamics: Implications for seo event studies and long-run performance., *Journal of Finance.* 61, 1009–1034.

Chan, K. C., and Nai-Fu Chen, 1991, Structural and return characteristics of small and large firms., *Journal of Finance* .

Chan, Louis K. C., Josef Lakonishok, and Theodore Sougiannis, 2001, The stock market valuation of research and development expenditures, *Journal of Finance* 51, 2431–2456.

Chen, Long, Robert Novy-Marx, and Lu Zhang, 2010, An alternative three-factor model., *Working Paper* .

Conrad, Jennifer S., Nishad Kapadia, and Yuhang Xing, 2012, What explains the distress risk puzzle: Death or glory?, *Working Paper* .

Cooper, Ilan, 2007, Asset pricing implications of nonconvex adjustment costs and irreversibility of investment., *Journal of Finance* 61, 139–170.

Da, Zhi, Q. Liu, and E. Schaumurg, 2014, A closer look at the short-term reversal., *Management Science* 60.

Dichev, Ilia D., 1998, Is the risk of bankruptcy a systematic risk?, *Journal of Finance* 1131–1147.

Dixit, Avinash K., and Robert S. Pindyck, 1994, *Investment under Uncertainty* (Princeton University Press).

Duffie, Darrell, and Kenneth J. Singleton, 2003, *Credit Risk: Pricing, Measurement, and Management* (Princeton University Press).

Fama, Eugene, and Kenneth R. French, 1992, The cross-section of expected stock returns., *Journal of Finance* 47, 427–465.

Fama, Eugene, and Kenneth R. French, 1993, Common risk factors in the returns on common stocks and bonds., *Journal of Financial Economics* 25, 2349.

Fama, Eugene, and Kenneth R. French, 1996, Multifactor explanations of asset-pricing anomalies., *Journal of Finance* 51, 55–84.

Fama, Eugene, and Kenneth R. French, 2015, A five-factor asset pricing model., *Forthcoming Journal of Financial Economics* .

Fama, Eugene F., and Ken French, 2008, Dissecting anomalies, *Jounal of Finance* 63.

Favara, Giovanni, Enrique Schroth, and Philip Valta, 2012, Strategic default and equity risk across countries., *Journal of Finance.* 67, 2051–2095.

Friewald, Nils, Chritian Wagner, and Josef Zechner, 2014, The cross-section of credit risk premia and equity returns., *Journal of Finance* 2419–2469.

Garlappi, Lorenzo, Tao Shu, and Hong Yan, 2008, Default risk, shareholder advantage, and stock returns, *Review of Financial Studies* 21, 2743–2778.

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

George, Thomas J., and Chuan-Yang Hwang, 2010, A resolution of the distress risk and leverage puzzles in the cross section of stock returns, *Journal of Financial Economics* 96, 56–79.

Griffin, John M., and Michael Lemmon, 2002, Book-to-market equity, distress risk, and stock returns, *Journal of Finance* 2317–2336.

Grullon, Gustavo, Evgeny Lyandres, and Alexei Zhdanov, 2010, Real options, volatility, and stock returns., *Journal of Finance Forthcoming* .

Hackbarth, Dirk, and Erwan Morellec, 2008, Stock returns in mergers and acquisitions, *Journal of Finance* 63, 1203–1242.

Heston, S. L., and R. Sadka, 2011, Seasonality in the cross-section of stock returns., *Journal of Financial Economics* 87.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad new travels slowly: Size,analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265–295.

Jegadeesh, N., and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency., *Journal of Finance* 48, 65–91.

Jiang, Guohua, Charles M.C. Lee, and Grace Yi Zhang, 2005, Information uncertainty and expectedstock returns, *Review of Accounting Studies* 10, 185–221.

Livdan, Dmitry, Horacio Sapriza, and Lu Zhang, 2009, Financially constrained stock returns., *Journal of Finance* 64, 1827–1862.

Lyandres, E., L. Sun, and L. Zhang, 2008, Investment-based underperformance following seasoned equity offerings., *Review of Financial Studies* 21, 2825–2855.

MacDonald, Robert, and Daniel Siegel, 1985, Investment and valuation of firms when there is an option to shut down., *International Economic Review* 26, 331–349.

MacDonald, Robert, and Daniel Siegel, 1986, The value of waiting to invest., *Quarterly Journal of Economics* 101, 707–727.

Majd, Saman, and Robert S. Pindyck, 1987, Time to build option value, and investment decisions., *Journal of Financial Economics* 18, 7–27.

Merton, Robert C., 1976, Option pricing when underlying stock returns are discontinuous, *Journal of Financial Economics* 3, 125–144.

Moskowitz, T., and M. Grinblatt, 1999, Do industries explain momenum?, *Journal of Finance* 54.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semidefinite, heteroskedastcity and autocorrelation consistent covariance-matrix., *Econometrica* 55, 703–708.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium., *Journal of Financial Economics* 108, 1–28.

Novy-Marx, Robert, and Mihail Velikov, 2014, A taxonomy of anomalies and their trading costs., *Working Paper* .

Ohlson, James, 1980, Financial ratios and the probabilistic prediction of bankruptcy, *Journal of Accounting Research* 18, 109–131.

Opler, Tim, and Sheridan Titman, 1994, Financial distress and corporate performance, *Journal of Finance* 49, 1015–1040.

Pindyck, Robert S., 1988, Irrevesible investment, capacity choice, and the value of the firm, *American Economic Review* 78, 969–985.

Piotroski, Joseph D., 2000, Value investing: The use of historical financial statement information to separate winners from losers., *Journal of Accounting Research* 38, 1–41.

Sagi, Jacob S., and Mark S. Seasholes, 2007, Firm-specific attributes and the cross-section of momentum., *Journal of Financial Economics* 84, 389–434.

Shumway, Tyler, 1997, The delisting bias in crsp data, *Journal of Finance* 52, 327–340.

Vassalou, Maria, and Yuhang Xing, 2004, Default risk in equity returns, *Journal of Finance* 59, 831–863.

Zhang, Frank X., 2006, Information uncertainty and stock returns., *Journal of Finance* 61, 105136.

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

Table I Model Parameters

This table reports the parameter values used to solve the model developed in Section II of the paper.

Model Parameters		
Price Dynamics	Variable Description	Values
μ	Drift term	0.06
σ^{id}	Idiosyncratic volatility	0.4
σ^{sys}	Systematic volatility	0.16
Operating Environment		
n	Number of firm's life stages until full maturity	3
f	Fixed operating cost	20
ξ_1	Production scale for stage $i = 1$ firm	1
ξ_2	Production scale for stage $i = 2$ firm	3
ξ_3	Production scale for stage $i = 3$ firm	4
I_1	Investment cost for stage $i = 1$ firm to expand	3
I_2	Investment cost for stage $i = 2$ firm to expand	5
λ_1	Probability of failure for stage $i = 1$ firm	$\in [0, 0.17]$
λ_2	Probability of failure for stage $i = 2$ firm	0.0135
λ_3	Probability of failure for stage $i = 3$ firm	0.007
Market Variables		
r	Riskless rate	0.04
μ_S	Drift of tradeable asset (Market)	0.12
σ_S	Diffusion of tradeable asset (Market)	0.2

Table II Model Solution: Dependence of Growth Option Value, Exercise Policy, Option Risk, Leverage Ratio, Growth Ratio and Systematic Risk on Failure Risk.

