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Does systematic distress risk drive the investment growth anomaly?

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ABSTRACT

Expanding on rational *Q* theory, this study demonstrates that less exposure to systematic distress risk partially explains the phenomenon of investment growth anomalies, wherein equities of firms with greater growth in capital investment display lower stock returns. Using the default yield spread between BAA- and AAA-rated corporate bonds as a proxy for a systematic distress risk factor driving the pricing kernel, I show that firms with high (low) capital investment have lower (higher) exposure to systematic distress risk and thus lower (higher) expected returns. Depending on model settings, the factor used here to measure systematic distress risk explains 30–40% of the investment growth effect. Overall, I conservatively conclude that a moderate part of investment growth anomaly can be viewed as compensation for systematic distress risk, even though many studies explain it as a result of behavioral mispricing.

> Firms that increase their level of capital investment the most tend to achieve lower stock returns for five subsequent years . . .. Our evidence is consistent with the hypothesis that investors tend to underestimate the importance of the unfavorable information about managerial intentions . . .. However, it is possible that the excess return associated with abnormal investment expenditures is in fact related to risk factors that are unrelated to the factors we consider.
>
> Titman, Wei, and Xie (2004), JFQA, Vol. 39, P.699.

1. Introduction

Titman, Wei, and Xie (2004) showed that firms with highly abnormal capital investments (ACI) earn significantly lower benchmark-adjusted returns—the so-called investment growth anomaly[1]. Existing literature offers two competing explanations for this anomaly: behavioral mispricing and rational *Q* theory. Consistent with Jensen's (1986) agency hypothesis, Titman et al. (2004) offered a mispricing-based explanation: investors underreact to managerial empire building through increased investment expenditures. Cooper et al. (2008) documented a significantly negative association between firms' asset growth and subsequent stock returns and found that investors overreact to past operating performance of firms with high asset growth. This finding coincides with the assertion that an asset's growth effect is most consistent with a mispricing hypothesis. Using a stock's price proximity to its 52-week high price as a measure of mispricing, George et al. (2014) interpreted their findings as corrections of mispricing, noting that stock returns on firms with high capital investment are not low when samples exclude stocks with prices farthest from their 52-week high prices.

The rational *Q* theory explains the negative investment–return relation by suggesting that firms tend to invest more when the cost of capital (expected return) is lower, which induces a higher net present value of new investments (e.g., Cochrane, 1991; Zhang, 2005; Xing, 2008; Li, Livdan, & Zhang, 2009; Liu, Whited, & Zhang, 2009; Li & Zhang, 2010; Chen, Novy-Marx, & Zhang, 2011; Cooper & Priestley, 2011; Lam & Wei, 2011). Theoretical models in Berk,

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[1] The investment growth anomaly has been extended in different contexts by later literature, e.g., Anderson and Garcia-Feijoo (2006), Fama and French (2006), Cooper, Gulen, and Schill (2008), Lyandres, Sum, and Zhang (2008), Xing (2008), Polk and Sapienza (2009), Li and Zhang (2010), Titman, Wei, and Xie (2011), Lam and Wei (2011), Lipson, Mortal, and Schill (2012), Stambaugh, Yu, and Yuan (2012), Watanabe, Xu, Yao, and Yu (2013), and George, Hwang, and Li (2014).

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Green, and Naik (1999) and Carlson, Fisher, and Giammarino (2006) similarly interpreted capital investment decisions as the exercise of risky firm growth options into less-risky assets instead. As firms undertake investment projects, the importance of growth options relative to existing assets declines, reducing the exposure to systematic risk and prompting lower average subsequent returns. Anderson and Garcia-Feijoo (2006) supported this theoretical predication with empirical evidence. Cooper and Priestley (2011) showed that low-investment firms tend to have higher loadings with respect to the Chen, Roll, and Ross (1986) factors than do high-investment firms and concluded that risk plays an important role in explaining the investment–return relation.

Expanding upon Q theory, which emphasizes risk differentials between high-ACI and low-ACI firms arising from differing sensitivities to underlying risk factors important for asset pricing, this paper focuses on the *systematic distress risk* dimension to explain the investment growth effect. This paper's main aim is to test the extent to which systematic distress risk drives the ACI return spread. The central hypothesis builds on rational Q theory: firms with high ACI face lower distress costs and therefore reduced exposure to systematic risk factors that entail distress costs. Accordingly, these firms have lower expected returns relative to firms with low ACI.

Q theory literature suggests that marginal Q represents the net present value of future cash flows generated from investing one additional unit of capital and reflects a firm's future profitability. A higher Q value indicates stronger future profitability, which results in a lower distress cost. Consequently, Q theory both predicts a positive investment–Q relation and implies that distress costs should be lower (higher) among firms with higher (lower) ACI. Consistent with this argument, my preliminary results indicate that high-ACI firms exhibit characteristics traditionally associated with lower distress costs: larger size, stronger earnings, lower financial leverage (Penman, Richardson, & Tuna, 2007), lower Ohlson's (1980) O-score, and a lower default likelihood (Vassalou & Xing, 2004), compared with low-ACI firms.

Because distress costs depress asset payoffs in low states and the occurrence of low states is at least partly systematic, these costs would enhance exposure to systematic risk (George & Hwang, 2010). That in turn implies that loadings for a systematic distress risk factor should be low (high) among firms with low (high) distress costs. Therefore, my finding that firms with high ACI tend to have lower distress costs is crucial because it suggests that exposure to systematic distress risk may explain the investment growth effect that is anomalous in the standard Fama–French four-factor model.

A systematic distress risk explanation of the investment growth anomaly must meet four tests: (i) identify a plausible distress risk factor driving the pricing kernel, (ii) show that exposure to this risk factor is priced, (iii) show that the risk factor loadings of high-ACI firms significantly differ from those of low-ACI firms, and (iv) show that spreads in loadings are large enough to explain return spreads between high-ACI and low-ACI firms. I offer evidence consistent with all four requirements.

First, I identify the investment growth anomaly in a sample spanning January 1969–December 2010 using 25 ACI portfolios as the basic set of test assets and find that high-ACI firms exhibit significantly lower expected returns than low-ACI firms. The average equally-weighted (value-weighted) return spread between high-ACI firms and low-ACI firms is significantly negative at −0.800% (−0.582%) per month. Consistent with Titman et al. (2004), Anderson and Garcia-Feijoo (2006), Xing (2008), and Cooper and Priestley (2011), the findings confirm that zero-investment portfolios from long high-ACI firms and short low-ACI firms yield statistically and economically negative abnormal returns.