This table reports the values of δ_i, P_i^*, Ω_i, $\frac{F}{V_i}$,$\frac{V_i}{F}$ and $\sigma_{R_1}^{sys}$ for alternate values of λ_i based on the model developed in Section II of the paper. The quantities are reported for $P = 5$. The parameterization of the model is reported in Table I.

λ_1	δ_1	P_1^*	Ω_1	$\frac{F}{V_1}$	$\frac{V_1}{F}$	V	$\sigma_{R_1}^{sys}$
0	11.8747	30.9922	1.36	2.8311	0.35322	44.1518	0.7151
0.0189	13.6423	34.484	1.3202	2.4523	0.40778	50.972	0.6379
0.0378	15.3625	38.3243	1.2872	2.1775	0.459242	57.4066	0.5816
0.0567	17.0157	42.5378	1.2595	1.9703	0.507537	63.4419	0.5391
0.0756	18.5914	47.1625	1.2362	1.8093	0.5527	69.0864	0.5059
0.0944	20.086	52.2525	1.2164	1.681	0.594884	74.3614	0.4795
0.1133	21.4998	57.8818	1.1994	1.5764	0.634357	79.2947	0.4578
0.1322	22.836	64.1516	1.1847	1.4896	0.671321	83.9162	0.4399
0.1511	24.0992	71.201	1.172	1.4163	0.706065	88.2563	0.4248
0.17	25.2946	79.2247	1.1607	1.3536	0.738771	92.3444	0.4118

Table III Frequency of Delistings Across Failure Risk Deciles

This table reports the proportion of stock delistings across O-Score decile groups among delisted stocks. Proportions of delistings for each O-Score group are reported for years -6, -5, -4, -3, -2 and -1 from the month of delisting. Panel A reports the proportion of stocks delisted due to bankruptcy or liquidation (CRSP delisting codes 400, 572 or 574). Panel B reports the proportion of stocks delisted due to negative performance other than bankruptcy or liquidation (CRSP delisting codes between 420 and 584 except 572 or 574). CRSP coding convention prior to 1987 does not differentiate bankruptcy or liquidation from performance. Hence, results are reported for post-1987 delistings only.

	Years from the month of delisting					
	-1	-2	-3	-4	-5	-6
O-Score Decile	(A) % of firms delisted due to bankruptcy or liquidation					
1	.	.	.	.	.	.
2	.	.	.	.	.	.
3	0.337	0.382	.	.	.	.
4	0.351	0.41	0.435	.	.	.
5	.	.	.	.	.	.
6	0.426	0.424	.	.	.	.
7	0.932	0.364	0.397	0.439	0.472	.
8	0.794	0.837	0.952	1.042	.	.
9	0.623	1.389	0.922	0.518	.	.
10	0.813	0.372	0.629	.	.	.
	(B) % of firms delisted due to poor performance					
1	0.69	1.465	1.792	2.326	1.66	0.905
2	0.332	1.37	0.707	1.111	0.415	0.877
3	1.65	0.673	1.083	1.908	2.5	1.31
4	1.929	0.694	1.754	1.569	2.049	1.304
5	1.356	1.418	2.465	1.527	0.816	2.294
6	1.754	2.749	2.817	1.639	1.277	3.39
7	2.484	3.136	4	1.984	1.316	1.415
8	3.774	2.667	3.571	4.603	5.238	4.688
9	4.361	6.944	3.687	5.181	4	4.43
10	16.531	13.755	11.94	10.692	7.362	6.993

Table IV Delisting Return and Failure Risk

This table reports mean O-Scores across quintile groups formed on the basis of return during the month of delisting. Mean O-Scores are reported for years -6, -5, -4, -3, -2 and -1 from the month of delisting. Panel A reports mean O-Scores based on delisting returns computed according to CRSP. Panel B reports mean O-Scores based on delisting returns corrected for biases following the Shumway (1997).

	Years from the month of delisting					
	-1	-2	-3	-4	-5	-6
return quintile	(A) Mean O-Score (sorts based on CRSP delisting return)					
1	-0.27	-0.36	-0.98	-1.11	-1.3	-1.51
2	-1.28	-1.1	-1.55	-1.73	-1.88	-1.9
3	-1.87	-1.57	-1.91	-2.09	-2.13	-1.97
4	-1.72	-1.53	-1.96	-2.18	-2.06	-2.08
5	-0.38	-0.48	-1.3	-1.38	-1.42	-1.48
	(B) Mean O-Score (sorts based on Shumway delisting return)					
1	-0.23	-0.33	-0.96	-1.1	-1.31	-1.52
2	-1.32	-1.16	-1.56	-1.73	-1.86	-1.89
3	-1.87	-1.56	-1.92	-2.08	-2.12	-1.96
4	-1.73	-1.52	-1.95	-2.17	-2.07	-2.07
5	-0.38	-0.47	-1.3	-1.39	-1.42	-1.49

Table V Summary Statistics: Characteristics of Firms Sorted on Failure Risk

Panel A of the table reports the mean O-Score, credit score, age, market equity, book-to-market ratio, book leverage ratio, market leverage ratio, and the mean number of return observations (N) with non-missing O-Scores values for each O-Score decile. Stocks are sorted evenly into 10 groups on the basis of their O-Score measure at the end of each June in our sample before summary statistics are computed. COMPUSTAT S&P issuer credit ratings are converted into numerical values where a higher value corresponds to a lower S&P credit rating. The full mapping follows Avramov, Chordia, Jostova, and Philipov (2012b): AAA=1, AA+=2, AA=3, AA-=4, A+=5, A=6, A-=7, BBB+=8, BBB=9, BBB-=10, BB+=11, BB=12, BB-=13, B+=14, B=15, B-=16, CCC+=17, CCC=18, CCC-=19, CC=20, C=21, D=22. Firm age is reported in years since the first stock return observation in CRSP. The construction of the other variables is described in the paper. The mean proportion of stocks with book financial and market financial leverage ratios below 0.3 for each O-Score decile is reported in Panel B. Panel C reports the mean proportion of stocks with book and market financial leverage above 0.7.