Second, using default yield spread (DEF, defined as monthly yield spread between BAA- and AAA-rated corporate bonds) as a measure of systematic distress risk factor[2], I show that high-ACI firms have substantially lower loadings with respect to a systematic distress risk factor than do low-ACI firms. The difference in DEF loading between high-ACI firms and low-ACI firms is significantly negative at −0.804.

Third, I present a significantly positive risk premium (the price of risk) for DEF at 0.327% per month for 25 ACI portfolios based on the two-stage Fama and MacBeth (1973) cross-sectional regressions (2SCRS), following the approach in Chen et al. (1986), Griffin, Ji, and Martin (2003), Sadka (2006) and Chen and Petkova (2012). This finding that DEF commands a positive price for risk in the cross-section of portfolios sorted by ACI is supported by Bali (2008), Bali and Engle (2010) and Bali, Brown, and Caglayan (2011), who suggested that because default premiums tend to be high in recessions, stocks (e.g., hedge funds) with higher (lower) exposure to a default premium are expected to have higher (lower) returns.

Finally, and most importantly, combined with a positive price of risk for DEF, I show that the difference in DEF loadings between high-ACI firms and low-ACI firms explains 30–40% of the cross-sectional variation of expected ACI portfolio returns, which conservatively suggests that systematic distress risk partially explains the investment growth anomaly.

As suggested by Pastor and Stambaugh (2003) and Chen and Petkova (2012), when all the risk factors in an asset-pricing model are tradable factors, the intercepts in the time-series regression can be interpreted as the risk-adjusted alphas. Motivated by this suggestion, I further employ Vassalou and Xing's (2004) firm-level default likelihood indictors (DLI) to construct a high-minus-low DLI portfolio as a tradable mimicking factor for distress risk, DLI^m. And then I estimate the DLI^m-augmented Fama–French four-factor model with the ACI return spread as a dependent variable to investigate the extent to which the ACI's alpha is reduced by DLI^m [3]. This test generates a direct estimate of the alphas and provides more intuitive evidence of the incremental contribution of systematic distress risk to the ACI return spread. The empirical results of this test indicate that about 30–40% of the ACI's alpha is explained by a tradable DLI^m-mimicking factor and thus explore the robustness of the findings mentioned above.

Although my overall evidence is tantalizing, it should be concluded with caution because systematic distress risk is shown to only account for 30–40% of the investment growth anomaly. Nevertheless, this study's importance arises from providing a possible distress-risk interpretation behind the cross-sectional pricing of investment growth. Several papers have documented the rational pricing explanation based on Q theory, wherein the investment growth effect relates to the time-varying risk caused by changes in the mix of assets in place and growth options (e.g., McDonald & Siegel, 1986; Majd & Pindyck, 1987; Berk et al., 1999; Gomes, Kogan, & Zhang, 2003; Zhang, 2005; Carlson et al., 2006; Cooper, 2006; Anderson & Garcia-Feijoo, 2006; Li et al., 2009; Liu et al., 2009). Focusing on the distress risk dimension, this paper adds to this literature by suggesting that a moderate part of investment growth anomaly can be viewed as compensation for systematic distress risk[4].

[2] Previous literature examining the effect of distress risk on equities focuses on the default yield spread to explain returns (e.g., Fama & Schwert, 1977; Keim & Stambaugh, 1986; Campbell, 1987; Fama & French, 1989). Further, Chen et al. (1986), Fama and French (1996), Jagannathan and Wang (1996) and Hahn and Lee (2001) consider variations of the default yield spread in asset-pricing tests. Motivated by these studies, I use the default yield spread to capture systematic distress risk.

[3] I wish to thank an anonymous referee for this constructive suggestion.

[4] Two recent papers that investigate the relationship between investment growth anomaly and default spreads are related to my work. Cooper and Priestley (2011) showed that the loadings (systematic risks) on Chen et al.'s (1986) factors (growth rate of industrial production, unexpected inflation, change in expected inflation,

This paper also contributes to the extensive asset-pricing literature seeking to understand how distress risk explains expected stock returns in the cross section and its relation to anomalous patterns (e.g., Chan & Chen, 1991; Fama & French, 1996; Dichev, 1998; Griffin & Lemmon, 2002; Vassalou & Xing, 2004; Campbell, Hilscher, & Szilagyi, 2008; Garlappi, Shu, & Yan, 2008; Chava & Purnanandam, 2010; George & Hwang, 2010; Kapadia, 2011; Avramov, Chordia, Jostova, & Philipov, 2013). Avramov et al. (2013) recently completed a comprehensive investigation of the relationship between various anomalies and distress risk, which is closely related to my work. Focusing on characteristic-based credit rating downgrades as a proxy for distress risk, Avramov et al. (2013) showed that anomalies such as the profitability of portfolio strategies based on firms' asset growth and capital investment are almost entirely generated by taking short positions in the worst-rated stocks. In contrast, my study focuses on a covariance-based measure of distress risk (i.e., exposure to systematic distress risk) and provides new evidence that the investment growth effect moderately reflects systematic distress risk. My findings complement Chan and Chen (1991), Fama and French (1996), and Kapadia (2011), who suggested that investors require a positive risk premium for bearing systematic distress risk.

The paper is organized as follows. Section 2 illustrates the selected sample and describes the data. Section 3 examines whether and how a systematic distress risk factor explains the investment growth anomaly. Section 4 concludes.

2. Data

The initial sample contains firms listed on the New York Stock Exchange, American Stock Exchange, or NASDAQ (CRSP share codes 10 and 11) for which (1) sufficient accounting data are available in the Compustat annual industrial file and (2) stock return data are available in CRSP. The initial sample period in the Compustat database spans 1965 to 2010[5]. Following Cooper et al. (2008) and George et al. (2014), I omit financial firms (four-digit SIC code between 6000 and 6999). Similar to Titman et al. (2004), I exclude firm years with annual net sales less than \$10 million and total assets less than \$10 million. All firm years must have non-negative data for the book value of equity. Following Titman et al. (2004), firm i's abnormal capital investment in year y ($ACI_{i,y}$) is defined as

$$ACI_{i,y} = \frac{CE_{i,y}}{\left(CE_{i,y-1} + CE_{i,y-2} + CE_{i,y-3}\right)/3} - 1 \quad (1)$$

where $CE_{i,y}$ is firm i's capital expenditure (Compustat item CAPX) scaled by its sales (Compustat item SALE) in year y[6]. Some of my analysis requires several variables for firm characteristics:

1. Tobin's Q, defined as the ratio of the market-to-book value of the firm's assets, where the market value of assets is estimated as the book value of assets (Compustat item AT) minus the book value of common equity (Compustat item CEQ) plus the market value of common equity (Compustat item PRCC_F × CSHO);
2. Total assets (TA), defined as the book value of total assets (Compustat item AT);
3. Returns on assets (ROA), defined as the ratio of the operating income after depreciation (Compustat item OIADP) to the book value of total assets;
4. Penman et al. (2007) financial leverage scaled by the market value of common equity (ND/P), defined as the difference between financial liabilities (FL) and financial assets (FA), where FL is the sum of long-term debt (Compustat item DLTT), debt in current liabilities (Compustat item DLC), carrying value of preferred stock (Compustat item PSTK), preferred dividends in arrears (Compustat item DVPA), and less-preferred treasury stock (Compustat item TSTKP), and FA is cash and short-term investments (Compustat item CHE);
5. Ohlson's (1980) O-Score, used to measure financial distress cost; and
6. Vassalou and Xing's (2004) default likelihood indicator (DLI), obtained from Maria Vassalou's website[7].

To deal with data outliers, these firm characteristic variables are winsorized at the upper and lower one percentiles.

Motivated by Fama and Schwert (1977), Chen et al. (1986), Keim and Stambaugh (1986), Campbell (1987), Fama and French (1989, 1996), Jagannathan and Wang (1996), Hahn and Lee (2001), and Vassalou and Xing (2004), I use default yield spared (DEF) as a proxy for a systematic distress risk factor, where DEF is defined as monthly yield spread between BAA-rated and AAA-rated corporate bonds[8]. To analyze asset pricing, I also use the Fama–French four factors: excess market return (MKT), small-minus-big size premium (SMB), high-minus-low value premium (HM), and momentum factor (MOM), which are collected from Kenneth R. French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)[9].

Table 1 reports descriptive statistics of DEF and the four Fama–French factors in Panel A and their Pearson correlations in Panel B. The average DEF from January 1969 to December 2010 is 1.11% with a standard deviation of 0.47%. Further, Panel B shows that DEF significantly and positively correlates with SMB (13.1%, $p < 0.01$) but is not correlated with MKT, HML, or MOM. This finding implies that SMB includes potentially significant distress-related information.

Table 2 reports univariate comparisons of firm characteristics for subsamples sorted by ACI. At the end of each year during 1968–2010[10], I sort-sampled stocks into 25 ACI portfolios using the NYSE breakpoints and calculated the time-series average of firm characteristics for each portfolio in the portfolio formation year. Consistent with Q theory predictions, firms with high (low) ACI tend toward high (low) Tobin's Q values. Difference in average Tobin's Q value is significantly positive between high-ACI and low-ACI firms (0.15, t-statistic of 7.39).

More importantly, comparing distress risk characteristics of high-ACI and low-ACI firms reveals that high-ACI firms tend to be

term premium, and default spread) largely explain the investment–return relation. However, they showed that the difference in loadings with respect to the mimicking portfolio for default spread between high and low investment-growth deciles is not statistically significant and thus seldom contributes to explaining the investment growth anomaly. Using 25 sorted investment-growth portfolios as test assets in estimating risk premiums yields different inferences, supporting the notion that default spread variations are important in explaining the investment growth anomaly. Alternatively, Prombutr, Phengpis, and Zhang (2012) used the default spread as a proxy for the business cycle to document that the investment growth anomaly can be explained by the conditional Fama–French three-factor model with factor loadings augmented with size and book-to-market (firm level) characteristics and the default spread (the business cycle variable). However, Prombutr et al. (2012) did not formally test the risk premium for the default spread and examine the incremental contribution of default spread to investment growth effect.

[5] I chose this period because of sample-selection concerns related to pre-1965 data in Compustat, as noted by Lemmon, Roberts, and Zender (2008).

[6] Titman et al. (p.680, 2004) note, "Using sales as the deflator, we implicitly assume that the benchmark level of capital expenditures will grow proportionately with sales.¨

[7] Data on DLI during 1971–1999 is obtained from Maria Vassalou's website (http://maria-vassalou.com/research/data/). I am grateful to Maria Vassalou for making the data available.

[8] Data on DEF is obtained from the Federal Reserve Bank of St. Louis.

[9] I am grateful to Kenneth R. French for making the data available.

[10] As my initial sample period runs from 1965 to 2010 and firms must have at least four years of data with which to calculate their ACI, the test period runs from 1968 to 2010.

Table 1
Descriptive statistics. This table reports descriptive statistics on a systematic distress risk factor (DEF) and on the Fama–French four factors in Panel A and their Pearson correlations in Panel B. DEF is measured as the monthly yield spread between BAA-rated and AAA-rated corporate bonds, which is obtained from the Federal Reserve Bank of St. Louis. MKT, SMB, HML, and MOM are the Fama–French four factors, which are collected from French's website. The test period runs from January 1969–December 2010 (504 months). Parentheses report *p* values.

Panel A: Summary statistics

	Mean	STD	MIN	MAX
DEF(%)	1.11	0.47	0.55	3.38
MKT(%)	0.41	4.70	−23.14	16.05
SMB(%)	0.08	3.22	−22.06	13.74
HML(%)	0.45	3.05	−9.93	13.88
MOM(%)	0.70	4.52	−34.75	18.40

Panel B: Correlations

	MKT	SMB	HML	MOM
DEF	0.062	0.131	−0.041	−0.071
	(0.16)	(<0.01)	(0.36)	(0.11)
MKT		0.281	−0.322	−0.097
		(<0.01)	(<0.01)	(0.03)
SMB			−0.163	−0.062
			(<0.01)	(0.16)
HML				−0.086
				(0.05)

Table 2
Firm characteristics by ACI portfolios. This table reports firm characteristics for 25 portfolios sorted by abnormal capital investment (ACI). The initial sample contains NYSE/AMEX/NASDAQ stocks with CRSP share codes of 10 or 11 from 1965 to 2010. Financial firms (four-digit SIC code between 6000 and 6999) are excluded. Firms with book values of total assets less than $10 million, net sales less than $10 million, and negative data for book values of equity are excluded. Because firms must have at least four years of data with which to calculate their ACIs, the table's test period runs from 1968 to 2010. At the end of each included year, I sort-sampled stocks into 25 ACI portfolios using the NYSE breakpoints and calculated the time-series average of firm characteristics. Tobin's *Q* is the ratio of the market-to-book value of the firm's assets. TA is the book value of the total assets. ROA is the ratio of the operating income after depreciation to the book value of the total assets. ND/P is Penman et al.'s (2007) financial leverage scaled by the market value of common equity. O-Score is Ohlson's (1980) measure of financial distress cost. DLI is Vassalou and Xing's (2004) default risk indictor for 1971–1999, obtained from Maria Vassalou's website. To deal with outliers in the data, these firm characteristic variables are winsorized at the upper and lower one percentiles. Difference in average between high-ACI and low-ACI portfolios is assessed using a *t*-test.

ACI portfolios	Tobin's *Q*	TA ($billions)	ROA (%)	ND/P (%)	O-Score	DLI (%)
High	1.49	0.83	7.32	49.15	−1.17	3.87
P24	1.52	1.35	8.52	44.39	−1.42	3.21
P23	1.53	1.65	9.13	45.12	−1.55	3.21
P22	1.52	1.73	9.20	42.97	−1.54	3.21
P21	1.53	1.80	9.50	41.48	−1.60	3.21
P20	1.55	1.98	9.80	39.78	−1.64	2.64
P19	1.52	2.19	9.84	42.46	−1.68	2.93
P18	1.54	2.18	9.78	40.92	−1.63	2.92
P17	1.51	2.42	9.67	45.02	−1.64	2.78
P16	1.51	2.57	9.74	42.49	−1.65	2.52
P15	1.50	2.50	9.83	40.47	−1.66	2.92
P14	1.49	2.64	9.74	42.87	−1.68	2.92
P13	1.51	2.53	9.64	41.06	−1.67	3.13
P12	1.50	2.31	9.56	43.35	−1.67	3.24
P11	1.48	2.35	9.49	42.77	−1.62	3.12
P10	1.47	2.09	9.24	42.57	−1.52	3.11
P9	1.47	2.17	9.16	44.77	−1.57	3.41
P8	1.46	1.88	8.97	45.58	−1.54	3.71
P7	1.46	1.72	8.87	46.87	−1.45	3.58
P6	1.42	1.64	8.51	49.47	−1.40	3.53
P5	1.41	1.26	8.28	53.80	−1.34	4.83
P4	1.43	1.14	7.88	57.25	−1.27	4.77
P3	1.39	0.91	7.15	59.14	−1.12	5.81
P2	1.35	0.75	6.58	62.03	−1.04	6.43
Low	1.34	0.64	5.13	73.98	−0.70	9.05
H–L	0.15	0.19	2.19	−24.83	−0.47	−5.18
[*t*-value]	[7.39]	[2.20]	[6.55]	[−4.84]	[−9.11]	[−6.90]

characterized by lower distress costs, including larger size, higher ROA, lower financial leverage, lower Ohlson's (1980) O-Score, and lower Vassalou and Xing's (2004) default likelihood[11]. For example, the average ROA of high-ACI firms is larger in magnitude and statistical significance than that of low-ACI firms (2.19%, *t*-statistic of 6.55), as well as the average default likelihood (DLI) of high-ACI firms is lower than that of low-ACI firms (−5.18%, *t*-statistic of −6.90). The discovery of lower distress costs is important because it intimates that distress risk may explain lower expected returns to high-ACI firms. This possibility is examined in the next section.

3. A distress risk factor in explaining the investment growth anomaly

3.1. Revisiting the investment growth anomaly

I begin by showing that the investment growth anomaly exists in my sample. Similar to Sadka (2006), I constructed 25 ACI portfolios as basic test assets[12]. Specifically, at the end of December for each year during 1968–2009, I sort-sampled stocks into 25 ACI portfolios using their NYSE breakpoints and then traced each portfolio's equally weighted monthly returns for a 12-month holding period[13]. Portfolio returns for the 12 post-ranking months are linked across 1969–2010 to construct one series of post-ranking returns per portfolio, reported in Table 3.

Table 3 shows that the investment growth anomaly appears in my sample. The second column in Table 3 reports average excess monthly returns (EXRET) of the 25 portfolios and shows that holding-period returns generally increase from the high-ACI portfolio to the low-ACI portfolio. The average return spread between the high-ACI and low-ACI portfolios is −0.800% per month with a *t*-statistic of −6.78. The fourth column in Table 3 shows the Fama–French four-factor alphas (Alpha 4FF) of the 25 portfolios and reveals that firms with high (low) ACI generally exhibit lower (higher) alphas. The difference in average Alpha 4FF between high- and low-ACI portfolios is −0.655% per month with a *t*-statistic of −5.53. Overall, the results in Table 3 confirm that the investment growth anomaly cannot be explained by the four Fama–French factors MKT, SMB, HML, and MOM, which is consistent with Titman et al. (2004), Anderson and Garcia-Feijoo (2006), Xing (2008) and Cooper and Priestley (2011).

3.2. DEF loadings and the price of risk for DEF in ACI portfolios

This subsection presents evidence of exposure to DEF across ACI portfolios and estimations of the price of risk for DEF based on the two-stage Fama–MacBeth (1973) cross-sectional regression. The first stage estimates a set of factor loadings for 25 ACI portfolios

[11] Our results are similar to Prombutr et al. (2012), who find that firms with high (low) investment growth tend to have larger (smaller) size, but the investment growth has a non-monotonic relationship with size.

[12] Using 25 momentum portfolios and 25 PEAD portfolios as basic test assets, Sadka (2006) showed that exposure to liquidity risk can largely explain the cross-sectional variation of expected momentum and PEAD portfolio returns. The advantage of using basic test assets that contain at least 25 portfolios is to mitigate the small sample bias when conducting the two-stage Fama–MacBeth (1973) cross-sectional regression.

[13] For the 25 ACI portfolios, the spread in average returns between high-ACI portfolio and low-ACI portfolio (P25–P1 ACI portfolios) is higher and more significant when using equally weighted portfolios (−0.800% per month with a *t*-statistic of −6.78) than when using value-weighted portfolios (−0.582% per month with a *t*-statistic of −2.89). In light of this, my analysis focuses on using equally weighted portfolios. Cooper and Priestley (2011) also focused on equally weighted portfolios to document that the negative investment growth–future returns relation can be explained by a set of macroeconomic risk factors. In untabulated results, I replicate these analyses using 25 value-weighted ACI portfolios as test assets and find similar results to those using equally weighted ACI portfolios as test assets.