	Full Sample	1	2	3	4	5	6	7	8	9	10
Panel A. Summary Statistics for O-Score Deciles											
O-Score	-0.99	-5.84	-3.55	-2.67	-2.04	-1.51	-1.01	-0.46	0.2	1.2	5.76
Credit Score	9.55	6.68	6.82	7.66	8.71	9.2	9.7	10.43	11.82	13.32	15.15
Age	12.51	11.77	14.52	15.48	15.79	16.44	16.03	14.6	12.68	10.65	7.46
Market Equity	1705.88	3471.85	3544.51	2920.14	2225.63	1711.6	1268.06	830.63	430.63	200.22	84.74
Book-to-market	0.82	0.49	0.67	0.73	0.82	0.89	0.97	1.01	1.06	1.04	0.63
Book leverage	0.44	0.18	0.28	0.35	0.4	0.45	0.49	0.52	0.56	0.59	0.5
Market leverage	0.34	0.08	0.17	0.24	0.31	0.37	0.41	0.45	0.49	0.49	0.32
N	1026726	102831	102660	102689	102661	102607	102732	102693	102657	102692	102504
Panel B. % of stocks with financial leverage below 0.3 for each O-Score Decile											
Book leverage		0.92	0.61	0.34	0.21	0.15	0.12	0.1	0.11	0.13	0.32
Market leverage		0.99	0.9	0.72	0.53	0.37	0.28	0.23	0.22	0.27	0.56
Panel C. % of stocks with financial leverage greater than 0.7 for each O-Score Decile											
Book leverage		0	0	0	0.01	0.03	0.05	0.11	0.21	0.33	0.32
Market leverage		0	0	0	0.02	0.03	0.05	0.1	0.18	0.26	0.15

Table VI Summary Statistics: Characteristics of Firms Sorted on Size and Book-to-Market Ratio.

This table reports the mean O-Score, credit score, age, market equity, book-to-market ratio, book leverage ratio, market leverage ratio, and the mean number of return observations (N) with non-missing O-Scores, the percentage of firms with book financial leverage and market financial leverage ratio lower than 0.3 and the percentage of firms with book financial leverage and market financial leverage ratio greater than 0.7 for each of the 25 5×5 size and book-to-market groups. The cut off values for each sort variable are based on NYSE firms at the end of each June. The 30th percentile cutoff points are determined at the end of each June based on each book financial leverage and market financial leverage ratio. COMPUSTAT S&P issuer credit ratings are converted into numerical values where a higher value corresponds to a lower S&P credit rating. The full mapping follows Avramov, Chordia, Jostova, and Philipov (2012b): AAA=1, AA+=2, AA=3, AA-=4, A+=5, A=6, A-=7, BBB+=8, BBB=9, BBB-=10, BB+=11, BB=12, BB-=13, B+=14, B=15, B-=16, CCC+=17, CCC=18, CCC-=19, CC=20, C=21, D=22. Firm age is reported in years since the first stock return observation in CRSP. The construction of the other variables is described in the paper.

	book-to-market					book-to-market					book-to-market				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
size	Panel A. O-Score					Panel B. Credit Score					Panel C. Market Equity				
1	1.4	-0.68	-0.87	-0.84	-0.36	14.77	13.82	13.13	12.85	13.57	84.3	88.23	83.93	78.88	58.37
2	-1.97	-2.24	-1.89	-1.53	-1.09	13.61	12.61	11.36	10.67	11.64	390.62	406.5	413.68	426.4	404.99
3	-2.8	-2.43	-1.86	-1.54	-1.26	12.12	10.71	9.82	9.35	10.2	898.36	965.99	952.29	981	899.87
4	-2.99	-2.33	-1.94	-1.6	-1.35	9.52	8.48	8.45	8.63	9.11	2341.05	2318.26	2230.45	2141.41	2182.32
5	-3.08	-2.52	-2.19	-1.94	-1.82	5.82	6.54	6.65	7.11	7.67	23807.3	17330.8	13822.2	10629.5	10312.3
	Panel D. Book-to-Market					Panel E. Book Leverage					Panel F. Market Leverage				
1	0.23	0.48	0.7	0.96	2.04	0.43	0.4	0.41	0.42	0.45	0.18	0.26	0.33	0.4	0.53
2	0.23	0.48	0.69	0.93	1.68	0.38	0.4	0.44	0.47	0.51	0.15	0.26	0.35	0.44	0.57
3	0.23	0.47	0.69	0.95	1.62	0.39	0.43	0.47	0.5	0.53	0.16	0.28	0.38	0.48	0.59
4	0.23	0.47	0.69	0.97	1.54	0.43	0.47	0.51	0.53	0.55	0.18	0.3	0.42	0.51	0.61
5	0.22	0.48	0.71	0.98	1.43	0.49	0.52	0.56	0.58	0.55	0.2	0.36	0.47	0.56	0.6
	Panel G. Age					Panel H. N					Panel I. % with Book Leverage below 0.3				
1	6.31	8.37	10.07	11.46	11.8	136692	96670	95982	104129	164715	0.37	0.39	0.35	0.33	0.28
2	7.43	11.58	14.86	16.72	16.41	44737	34813	31314	24992	18167	0.45	0.36	0.27	0.21	0.16
3	10.1	14.98	17.73	19.99	19.84	33860	25023	19619	16295	12127	0.43	0.28	0.2	0.14	0.1
4	14.23	20.22	22.14	23.13	23.24	28786	21079	15555	14141	9628	0.33	0.19	0.12	0.1	0.07
5	22.78	25.56	25.44	25.66	25.82	31911	17052	11996	10046	7056	0.21	0.09	0.04	0.04	0.05
	Panel J. % with Market Leverage below 0.3					Panel K. % with Book Leverage above 0.7					Panel L. % with Market Leverage above 0.7				
1	0.8	0.65	0.51	0.38	0.21	0.19	0.11	0.11	0.1	0.13	0.03	0.04	0.06	0.1	0.28
2	0.85	0.67	0.43	0.27	0.13	0.13	0.09	0.09	0.11	0.17	0.01	0.03	0.04	0.09	0.3
3	0.85	0.6	0.35	0.2	0.1	0.13	0.1	0.12	0.13	0.15	0.02	0.03	0.06	0.12	0.3
4	0.81	0.57	0.27	0.14	0.06	0.16	0.11	0.13	0.15	0.15	0.01	0.03	0.07	0.15	0.34
5	0.8	0.4	0.17	0.07	0.06	0.17	0.15	0.19	0.2	0.14	0.02	0.05	0.12	0.22	0.26

Table VII Size and Book-to-Market Portfolio Returns.

This table reports intercept estimates from regressing each of the 5 × 5 size and book-to-market portfolio returns on the three factors of Fama and French (1993). At the end of each June, stocks are sorted into 5 groups based on market equity (size) and, separately, into 5 groups based on book-to-market ratio where the cutoff values are based on NYSE firms, then monthly value-weighted portfolio returns are computed for each of the 25 (5 × 5) groups. The regression model estimated is

$$r_t - r_{f,t} = \alpha + \gamma_1 SMB_t + \gamma_2 HML_t + \gamma_3 MKTRF_t + \epsilon_t$$

where r_t is portfolio return, $r_{f,t}$ is the monthly riskless rate, SMB, HML and $MKTRF$ are the factors that proxy for size, book-to-market and the market risk premium, respectively. Estimates are also reported for the zero-cost portfolios (column and row labeled 5-1) and for the equally-weighed portfolios along each one-way rank classification of size and book-to-market (column and row labeled Mean). All portfolios are rebalanced monthly and the reported intercepts are annualized. Newey and West (1987) robust t-statistics are reported in square brackets.