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Table 3
Post-ranking returns by ACI portfolios. This table reports the post-ranking returns for 25 portfolios sorted by ACI. The initial sample contains NYSE/AMEX/NASDAQ stocks with CRSP share codes of 10 or 11 from 1965 to 2010. Financial firms (four-digit SIC code between 6000 and 6999) are excluded. Firms with book values of total assets less than $10 million, net sales less than $10 million, and negative data for the book value of equity are also excluded. At the end of each year during 1968–2009, I sort-sampled stocks into 25 portfolios using the NYSE breakpoints and then traced subsequent equally weighted monthly returns for a 12-month holding period. The portfolio returns for the 12 post-ranking months are linked across years (1969–2010) to construct one series of post-ranking returns for each portfolio. EXRET is the excess monthly returns (excess of the 30-day T-bill rate). Alpha 4FF is the Fama–French four-factor alphas from the regressions of portfolios' post-ranking excess returns on the four Fama–French factors. H–L denotes the return spreads between high-ACI and low-ACI portfolios.

ACI portfolios	EXRET (%)	*t*-Value (EXRET)	Alpha 4FF (%)	*t*-Value (Alpha 4FF)
High	0.303	1.02	−0.143	−1.26
P24	0.545	1.95	0.074	0.73
P23	0.656	2.43	0.154	1.62
P22	0.597	2.18	0.130	1.33
P21	0.693	2.59	0.207	2.27
P20	0.767	2.88	0.250	2.68
P19	0.840	3.29	0.340	4.03
P18	0.889	3.38	0.371	3.99
P17	0.700	2.72	0.171	1.86
P16	0.852	3.28	0.343	3.50
P15	0.991	3.80	0.455	4.87
P14	0.779	3.12	0.213	2.46
P13	0.978	3.75	0.465	4.69
P12	0.948	3.69	0.446	4.84
P11	0.857	3.37	0.360	3.89
P10	0.918	3.49	0.360	3.80
P9	0.971	3.67	0.406	4.64
P8	0.963	3.60	0.410	4.39
P7	0.972	3.61	0.398	3.97
P6	1.005	3.69	0.493	4.59
P5	0.790	2.89	0.194	1.90
P4	1.034	3.71	0.496	4.65
P3	0.938	3.23	0.375	3.43
P2	1.066	3.59	0.466	3.62
Low	1.103	3.53	0.512	3.63
H–L	−0.800	−6.78	−0.655	−5.53

using a full-sample time-series regression model spanning January 1969–December 2010[14]:

$$R_t^p = \beta_0^p + \beta_{\text{MKT}}^p \text{MKT}_t + \beta_{\text{SMB}}^p \text{SMB}_t + \beta_{\text{HML}}^p \text{HML}_t + \beta_{\text{MOM}}^p \text{MOM}_t + \beta_{\text{DEF}}^p \text{DEF}_t + u_t^p \quad (2)$$

where R_t^p is excess monthly returns (exceeding the 30-day T-bill rate) for ACI portfolio p in month t, p = High, P24,. . ., and Low.

Panel A of Table 4 reports DEF loadings (β_{DEF}) for 25 ACI portfolios and shows that high-ACI firms exhibit significantly negative β_{DEF}, and low-ACI firms exhibit significantly positive β_{DEF}. This leads to a significantly negative difference in β_{DEF} between high-ACI and low-ACI portfolios (−0.804, t-statistic of −3.27). As Bali (2008), Bali and Engle (2010), and Bali et al. (2011) suggested, default spread tends to be high in recessions; stocks (e.g., hedge funds) with higher (lower) exposure to default spread are expected to have higher (lower) returns. Therefore, my finding of the significantly negative difference in β_{DEF} between high-ACI and low-ACI portfolios suggests that firms with substantially higher (lower) capital expenditures tend to experience lower (higher) exposure to systematic distress risk, which in turn implies lower (higher) expected returns.

The results in Panel A of Table 4 support the view that DEF is vital in explaining the investment growth anomaly. The price of risk for DEF for the 25 ACI portfolios is further estimated using a second-stage cross-sectional regressions model:

$$R_t^p = \gamma_0 + \gamma_{\text{MKT}}\hat{\beta}_{\text{MKT}}^p + \gamma_{\text{SMB}}\hat{\beta}_{\text{SMB}}^p + \gamma_{\text{HML}}\hat{\beta}_{\text{HML}}^p + \gamma_{\text{MOM}}\hat{\beta}_{\text{MOM}}^p + \gamma_{\text{DEF}}\hat{\beta}_{\text{DEF}}^p + e_t^p \quad (3)$$

where $\hat{\gamma}$ is a vector of the prices of risk. $\hat{\beta}_{\text{MKT}}^p$, $\hat{\beta}_{\text{SMB}}^p$, $\hat{\beta}_{\text{HML}}^p$, $\hat{\beta}_{\text{MOM}}^p$, and $\hat{\beta}_{\text{DEF}}^p$ are vectors of the factor loadings estimated in Eq. (2). The adjusted R^2 in the model is generated using one cross-sectional regression of the time-series average excess return of each portfolio on its factor loadings (Jagannathan & Wang, 1996; Sadka, 2006). Because Eq. (3) is subject to the errors-in-variables problem, I calculate the Fama–MacBeth t-statistics using Shanken's (1992) adjusted standard errors to correct for this bias. Panel B of Table 4 reports the estimates.

As shown in Model (2), Panel B of Table 4, the estimate of prices of risk for DEF ($\hat{\gamma}_{\text{DEF}}$) is significantly positive after controlling for the four Fama–French factors (0.327% with a t-statistic of 3.40), suggesting that DEF loadings ($\hat{\beta}_{\text{DEF}}$) represent a significant determinant of expected returns for the 25 ACI portfolios. A comparison of Models (1) and (2) reveals that adding DEF increases the adjusted R^2 by approximately 11%.

In sum, Table 4 shows that firms with high (low) ACI tend to experience negative (positive) DEF loadings and that the price of risk for DEF is significantly positive, indicating that assets that covary negatively (positively) with DEF should have lower (higher) expected returns. The next subsection tests the extent to which DEF drives theACI return spread.

3.3. Incremental contribution of DEF

Because the DEF factor is priced as shown in Table 4, its price of risk is employed to estimate the incremental contribution of DEF to theACI return spread. Following Liu and Zhang (2008), I measure the incremental contribution of DEF as $E\left[\text{HML}^{\beta_{\text{DEF}}} \times \hat{\gamma}_{\text{DEF}}\right]$, where $\text{HML}^{\beta_{\text{DEF}}}$ is the difference in β_{DEF} between high-ACI and low-ACI portfolios reported in Panel A of Table 4 and $\hat{\gamma}_{\text{DEF}}$ is the price of risk for DEF estimated by the two-stage Fama–MacBeth (1973) cross-sectional regression reported in Panel B of Table 4. Table 5 shows that the ratio of $E\left[\text{HML}^{\beta_{\text{DEF}}} \times \hat{\gamma}_{\text{DEF}}\right]$ to raw return spread between high-ACI and low-ACI portfolios ($\text{HML}^R = -0.800\%$) reported in Table 3 is about 33%. The findings suggest that DEF explains approximately one-third of the average return spread between high-ACI and low-ACI portfolios. Exposure to a systematic distress risk factor can thus be seen as important in driving the high-minus-low ACI return spread.