	book-to-market						
size	1	2	3	4	5	5-1	Mean
1	-5.5605***	3.1783**	2.7962**	3.4110***	2.4824**	8.0429***	1.2615
	[-3.3190]	[2.0815]	[2.4823]	[3.5892]	[2.1561]	[4.3104]	[1.3449]
2	-1.6737	0.0837	1.7327	1.2034	-1.7025	-0.0288	-0.0713
	[-1.5071]	[0.0709]	[1.4834]	[1.2010]	[-1.3180]	[-0.0198]	[-0.0945]
3	0.0291	1.7887	-0.7231	0.0182	0.4238	0.3946	0.3073
	[0.0258]	[1.2018]	[-0.5566]	[0.0143]	[0.2962]	[0.2101]	[0.3597]
4	2.1421*	0.8103	-0.567	-1.1286	0.2589	-1.8833	0.3031
	[1.9215]	[0.6541]	[-0.4167]	[-0.7980]	[0.1725]	[-1.0777]	[0.3368]
5	2.4107***	0.3107	0.3694	-1.9892	-1.0861	-3.4968*	0.0031
	[2.8531]	[0.2628]	[0.3292]	[-1.5624]	[-0.6101]	[-1.7543]	[0.0061]
5-1	7.9712***	-2.8676	-2.4268*	-5.4002***	-3.5685*		-1.2584
	[4.2738]	[-1.4195]	[-1.6883]	[-3.7798]	[-1.6735]		[-1.2707]
Mean	-0.5304	1.2343	0.7216	0.3029	0.0753	0.6057	
	[-0.7366]	[1.5593]	[0.9540]	[0.3873]	[0.0878]	[0.6036]	

Table VIII Failure Risk Portfolio Returns.

This table reports average portfolio returns across O-Score decile. At the end of each June, stocks are sorted evenly into 10 groups on the basis of the O-Score measures, then monthly value-weighted portfolio returns are computed for each O-Score decile. Panel A reports mean unadjusted returns, mean risk-adjusted returns relative to the CAPM, the 3-factor model of Fama and French (1993), and the 4-factor model of **?**. Panels B and C report O-Score sorted portfolio returns for book financial leverage and market financial leverage terciles after stocks are additionally sorted on the basis of their respective leverage ratios. Mean returns are also reported for the zero-cost portfolio which invests in the highest O-Score portfolio funded from a short position in the lowest O-Score portfolio (column labeled 10-1). All portfolios are rebalanced monthly and the reported returns are annualized. Newey and West (1987) robust t-statistics are reported in square brackets.

	1	2	3	4	5	6	7	8	9	10	10-1
Panel A. O-Score decile portfolio returns											
mean return	7.4991*	6.1754**	7.9700***	7.6293***	7.2762**	7.5168**	6.9261**	9.0552**	4.6442	-1.0716	-8.5708**
	[1.8841]	[2.1080]	[2.8943]	[2.6355]	[2.4803]	[2.5060]	[2.0707]	[2.2830]	[0.9482]	[-0.1618]	[-2.0121]
CAPM alpha	0.1828	0.1049	2.1573*	1.5856*	1.4567	1.6579*	0.5634	1.5377	-3.8000*	-11.1184***	-11.3012***
	[0.0897]	[0.1031]	[1.9343]	[1.6783]	[1.3144]	[1.6762]	[0.3969]	[0.9784]	[-1.6507]	[-2.7462]	[-2.9356]
3-factor alpha	3.6818**	0.9248	1.8579**	0.8902	-0.0765	0.4827	-1.3138	0.505	-3.7267**	-9.2697***	-12.9515***
	[2.4430]	[0.9741]	[1.9692]	[0.9613]	[-0.0755]	[0.4839]	[-1.0391]	[0.4051]	[-1.9772]	[-3.3449]	[-4.4782]
4-factor alpha	3.3976**	1.2687	1.1929	1.1571	-0.3269	-0.291	-1.5178	0.8478	-2.8266	-8.0470***	-11.4446***
	[2.3824]	[1.2266]	[1.1821]	[1.2030]	[-0.3246]	[-0.2711]	[-1.0751]	[0.6737]	[-1.5056]	[-2.8266]	[-3.7919]
Panel B. O-Score decile portfolio 3-factor alphas for each book leverage tercile											
1	0.7925	-0.2692	0.2141	2.7737	-1.8436	-0.8149	-3.962	-3.5424	-0.6518	-9.9782***	-10.7707***
	[0.3504]	[-0.0937]	[0.0802]	[0.7985]	[-0.9250]	[-0.3464]	[-1.5292]	[-1.4063]	[-0.1741]	[-2.7602]	[-2.6765]
2	1.6192	2.8305	-1.9542	-2.4202*	-0.1987	-2.1202	-1.6327	-0.7299	-0.8268	-8.2280**	-9.8472**
	[0.7330]	[1.2653]	[-1.0288]	[-1.7356]	[-0.1244]	[-1.3049]	[-1.0933]	[-0.3826]	[-0.2077]	[-2.2780]	[-2.5874]
3	3.8522**	1.389	2.4842**	1.5412	0.4962	1.4687	-0.2095	1.5401	-5.8400***	-7.4198**	-11.2720***
	[2.3914]	[1.2326]	[2.1601]	[1.4523]	[0.3920]	[1.0746]	[-0.1371]	[1.0110]	[-2.6895]	[-2.0838]	[-2.7778]
Panel C. O-Score decile portfolio 3-factor alphas for each market leverage tercile											
1	2.7746	-1.7364	3.8298**	0.233	-1.129	0.2687	-5.9049***	-2.9233	-4.3342	-14.4574***	-17.2320***
	[1.3222]	[-0.9316]	[2.1745]	[0.1410]	[-0.6164]	[0.1690]	[-2.7430]	[-1.4690]	[-1.4488]	[-4.6561]	[-5.0132]
2	0.9869	3.7581**	1.2006	-0.3751	0.6288	-0.6163	-1.1209	1.8413	-5.5625**	-4.0963	-5.0832
	[0.4670]	[2.2415]	[0.8027]	[-0.2805]	[0.3979]	[-0.3647]	[-0.7589]	[0.9137]	[-1.9994]	[-0.9247]	[-1.0904]
3	2.767	0.5054	1.3047	2.7202*	0.0997	0.9575	-0.4619	2.506	-0.8832	-4.6115	-7.3785*
	[1.4917]	[0.3222]	[0.9542]	[1.9242]	[0.0718]	[0.5670]	[-0.2553]	[1.2415]	[-0.3685]	[-1.2389]	[-1.7275]

Table IX Economic Distress versus Financial Distress: Returns Across Components of O-Score.