3.4. Considering the mimicking factor for distress risk in Vassalou and Xing (2004)

The evidence presented in the previous subsections reveals that DEF is priced in the cross-section of portfolios sorted by ACI. To control further for the choice of systematic distress risk factor, all the analyses in the previous subsections are further performed using a factor-mimicking portfolio for distress risk constructed based on Vassalou and Xing's (2004) firm-level default likelihood indictors (DLI). Specifically, at the end of each month throughout December 1970–November 1999, I sort-sampled stocks into 25 DLI portfolios based on their most recent monthly DLI then calculate the equally weighted returns over the next month for each portfolio. Similar to Fama and French (1993) and Pastor and Stambaugh (2003), I then

[14] Liu and Zhang (2008) suggested that full-sample loading estimations should be more precise than loading estimations based on rolling regressions and extending windows regressions if the true factor loadings are constant. Thus, I focus on the analysis using the full-sample regression to estimate factor loadings in the first-stage estimation, following Black, Jensen, and Scholes (1972), Fama and French (1992), Lettau and Ludvigson (2001) and Sadka (2006).

Table 4
DEF loadings and the price of risk for DEF for ACI portfolios. This table reports DEF factor loadings (β_{DEF}) for 25 ACI portfolios, the difference in β_{DEF} between high-ACI and low-ACI portfolios in Panel A, and the prices of risk for DEF estimated using the two-stage Fama–MacBeth (1973) cross-sectional regressions in Panel B. In the first stage, I estimate factor loadings using full-sample regressions based on the following model during January 1969–December 2010: $R_t^p = \beta_0^p + \beta_{MKT}^p MKT_t + \beta_{SMB}^p SMB_t + \beta_{HML}^p HML_t + \beta_{MOM}^p MOM_t + \beta_{DEF}^p DEF_t + u_t^p$ where R_t^p is excess monthly returns (excess of the 30-day T-bill rate) for ACI portfolio p in month t, p = High, P24,. . ., and Low. After generating a vector of factor loadings ($\hat{\beta}_{MKT}^p$, $\hat{\beta}_{SMB}^p$, $\hat{\beta}_{HML}^p$, $\hat{\beta}_{MOM}^p$, and $\hat{\beta}_{DEF}^p$), the second-stage cross-sectional regressions model is tested: $R_t^p = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT}^p + \gamma_{SMB}\hat{\beta}_{SMB}^p + \gamma_{HML}\hat{\beta}_{HML}^p + \gamma_{MOM}\hat{\beta}_{MOM}^p + \gamma_{DEF}\hat{\beta}_{DEF}^p + e_t^p$ where $\hat{\gamma}$ is a vector of the prices of risk. The intercepts ($\hat{\gamma}_0$) and the prices of risk ($\hat{\gamma}$) are the percentage per month. The adjusted R^2 in each model is generated using one cross-sectional regression of the time-series average excess return of each portfolio on its factor loadings. The Fama–MacBeth t-statistics calculated from the Shanken (1992) method are reported in square brackets.

Panel A: Loadings on DEF

ACI Portfolios	$\hat{\beta}_{DEF}$	t-value ($\hat{\beta}_{DEF}$)
High	−0.667	−2.81
P24	−0.276	−1.29
P23	−0.045	−0.22
P22	0.286	1.40
P21	0.094	0.49
P20	−0.296	−1.52
P19	0.000	0.00
P18	0.271	1.39
P17	0.205	1.06
P16	0.233	1.13
P15	0.203	1.04
P14	0.142	0.78
P13	0.547	2.64
P12	0.328	1.70
P11	0.152	0.79
P10	0.392	1.98
P9	0.253	1.38
P8	0.054	0.28
P7	0.194	0.92
P6	0.129	0.57
P5	−0.163	−0.76
P4	0.168	0.75
P3	0.416	1.82
P2	0.212	0.78
Low	0.137	0.46
H–L	−0.804	−3.27

Panel B: Price of risk for DEF

Model	$\hat{\gamma}_0$	$\hat{\gamma}_{MKT}$	$\hat{\gamma}_{SMB}$	$\hat{\gamma}_{HML}$	$\hat{\gamma}_{MOM}$	$\hat{\gamma}_{DEF}$	Adj. R^2
(1)	1.018	−0.771	0.16	2.136	1.079		0.536
	[1.28]	[−0.96]	[0.59]	[4.52]	[2.03]		
(2)	0.749	−0.194	0.339	0.686	1.665	0.327	0.645
	[0.94]	[−0.24]	[1.20]	[1.18]	[2.93]	[3.40]	

used the P25–P1 return spread between high-DLI and low-DLI portfolios in month t as a proxy for a systematic distress risk factor, as denoted by DLI_t^m. The unreported result shows that the average return of portfolio DLI^m over the period January 1971–December 1999 is 1.79% per month with a t-statistic of 4.56. This number is larger than the 5–1 and 10–1 default risk premiums reported in Vassalou and Xing's (2004) Table III, suggesting that default risk is important for equities pricing.

After constructing DLI^m, I augment DLI^m to the Fama–French four-factor model to examine whether it can explain the high-minus-lowACI return spread based on the following time-series regression:

$$HML_t^R = \alpha + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{MOM} MOM_t + \beta_{DLI^m} DLI_t^m + u_t \quad (4)$$

where HML_t^R is the return spread between high-ACI and low-ACI portfolios in month t (P25–P1 ACI portfolio). I first estimate the loadings on DLI^m and the price of risk for DLI^m for 25 ACI portfolios and then examine the incremental contribution of DLI^m to the ACI return spread based on the two-stage Fama–MacBeth (1973) cross-sectional regressions. Table 6 reports the results.