This table reports mean risk-adjusted returns relative to the 3-factor model of Fama and French (1993) for each decile of each component of the O-Score measure. At the end of each June, stocks are separately and evenly sorted into ten groups based on $lt2at = \frac{TotalLiabilities_t}{TotalAssets_t}$, $wc2at = -\frac{WorkingCapital_t}{TotalAssets_t}$, $lc2ac = \frac{CurrentLiabilities_t}{CurrentAssets_t}$, $logat = -log(TotalAssets_t)$, $ni2at = -\frac{NetIncome_t}{TotalAssets_t}$, $fo2lt = -\frac{FundsFromOperations_t}{TotalLiabilities_t}$, $\Delta ni = -\frac{NetIncome_t - NetIncome_{t-1}}{|NetIncome_t|+|NetIncome_{t-1}|}$, and into two groups based on the value of the dummies $ltatdummy$ = (1 if $TotalLiabilities_t > TotalAssets_t$, 0 otherwise) and $nidummy$ = (1 if Net Loss for the last 2 yrs, 0 otherwise), then monthly value-weighted portfolio returns are computed for each group. Mean portfolio returns are also reported for the zero-cost portfolio which invests in the top decile portfolio from the funds of a short position in the bottom decile portfolio (column labeled 10-1 or 1-0). All portfolios are rebalanced monthly and the reported returns are annualized. Newey and West (1987) robust t-statistics are reported in square brackets.

	0	1	2	3	4	5	6	7	8	9	10	10-1 or 1-0
						O-Score component decile portfolio alphas						
$lt2at$		-1.5166	4.0095*	0.9325	1.684	-0.2709	1.8804**	0.4317	1.4333	0.4971	-2.5281**	-1.0115
		[-0.7975]	[1.8384]	[0.4918]	[1.2084]	[-0.2525]	[2.1598]	[0.4025]	[1.4811]	[0.4278]	[-1.9747]	[-0.4049]
$wc2at$		0.1531	2.9635	1.8203	2.9734	1.9245	1.4246	0.3617	0.5687	-2.5514**	2.0972**	1.9441
		[0.0699]	[1.2510]	[0.9617]	[1.5926]	[1.2390]	[1.2368]	[0.3462]	[0.6017]	[-2.5537]	[2.2328]	[0.7961]
$lc2ac$		-0.8646	-0.0847	0.3653	1.7046	3.4237**	1.6581	-0.2187	0.9922	1.5248*	1.5573	2.422
		[-0.4381]	[-0.0410]	[0.2193]	[1.0194]	[2.0206]	[1.3649]	[-0.2111]	[0.9238]	[1.6597]	[1.5634]	[1.0772]
$ltatdummy$	0.4731*	1.702										1.2825
	[1.7117]	[0.3858]										[0.2900]
$logat$		0.6269	0.121	0.8135	1.4126	1.4121	0.4502	-1.0022	0.1934	-3.481	-9.4001***	-10.0270***
		[1.5772]	[0.1426]	[0.8100]	[1.0299]	[0.9241]	[0.3380]	[-0.5770]	[0.1046]	[-1.5668]	[-3.3488]	[-3.4476]
$ni2at$		3.5665***	2.0744*	0.5703	0.5417	-0.8003	-0.5596	-3.9159**	-3.6289*	-2.3233	-5.1783	-8.7448**
		[3.3044]	[1.7366]	[0.5268]	[0.5879]	[-0.7014]	[-0.7274]	[-2.5133]	[-1.9211]	[-0.8050]	[-1.5066]	[-2.4821]
$fo2lt$		3.4883**	1.9495*	3.0461***	1.0946	-0.4725	-0.3011	-2.4875**	-4.1601***	-2.6831	-7.7202**	-11.2085***
		[2.0142]	[1.8902]	[2.6510]	[1.0835]	[-0.4770]	[-0.3451]	[-2.4990]	[-2.8563]	[-0.8630]	[-2.3259]	[-3.5504]
$nidummy$	0.5893*	-3.5337										-4.123
	[1.8980]	[-1.3614]										[-1.5206]
Δni		1.2759	-1.4506	2.1794*	1.5847	1.2309	1.9542**	-1.2946	-1.5189	-2.2629	-4.5553**	-6.0065***
		[0.8024]	[-1.1454]	[1.7706]	[1.5718]	[1.5734]	[2.0028]	[-1.2810]	[-1.2217]	[-0.9429]	[-2.1980]	[-2.7764]

Table X Failure Risk as a Risk Factor for Small Growth.

This table reports the coefficient estimates from regressing the returns of a small growth trading strategy on the returns of a high failure risk trading strategy, and vice versa. At the end of each June, firms are sorted into five groups on the basis of size and into five groups on the basis of book-to-market ratio where the cutoff values are determined by NYSE firms, and separately into 10 equally-sized groups on the basis of the O-Score measures. SG denotes the return on the zero-cost trading strategy which invests in the lowest size and the lowest book-to-market ratio portfolio funded from a short position in the middle size and the middle book-to-market portfolio. $FAIL$ denotes the return on the zero-cost trading strategy which invests in the top O-Score portfolio funded from a short position in the bottom O-Score portfolio. The estimated regression model is

$$Y_t = \alpha + \gamma_1 SMB_t + \gamma_2 HML_t + \gamma_3 MKTRF_t + \gamma_4 X_t + \epsilon_t$$

where SMB, HML and $MKTRF$ are the Fama and French (1993) factors that proxy for size, book-to-market and the market risk premium respectively, and Y and X are the placeholders for SG or $FAIL$. The trading strategies are rebalanced monthly. Column $\alpha \times 12$ corresponds to annualized intercept estimates. Newey and West (1987) robust t-stats are reported in square brackets.

Y	$\alpha \times 12$	SMB	HML	$MKTRF$	$FAIL$	SG	Adj. RSq
SG	-5.5974**	0.9782***	-0.9516***	0.1138***			0.6848
	[-2.4671]	[9.4108]	[-8.1227]	[2.6929]			
SG	-0.8528	0.4655***	-1.0124***	0.0287	0.3663***		0.7574
	[-0.3250]	[4.5708]	[-8.7040]	[0.5691]	[6.4425]		
$FAIL$	-12.9519***	1.3994***	0.166	0.2322***			0.4959
	[-4.4784]	[11.2867]	[1.4110]	[3.5940]			
$FAIL$	-9.3967***	0.7782***	0.7704***	0.1599***		0.6351***	0.6121
	[-3.2027]	[7.1636]	[4.7484]	[2.6048]		[7.4782]	

Table XI Growth Intensity and the Return-Relation Between Small Growth and Failure Risk.

This table reports the coefficient estimates from regressing the returns of a small growth trading strategy on the returns of a high failure risk trading strategy where the trading strategies are constructed from subsamples of firms grouped by alternate measures of growth option intensity. At the end of each June, firms are sorted into five groups on the basis of size and into five groups on the basis of book-to-market ratio where the cutoff values are determined by NYSE firms, and separately into 10 equally-sized groups on the basis of the O-Score measure. In each O-Score and each size × book-to-market group, stocks are sorted into three equally-sized subgroups based on the growth option intensity criterions prior to the construction of the trading strategies and estimations. The entire procedure and estimations are repeated for each alternate measure of growth option intensity: market-to-book ratio (M/B), firm size (measured by total asset value), future sales growth, and R&D to total assets (R&D). SG denotes the return on a zero-cost trading strategy which invests in the lowest size and the lowest book-to-market ratio portfolio funded from a short position in the middle size and the middle book-to-market ratio portfolio. $FAIL$ denotes the return on the zero-cost trading strategy which invests in the top O-Score portfolio funded from a short position in the lowest O-Score portfolio. The estimated regression model is

$$SG_t = \alpha + \gamma_1 SMB_t + \gamma_2 HML_t + \gamma_3 MKTRF_t + \gamma_4 FAIL_t + \epsilon_t$$

where SMB, HML and $MKTRF$ are the Fama and French (1993) factors that proxy for size, book-to-market and the market risk premium respectively. The trading strategies are rebalanced monthly. Column $\alpha \times 12$ corresponds to annualized intercept estimates. Newey and West (1987) robust t-stats are reported in square brackets.

	$\alpha \times 12$	SMB	HML	$MKTRF$	$FAIL$	Adj. RSq
			Panel A. M/B			
1	-1.6116	0.7403***	-0.7008***	0.0406	0.2398***	0.6351
	[-0.5686]	[6.1382]	[-5.5170]	[0.6008]	[6.5059]	
2	-1.1496	0.5596***	-0.9163***	-0.0491	0.1677***	0.5226
	[-0.4456]	[4.9367]	[-6.6424]	[-0.9189]	[3.6318]	
3	-1.7895	0.3762**	-0.8122***	0.0322	0.4056***	0.5583
	[-0.5231]	[2.2698]	[-5.7460]	[0.4433]	[6.4284]	
			Panel B. Size			
1	-3.7031	0.5060***	-0.5530***	-0.1275**	0.5240***	0.5228
	[-1.2775]	[4.8969]	[-4.5234]	[-2.3569]	[10.4918]	
2	0.8229	0.6172***	-1.0034***	0.0877	0.4615***	0.703
	[0.2887]	[4.5599]	[-9.5010]	[1.5029]	[10.9592]	
3	-0.4387	0.6444***	-0.8503***	0.0361	0.2498***	0.6295
	[-0.1429]	[5.4620]	[-5.7541]	[0.5713]	[4.9319]	
			Panel C. Sales Growth			
1	-2.0652	0.6864***	-0.8851***	-0.0063	0.2040***	0.5373
	[-0.6037]	[6.1488]	[-5.4375]	[-0.1119]	[5.1298]	
2	0.7455	0.5586***	-0.8749***	-0.0156	0.2267***	0.597
	[0.2804]	[4.6477]	[-6.6580]	[-0.2485]	[4.9528]	
3	3.7686	0.4893***	-0.7408***	0.0774	0.3210***	0.5996
	[1.2769]	[3.1044]	[-5.8367]	[1.2508]	[7.1980]	
			Panel D. R&D			
1	-6.5703**	0.1697*	-0.6216***	0.0516	0.1970***	0.3167
	[-2.1948]	[1.8147]	[-4.9524]	[1.0697]	[3.3936]	
2	0.3408	0.6378***	-1.0755***	0.0702	0.2838***	0.5617
	[0.0898]	[3.9546]	[-6.4199]	[0.9021]	[5.6368]	
3	0.9392	0.1271	-0.4979***	-0.1513*	0.4615***	0.4704
	[0.2822]	[0.8209]	[-3.4355]	[-1.6683]	[9.2406]	

Table XII Month of the Year and the Return-Relation Between Small Growth and Failure Risk.

This table reports the coefficient estimates from regressing the returns of a small growth trading strategy on the returns of a high failure risk trading strategy for each month of the year. At the end of each June, firms are sorted into five groups on the basis of size and into five groups on the basis of book-to-market ratio where the cutoff values are determined by NYSE firms, and separately into 10 equally-sized groups on the basis of the O-Score measures. SG denotes the return on the zero-cost trading strategy which invests in the lowest size and the lowest book-to-market ratio portfolio from the funds of a short position in the middle size and the middle book-to-market portfolio. $FAIL$ denotes the return on the zero-cost trading strategy which invests in the top O-Score portfolio funded from a short position in the bottom O-Score portfolio. The estimated regression model is

$$SG_t = \alpha + \gamma_1 SMB_t + \gamma_2 HML_t + \gamma_3 MKTRF_t + \gamma_4 FAIL_t + \epsilon_t$$

where SMB, HML and $MKTRF$ are the Fama and French (1993) factors that proxy for size, book-to-market and the market risk premium respectively. The trading strategies are rebalanced monthly. Column $\alpha \times 12$ corresponds to annualized intercept estimates. Newey and West (1987) robust t-stats are reported in square brackets.

Month	$\alpha \times 12$	SMB	HML	$MKTRF$	$FAIL$	Adj. RSq
			SG regressed on $FAIL$ by Month			
Jan	13.188	1.4631**	-0.928	0.2043	0.2065	0.5265
	[1.0156]	[2.3579]	[-1.6735]	[0.9114]	[1.2275]	
Feb	-6.734	0.4583**	-0.9470***	-0.075	0.5053***	0.9547
	[-1.4587]	[2.6371]	[-12.076]	[-1.1703]	[5.4471]	
Mar	-5.573	0.4455**	-0.9696***	0.0246	0.2924***	0.8567
	[-1.2427]	[2.5602]	[-7.2120]	[0.2213]	[4.1125]	
April	-6.897	0.4808	-1.3161***	0.0843	0.3900**	0.7399
	[-0.7302]	[1.4415]	[-3.4156]	[0.5240]	[2.7514]	
May	0.2717	0.5181**	-0.482	0.0942	0.4349***	0.719
	[0.0492]	[2.2822]	[-1.4456]	[0.5994]	[3.3806]	
June	-1.779	0.5837***	-1.1913***	0.2031*	0.2437***	0.938
	[-0.4012]	[2.9232]	[-8.1056]	[2.0526]	[2.9525]	
July	0.7606	0.8660***	-0.9503***	-0.139	0.0264	0.6574
	[0.0987]	[4.0198]	[-6.3921]	[-1.1030]	[0.2411]	
Aug	-8.6237*	0.4154**	-0.6253***	0.0646	0.3182***	0.7773
	[-1.8901]	[2.7697]	[-5.6485]	[1.3855]	[5.4745]	
Sept	-1.136	0.016	-1.2427***	-0.081	0.3430***	0.6865
	[-0.2786]	[0.0766]	[-3.8956]	[-0.7391]	[3.0843]	
Oct	-5.503	0.4582***	-0.5749***	0.1852***	0.1345	0.7379
	[-0.6508]	[2.8333]	[-2.8647]	[3.9973]	[1.0167]	
Nov	-12.3607*	0.4963***	-1.2378***	0.1369	0.3275***	0.874
	[-1.7577]	[3.3016]	[-10.476]	[1.6218]	[3.9344]	
Dec	2.0464	0.0057	-1.5809***	-0.099	0.4557**	0.6861
	[0.1348]	[0.0176]	[-4.3444]	[-0.3934]	[2.1119]	
Non-Jan	-2.344	0.3996***	-1.0443***	0.0155	0.3610***	0.8009
	[-1.1365]	[4.3737]	[-12.206]	[0.4488]	[6.7303]	

Table XIII The Return-Relation Between Small Growth and Failure Risk Across Sub-Periods and Sub-Samples.