Using DLI^m as a systematic distress risk factor, the results in Table 6 support those in the previous subsections. At first, columns 2–5 in Panel A of Table 6 show that average equally weighted return spreads between high-ACI and low-ACI portfolios (P25–P1 ACI portfolio) during 1971–1999 is −0.832% per month, t-statistic of −5.86; its risk-adjusted alpha based on the four Fama–French factors remains significant (−0.640% per month, t-statistic of −4.45). This suggests the existence of investment growth anomaly in a period during 1971–1999. Second, columns 6 and 7 in Panel A of Table 6, which include the four Fama–French factors plus DLI^m, show that DLI^m loading generally increases from high ACI- to low-ACI portfolios and that the difference in DLI^m loadings between high-ACI and low-ACI portfolios is significantly negative (−0.138, t-statistic of −5.82), suggesting that the systematic distress risk associated with DLI^m loading is an important determinant of expected returns for the 25 ACI portfolios. Third, Panel B of

Table 5
Incremental contribution of DEF. This table reports the incremental contribution of DEF to the ACI return spread. The incremental contribution of DEF is measured as $E\left[HML^{\hat{\beta}_{DEF}} \times \hat{\gamma}_{DEF}\right]$, where $HML^{\hat{\beta}_{DEF}}$ is the differences in β_{DEF} between high-ACI and low-ACI portfolios reported in Panel A of Table 4 and $\hat{\gamma}_{DEF}$ is the price of risk for DEF from the two-stage Fama–MacBeth (1973) cross-sectional regression estimated in Panel B of Table 4 The ACI return spread, as denoted by HML^R, is the raw return spread between high-ACI and low-ACI portfolios (P25–P1 ACI portfolio) reported in Table 3.

$E\left[HML^{\hat{\beta}_{DEF}} \times \hat{\gamma}_{DEF}\right]$	$\left(E\left[HML^{\hat{\beta}_{DEF}} \times \hat{\gamma}_{DEF}\right]\right)/HML^R$
−0.804 × 0.327 = −0.263	−0.263/−0.800 = 33%

Table 6

Post-ranking returns, loadings on DLI^m, price of risk for DLI^m for 25 ACI portfolios and incremental contribution of DLI^m. Panel A reports post-ranking returns and loadings on DLI^m for 25 ACI portfolios during January 1971–December 1999. EXRET is the excess monthly returns (excess of the 30-day T-bill rate). Alpha 4FF is the Fama–French four-factor alphas from the regressions of portfolios' post-ranking excess returns on the Fama–French four factors. Loadings on DLI^m for 25 ACI portfolios are estimated using full-sample regressions during January 1971–December 1999: $R_t^p = \beta_0 + \beta_{MKT}^p MKT_t + \beta_{SMB}^p SMB_t + \beta_{HML}^p HML_t + \beta_{MOM}^p MOM_t + \beta_{DLI^m}^p DLI_t^m + u_t^p$ where R_t^p is excess monthly returns for ACI portfolio p in month t, where p = High, P24,. . ., and Low. At the end of each month during December 1970 to November 1999, I sort-sampled stocks into 25 DLI portfolios based on their most recent monthly DLI and then calculated the equally weighted returns over the next month for each portfolio. DLI_t^m is a proxy for a systematic distress risk factor, defined as the P25–P1 return spread between high-DLI and low-DLI portfolios in month t. Panel B reports the price of risk for DLI^m for 25 ACI portfolios, estimated based on the two-stage Fama–MacBeth (1973) cross-sectional regressions. In the first stage, I generate a vector of factor loadings ($\hat{\beta}_{MKT}^p$, $\hat{\beta}_{SMB}^p$, $\hat{\beta}_{HML}^p$, $\hat{\beta}_{MOM}^p$, and $\hat{\beta}_{DLI^m}^p$). The second-stage cross-sectional regressions model is then tested: $R_t^p = \gamma_0 + \gamma_{MKT}\hat{\beta}_{MKT}^p + \gamma_{SMB}\hat{\beta}_{SMB}^p + \gamma_{HML}\hat{\beta}_{HML}^p + \gamma_{MOM}\hat{\beta}_{MOM}^p + \gamma_{DLI^m}\hat{\beta}_{DLI^m}^p + e_t^p$ where $\hat{\gamma}$ is a vector of the prices of risk. The intercepts ($\hat{\gamma}_0$) and the prices of risk ($\hat{\gamma}$) are the percentages per month. The adjusted R^2 in each model is generated using one cross-sectional regression of the time-series average excess return of each portfolio on its factor loadings. The Fama–MacBeth t statistics calculated from the Shanken (1992) method are reported in square brackets. Panel C reports the incremental contribution of DLI^m to the ACI return spread. The incremental contribution of DLI^m is measured as $E\left[HML^{\hat{\beta}_{DLI^m}} \times \hat{\gamma}_{DLI^m}\right]$, where $HML^{\hat{\beta}_{DLI^m}}$ is the differences in $\hat{\beta}_{DLI^m}$ between high-ACI and low-ACI portfolios reported in Panel A and $\hat{\gamma}_{DLI^m}$ is the price of risk for DLI^m estimated in Panel B. The ACI return spread, as denoted by HML^R, is the raw return spread between high-ACI and low-ACI portfolios reported in Panel A.

Panel A: Post-ranking returns and loadings on DLI^m

ACI portfolios	EXRET (%)	t-Value (EXRET)	Alpha 4FF (%)	t-Value (Alpha 4FF)	$\hat{\beta}_{DLI^m}$	t-Value ($\hat{\beta}_{DLI^m}$)
High	0.390	1.21	−0.254	−2.41	0.095	5.42
P24	0.603	1.95	−0.049	−0.52	0.083	5.24
P23	0.660	2.15	−0.015	−0.17	0.062	4.05
P22	0.633	2.02	−0.054	−0.58	0.068	4.27
P21	0.811	2.69	0.175	1.86	0.076	4.76
P20	0.969	3.18	0.273	2.86	0.055	3.39
P19	0.946	3.26	0.302	3.44	0.056	3.76
P18	0.898	3.02	0.300	3.00	0.060	3.51
P17	0.829	2.89	0.164	1.69	0.011	0.65
P16	0.862	2.90	0.211	2.32	0.043	2.75
P15	1.100	3.78	0.378	4.16	0.037	2.38
P14	0.805	2.82	0.120	1.43	0.049	3.44
P13	0.990	3.40	0.352	3.58	0.088	5.35
P12	0.968	3.24	0.243	2.51	0.070	4.28
P11	0.940	3.23	0.313	3.36	0.042	2.63
P10	0.882	3.00	0.170	1.92	0.080	5.43
P9	1.023	3.36	0.283	3.35	0.064	4.54
P8	0.959	3.16	0.284	3.13	0.073	4.81
P7	0.902	2.96	0.220	2.31	0.110	7.13
P6	1.065	3.47	0.400	4.01	0.105	6.41
P5	0.955	3.07	0.250	2.64	0.113	7.40
P4	0.991	3.11	0.300	3.05	0.147	9.78
P3	1.033	3.13	0.276	2.70	0.154	9.87
P2	1.144	3.38	0.351	3.38	0.163	10.40
Low	1.221	3.37	0.386	3.06	0.233	13.09
H–L	−0.832	−5.86	−0.640	−4.45	−0.138	−5.82

Panel B: Price of risk for DLI^m

Model	$\hat{\gamma}_0$	$\hat{\gamma}_{MKT}$	$\hat{\gamma}_{SMB}$	$\hat{\gamma}_{HML}$	$\hat{\gamma}_{MOM}$	$\hat{\gamma}_{DLI^m}$	Adj. R^2
(1)	0.098	0.857	−0.423	2.199	1.772		0.355
	[0.14]	[1.16]	[−1.51]	[3.63]	[3.27]		
(2)	1.739	−0.081	−1.695	2.379	2.103	2.960	0.558
	[2.40]	[−0.11]	[−4.27]	[3.84]	[3.80]	[3.36]	

Panel C: Incremental contribution of DLI^m

$E\left[HML^{\hat{\beta}_{DLI^m}} \times \hat{\gamma}_{DLI^m}\right]$	$E\left[HML^{\hat{\beta}_{DLI^m}} \times \hat{\gamma}_{DLI^m}\right] / HML^R$
−0.138 × 2.960 = −0.408	−0.408/−0.832 = 49%

Table 6 shows that the price of risk for DLI^m for the 25 ACI portfolios is significantly positive (2.960%, t-statistic of 3.36) based on the two-stage Fama–MacBeth (1973) cross-sectional regression, consistent with Table 4. Finally, Panel C of Table 6 shows that the combined effect of DLI^m loading (−0.138) and its price of risk (2.960%) accounts for 49% of the high-minus-low ACI return spread.

Another advantage of using the mimicking factor DLI^m for systematic distress risk is that it is a tradable portfolio, which can directly serve as an explanatory factor for investigating the extent to which the ACI return spread is reduced by DLI^m. As mentioned by Pastor and Stambaugh (2003) and Chen and Petkova (2012), when all the risk factors in an asset-pricing model are tradable portfolios, the intercepts in the time-series regression can be interpreted as the risk-adjusted alphas. Therefore, replacing a non-tradable DEF with a tradable DLI^m in a time-series regression model as specified in Eq. (4) will generate a direct estimate of the alphas and provide more intuitive evidence of the incremental contribution of systematic distress risk to the ACI return spread. Table 7 reports the ACI's alphas and the coefficient estimates.

Model (1) of Table 7 shows the average return spread between high-ACI and low-ACI portfolios is −0.832% per month with a t-statistic of −5.86, which mirrors those in the second and third columns of Table 6. By considering DEF^m as the only explanatory factor, Model (2) shows that the coefficient on DEF^m is significantly negative (−0.150, t-statistic of −8.43). This implies that the DEF^m loading of high-ACI stocks is significantly lower than that of low-ACI stocks, which is consistent with the findings in Table 6. More importantly, a comparison of Model (1) with Model (2) shows that once DEF^m is added into the model as an explanatory factor, the alpha reduces from −0.832% to −0.564% per month, a reduction approximately to 32%. This number represents the extent to which the ACI return spread is reduced by DEF^m. Similarly,

Table 7
Alphas from the regressions of the ACI return spread on the DLI^m-mimicking factor. This table reports the alphas (in percentages per month) for the ACI return spread when regressed on DLI^m, controlling for the four Fama–French factors during January 1971–December 1999. The time-series regression model is set as follows: $HML_t^R = \alpha + \beta_{MKT}MKT_t + \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{MOM}MOM_t + \beta_{DLI^m}DLI_t^m + u_t$ where HML_t^R is the equally weighted return spread between high-ACI and low-ACI portfolios in month *t* (as reported in Table 6). DLI_t^m is a proxy for a systematic distress risk factor, defined as the P25–P1 return spread between high-DLI and low-DLI portfolios in month *t*. DLI data are obtained from Maria Vassalou's website. The *t*-statistics are reported in square brackets.

	DLI^m as the only Regressor		Controlling for the Fama–French Four Factors	
	(1)	(2)	(3)	(4)
α	**−0.832**	**−0.564**	**−0.640**	**−0.426**
	[−5.86]	**[−4.23]**	**[−4.45]**	**[−3.00]**
MKT			−0.054	−0.008
			[−1.58]	[−0.24]
SMB			−0.293	−0.106
			[−5.95]	[−1.86]
HML			−0.177	−0.070
			[−3.22]	[−1.26]
MOM			−0.077	−0.127
			[−1.91]	[−3.23]
DLI^m		−0.150		−0.138
		[−8.43]		[−5.82]
Adj. R^2	–	0.168	0.114	0.191

compared to the Fama–French four-factor alpha in Model (3), the alpha from the Fama–French four-factor model augmented with DEF^m in Model (4) is moderately smaller. The alpha reduces by approximately 33%.

The results in Table 7 are comparable to those in the previous subsections, thus providing more robust and intuitive evidence that the premium on a tradable mimicking factor for distress risk, DEF^m, can explain approximately 30–40% of the high-minus-low ACI return spread.

4. Conclusion

This paper empirically demonstrated that equity market perceptions of firm exposure to systematic distress risk partially explain the existence of the investment growth anomaly. Building upon rational Q theory, my central hypothesis is that the lower expected returns to firms with substantially increased capital investment can be attributable to less exposure to systematic distress risk. By utilizing DEF as a proxy for a systematic distress risk factor, my empirical results support four conclusions:

Stocks from firms with abnormally high (low) capital investment have substantially lower (higher) loadings on the distress risk factor.

The distress risk factor is positively priced in the cross-section of 25 ACI portfolios.

Combining the effect of distress risk loadings and their price of risk shows that systematic distress risk accounts for 30–40% of the investment growth anomaly.

These conclusions remain when using a tradable factor-mimicking portfolio for distress risk constructed in Vassalou and Xing (2004) to capture the variations of systematic distress risk.

Building upon my overall evidence that systematic distress risk is shown to only account for about 30–40% of the investment growth anomaly, I conclude this study with caution that low returns on stocks from firms with abnormally high capital investment result partially from these firms' less exposure to systematic distress risk. This study's importance arises from conservatively suggesting that the investment growth anomaly is a risk-driven phenomenon, although many studies follow Titman et al. (2004) and explain it as being a result of behavioral mispricing.

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