The table reports the coefficient estimates from regressing small growth trading strategy returns on high O-Score trading strategy returns formed from different sample periods, from recessionary and expansionary months, from the sample which excludes stocks with price below $3, from the sample of firms which excludes the lowest size decile, and from the sample which excludes exchange-delisted stocks up to one year prior to the month of delisting. At the end of each June in each subsample, firms are sorted into five groups on the basis of size and into five groups on the basis of book-to-market ratio where the cutoff values are determined by NYSE firms, and separately into 10 equally-sized groups based on O-Scores. SG denotes the return on the zero-cost trading strategy which invests in the lowest size and the lowest book-to-market portfolio from the funds of a short position in the middle size and the middle book-to-market portfolio. $FAIL$ is the return on the zero-cost trading strategy which invests in the top O-Score decile portfolio funded from a short position in the bottom O-Score portfolio. The regression model is

$$SG_t = \alpha + \gamma_1 SMB_t + \gamma_2 HML_t + \gamma_3 MKTRF_t + \gamma_4 FAIL_t + \epsilon_t$$

where SMB, HML and $MKTRF$ are the Fama and French (1993) factors that proxy for size, book-to-market and the market risk premium respectively. All portfolios and trading strategies are rebalanced monthly. Column $\alpha \times 12$ corresponds to annualized intercept estimates. Newey and West (1987) robust t-stats are reported in square brackets.

Sample Period	$\alpha \times 12$	SMB	HML	$MKTRF$	$FAIL$	Adj. RSq
			Panel A. SG regressed on $FAIL$ by period			
1980 to 1987	-1.487	0.4675***	-0.8780***	0.0467	0.2376***	0.756
	[-0.4870]	[3.6694]	[-9.6183]	[0.9295]	[3.2302]	
1988 to 1995	-3.117	0.5222***	-0.8840***	0.0728	0.3122***	0.7137
	[-0.9828]	[4.0744]	[-7.0219]	[1.1169]	[4.7531]	
1996 to 2001	13.469	0.1234	-1.4999***	-0.2210**	0.5020***	0.8417
	[1.6066]	[0.7630]	[-8.5428]	[-2.0622]	[5.2365]	
2002 to 2010	-8.5282***	0.3518**	-0.6025***	0.0442	0.3076***	0.4838
	[-2.6815]	[2.2973]	[-3.9216]	[0.5380]	[4.0272]	
non-recession months	1.3252	0.4133***	-1.1792***	-0.016	0.3845***	0.7881
	[0.4988]	[4.4089]	[-11.313]	[-0.3355]	[7.0624]	
recession months	-6.194	0.4821*	-0.3790***	0.0194	0.3641**	0.6491
	[-1.0011]	[1.9238]	[-3.5038]	[0.3050]	[2.4840]	

Sample Filter	$\alpha \times 12$	SMB	HML	$MKTRF$	$FAIL$	Adj. RSq
			Panel B. SG regressed on $FAIL$ by filter			
price filter	3.5289	0.4803***	-0.8380***	0.0403	0.3375***	0.7171
	[1.5240]	[5.6995]	[-9.3422]	[0.9552]	[6.7312]	
size filter	-0.835	0.2952***	-0.8808***	-0.009	0.4423***	0.7088
	[-0.3182]	[2.7481]	[-7.6941]	[-0.1836]	[7.8776]	
delisting filter	0.1545	0.2980***	-0.8516***	-0.007	0.4219***	0.7039
	[0.0590]	[2.8139]	[-7.3080]	[-0.1478]	[7.9940]	

Table XIV Failure Risk and Anomalies

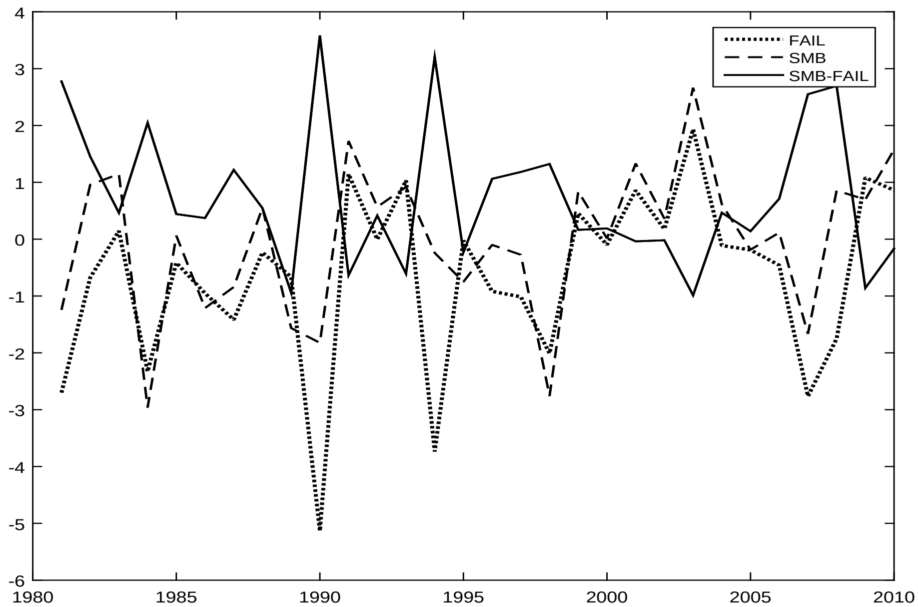
This table reports the abnormal returns of several asset pricing anomalies relative to the Fama and French 3-factor model (FF-3), 4-factor model (FF-4), and 2-factor models made up of the market risk premium and a factor constructed from a long position in the top $FAIL$ portfolio funded from a short position in the bottom $FAIL$ portfolio, and separately, 2-factor models with $FAIL$ factors constructed from the sample of the most growth intensive firms for various anomaly trading strategies and alternate measures of growth intensity (book to market, Size, Sales Growth and R&D Capital). Loadings on the $FAIL$ factor are also reported in the table. The regression model is: $r_t = \gamma_0 + \gamma_1 MKTRF_t + \gamma_2 FAIL_t$, where r_t, $MKTRF_t$ and $FAIL_t$ are the time t anomaly return, market risk premium and the failure risk strategy return, respectively. The construction of the anomaly returns and $FAIL$ factors is described in the paper. The intercept estimates are annualized and expressed in %. Newey and West (1987) robust t-stats are reported in square brackets. The sample spans from July 1981 through December 2010, and is determined by the reliability of the COMPUSTAT variables used in the computation of the O-Score measures (Dichev (1998)).

	FF-3	FF-4	2-Factor Model									
			Pricing Error					Loading on $FAIL$				
Anomaly				M/B	Size	Sale	R&D		M/B	Size	Sale	R&D
Asset Ret.	14.1942***	10.2845***	6.6616***	6.4114**	8.3480***	11.0964***	9.0410***	-0.4785***	-0.3980***	-0.2523***	-0.2479***	-0.3223***
	[5.2897]	[3.8657]	[2.6771]	[2.3480]	[2.9917]	[3.8643]	[3.2715]	[-15.296]	[-9.1078]	[-5.2603]	[-8.3746]	[-11.779]
Asset Turnover	7.0114**	6.2972**	4.4151	4.8786	4.2894	6.2221**	5.5349*	-0.1655***	-0.0989**	-0.1353***	-0.0823***	-0.0798**
	[2.5227]	[2.2089]	[1.4501]	[1.5497]	[1.3789]	[1.9988]	[1.7999]	[-4.5153]	[-2.3329]	[-3.7359]	[-2.6401]	[-2.1596]
Book Eq. Ret.	15.1984***	11.0572***	8.0954**	7.9633**	8.9496***	12.6057***	10.4960***	-0.4659***	-0.3797***	-0.2990***	-0.2427***	-0.3049***
	[4.6772]	[3.5533]	[2.5862]	[2.3174]	[2.7585]	[3.6305]	[3.1230]	[-8.9158]	[-5.6007]	[-4.7620]	[-4.9495]	[-6.8192]
F-Score	7.1946**	4.9934*	2.3603	2.444	2.9704	6.1321**	4.0677	-0.3710***	-0.2890***	-0.2429***	-0.1981***	-0.2645***
	[2.2834]	[1.7217]	[0.8736]	[0.8341]	[0.9737]	[2.1442]	[1.5090]	[-5.5349]	[-4.2992]	[-3.9796]	[-3.3317]	[-4.2383]
Gross Margin	6.3226***	6.8226***	0.5507	0.2085	2.3156	2.7084	1.5825	-0.2295***	-0.2065***	-0.0562	-0.1402***	-0.1662***
	[3.5129]	[3.6166]	[0.2837]	[0.1059]	[1.0898]	[1.2950]	[0.7820]	[-8.0653]	[-7.0148]	[-1.5570]	[-5.0893]	[-7.9850]
Gross Profit	8.2029***	7.4218***	4.5833**	4.6277**	5.5521***	6.4779***	5.5907***	-0.1704***	-0.1324***	-0.0649**	-0.0805***	-0.0978***
	[3.9319]	[3.6958]	[2.2499]	[2.2793]	[2.6148]	[2.9962]	[2.6468]	[-5.3787]	[-4.6229]	[-2.3049]	[-3.1487]	[-4.5817]
Idio. Volatility	16.5167***	11.6585***	11.3355***	11.5526***	12.5847***	16.4733***	14.4000***	-0.6293***	-0.4850***	-0.3974***	-0.3606***	-0.4308***
	[5.5803]	[3.8644]	[2.9221]	[2.6512]	[2.9777]	[4.0357]	[3.6153]	[-7.9572]	[-4.9437]	[-4.3275]	[-4.9668]	[-6.2416]
Ind. Momentum	10.5800**	7.6950*	6.7083	5.6647	6.8603	8.8782**	7.2368*	-0.1196	-0.1685**	-0.0813	-0.0681	-0.0876
	[2.5147]	[1.8566]	[1.5919]	[1.3085]	[1.6164]	[2.1069]	[1.7443]	[-1.4117]	[-2.1925]	[-1.1983]	[-1.6013]	[-1.4302]
Ind. Reversal	5.1760**	8.7848***	6.3995**	6.7275**	6.4796**	5.9635**	6.0896**	0.0646	0.0744	0.0549	0.0358	0.0447
	[1.9722]	[3.4207]	[2.3201]	[2.4061]	[2.3698]	[2.1952]	[2.3074]	[0.6947]	[0.9514]	[0.8424]	[0.5957]	[0.6172]
Investment	5.0892**	4.6359**	7.9073***	7.8527***	7.5199***	7.1420***	7.5139***	0.0853**	0.0640*	0.0391	0.0586**	0.0607**
	[2.5154]	[2.2384]	[3.7247]	[3.6564]	[3.4390]	[3.2683]	[3.5201]	[2.3528]	[1.8560]	[1.0279]	[2.2499]	[2.1388]
Market Eq. Ret.	14.0767***	8.7616***	10.4514***	10.6569***	10.4498***	13.9114***	12.3277***	-0.3601***	-0.2718***	-0.2760***	-0.1870***	-0.2335***
	[4.2170]	[2.7757]	[2.9137]	[2.8490]	[2.9678]	[3.7514]	[3.3639]	[-7.0588]	[-4.0622]	[-4.7874]	[-3.6353]	[-5.2398]
Momentum	19.6587***	3.6474**	15.1136***	15.8042***	14.3297***	17.4438***	16.0367***	-0.1416	-0.0639	-0.1616	-0.0274	-0.072
	[4.7212]	[2.0742]	[2.9147]	[3.3174]	[2.6398]	[3.6459]	[3.3076]	[-0.9528]	[-0.5248]	[-1.3491]	[-0.2946]	[-0.6566]
Net Issue	8.2603***	7.7311***	7.5234***	7.5017***	7.5854***	9.2251***	8.3924***	-0.1717***	-0.1380**	-0.1273***	-0.1031**	-0.1140***
	[3.6588]	[3.2164]	[3.0281]	[2.8911]	[3.0694]	[3.7178]	[3.4087]	[-3.5490]	[-2.4602]	[-2.9614]	[-2.4441]	[-3.0049]
SR Reversal	-1.1958	2.6685	1.2775	2.032	1.0386	-0.0918	0.8147	0.1099	0.1405*	0.068	0.0688	0.083
	[-0.3671]	[0.8639]	[0.3910]	[0.6107]	[0.3159]	[-0.0278]	[0.2541]	[1.2703]	[1.9060]	[1.1233]	[1.3608]	[1.2036]
Seasonality	10.9637***	9.7750***	7.8931***	8.0978***	9.3794***	9.3489***	8.3055***	-0.1285**	-0.0877*	0.0023	-0.0725*	-0.1106**
	[4.0026]	[3.5518]	[2.7413]	[2.8558]	[3.1397]	[3.2737]	[2.9561]	[-2.3686]	[-1.8021]	[0.0505]	[-1.6612]	[-2.5719]
Value	-1.2999	-1.0056	7.5126**	7.6428**	6.8731*	6.2266*	6.7951**	0.1076*	0.0947*	0.0391	0.035	0.0531
	[-0.8156]	[-0.6092]	[2.2070]	[2.2578]	[1.9506]	[1.8238]	[2.0040]	[1.7476]	[1.7847]	[1.0488]	[0.8327]	[1.2410]
Size	-2.117	-2.1726	6.4651***	7.0565**	4.6978	2.0021	3.7438	0.5788***	0.5017***	0.3236***	0.3677***	0.4065***
	[-1.5016]	[-1.4282]	[2.6778]	[2.3702]	[1.4191]	[0.6835]	[1.4461]	[9.7656]	[7.4565]	[3.8644]	[6.7225]	[8.1469]
Root Mean Sq. Pricing Error	10.4564	7.4608	7.6300	7.7678	7.8501	9.5718	8.5252					

Figure 1. Performance of the Trading Strategies Based on Size, Book-to-Market, Failure Risk and Small Growth.

The figure shows the performance of trading strategies formed on the basis of size (SMB), book-to-market (HML), failure risk ($FAIL$) and of the long-short strategies SMB minus $FAIL$ and HML minus $FAIL$. The performance of the trading strategies is measured at the end of each year in the sample as the annualized Sharpe ratio over the preceding year. The sample period spans from 1981 to 2010.

(a) $FAIL, SMB, SMB - FAIL$



(b) $FAIL, HML, HML - FAIL$