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Real investment and risk dynamics ☆

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ABSTRACT

We ask to what extent the negative relation between investment and average stock returns is driven by risk. We show that: (i) the average return spread between low and high asset growth and investment portfolios is largely accounted for by their spread in systematic risk, as measured by the loadings on the Chen, Roll, and Ross (1986) factors; (ii) as predicted by *q*-theory and real options models, systematic risk falls during large investment periods; (iii) the returns of factors formed on the investment-to-assets, asset growth, and investment growth all forecast aggregate economic activities. Our evidence suggests that risk plays an important role in explaining the investment-return relation.

1. Introduction

We provide evidence in support of a risk-based interpretation of the role of investment in driving the cross-section of average stock returns. This finding is important since recent empirical work documents that an investment factor, defined as the return on a portfolio of low investment stocks over the return on a portfolio of high investment stocks, can explain much of the cross-section of average returns.[1]

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[1] For example, Xing (2008) finds that an investment factor contains information similar to the Fama and French (1993) value factor high minus low (HML), and can explain the value effect. Lyandres, Sun, and Zhang (2008) find that the post Seasoned Equity Offerings (SEO) underperformance substantially diminishes when a low minus high investment portfolio is added as a common risk factor. Chen, Novy-Marx, and Zhang (2010) show that a three-factor model, where the factors are the market portfolio, an investment factor, and a return on assets factor, explains much of the average return spreads across test assets formed on short-term prior returns, failure probability, *O*-score, earnings surprises, accruals, net stock issues, and stock valuation ratios. Wu, Zhang, and Zhang (2010) apply the *q*-theory to understand the accrual anomaly and provide evidence that adding an investment factor into standard factor regressions substantially reduces the magnitude of the accrual anomaly, often to insignificant levels. The motivation for the incorporation of the investment factor as a common risk factor is based in part on a set of empirical studies that show a strong negative cross-sectional relation between real investment (and asset growth) and future stock returns (see Anderson and Garcia-Feijoo, 2006; Xing, 2008; and Cooper, Gulen, and Schill, 2008).

Our central findings can be summarized as follows. First, low investment firms have substantially higher loadings with respect to the Chen, Roll, and Ross (1986) factors than high investment firms. The dispersion in the loadings between low and high investment firms is particularly large with respect to the growth rate of industrial production, which is a prominent and highly procyclical macroeconomic variable, and the term spread factor, which has substantial forecasting power for macroeconomic activity.[2] These findings hold regardless of whether investment is measured as investment-to-assets, asset growth, or the growth of capital expenditures.

Second, industrial production growth and the term spread are priced risk factors, and coupled with the spread in the loadings with respect to these factors across low and high investment portfolios, the implied expected returns spread can account for much of the spread in average return across these portfolios. Third, the dynamics of systematic risk around both large investment periods and around disinvestment periods are consistent with the predictions of both the *q*-theory of investment and of real option models. We find that systematic risk falls during high investment periods and rises in disinvestment periods.

Fourth, the investment factors contain information about future real industrial production growth, future real gross domestic product (GDP) growth, future real corporate earnings growth, and future real aggregate investment growth. Like the market portfolio, the investment factors earn low returns just before recessions. This evidence lends support to the interpretation of these factors as common risk factors that investors require a premium for holding.[3]

In addition to the empirical work that relates investment to the cross-section of returns, an investment factor arises as a result of the *q*-theory of investment (Cochrane, 1991; Li, Livdan, and Zhang, 2009; and Liu, Whited, and Zhang, 2009). However, the stream of recent papers that shows the first-order importance of investment for the cross-section of average returns stays away from the risk interpretation of the investment effect because of the *q*-theory's partial equilibrium nature. For example, Liu, Whited, and Zhang (2009) note that "… because we do not parameterize the stochastic discount factor, our work is silent about why average return spreads across characteristics-sorted portfolios are not matched with spreads in covariances empirically." Lyandres, Sun, and Zhang (2008) and Chen, Novy-Marx, and Zhang (2010) also note that they do not interpret the investment factor as a risk factor. Li and Zhang (2010) also try to disentangle the risk, and non-risk, based theories of the investment-return relation. In particular, Li and Zhang derive from *q*-theory that investment frictions should steepen the investment-return relation. However, the evidence is not supportive. In fact, limits-to-arbitrage proxies often dominate investment frictions proxies in explaining the magnitude of the investment-to-assets and asset growth effects in cross-sectional returns. By providing evidence for the role of risk in the investment effect in stock returns, our paper fills an important gap in the literature.

The rest of the paper is organized as follows. Section 2 reviews the risk-based and behavioral explanations for the investment-return relation and presents testable hypotheses concerning the role of risk in this relation. Section 3 describes the data and variable construction. Section 4 shows that the loadings with respect to the Chen, Roll, and Ross (1986) factors vary with investment, provides evidence that the Chen, Roll, and Ross (1986) factors are priced risk factors, and quantifies the effect of the loadings with respect to the factors in driving the investment-return relation. Section 5 explores the dynamics of systematic risk around periods of high investment and around periods of disinvestment. In Section 6, we present our results on the relation between the investment factors and future economic activity. Section 7 concludes.

2. Hypothesis development

The investment-return relation is consistent with both risk-based explanations and behavioral explanations. Our paper sheds some light on the contribution of these rival explanations by presenting evidence that the bulk of the investment-return relation can be explained by differential exposure to macroeconomic risk factors. However, even though we find that risk plays an important role in explaining the investment-return relation, completely disentangling these two schools of thought is difficult, if not impossible. In Section 2.1, we review the prominent risk-based and behavioral explanations offered for the investment-return relation, and in Section 2.2, we present testable hypotheses.

2.1. Explanations for the investment-return relation

Several models provide risk-based explanations for the negative investment-return relation. Berk, Green, and Naik (1999) present a model showing that the level of investment increases with the availability of low risk projects. Consequently, investing in these projects reduces expected returns because the firm's systematic risk is the average of the systematic risk of its mix of assets in place. Investment will, therefore, be followed by low average returns. Berk, Green, and Naik (2004) present a model of a multistage investment project in which uncertainty is resolved with investment, implying that the risk premium declines with investment.

Zhang (2005) presents a neoclassical industry equilibrium model with rational expectations and shows that costly reversibility of capital investment and a countercyclical price of risk lead to assets in place being harder to reduce. This mechanism renders firms with assets in place riskier than firms with growth options, especially in bad times. This theoretical prediction can be linked directly to the investment-return relation as follows. Due to costly reversibility, low investment firms are likely to be burdened with unproductive capital, finding it difficult to reduce their capital stocks, especially in bad times. Hence, in times of economic downturns when the price of risk is high, their dividends and returns covary with economic downturns more than the

[2] See, for example, Stock and Watson (1989), Chen (1991), Estrella and Hardouvelis (1991), Lettau and Ludvigson (2002), and Estrella (2005).

[3] Relatedly, Fama (1981) finds that the return on the market portfolio predicts GDP growth and Liew and Vassalou (2000) find similar evidence regarding the ability of the HML and small minus big (SMB) factors to predict GDP growth.

dividends and returns of high investment firms. As Zhang shows, this gives rise to an unconditional risk premium. Cooper (2006) presents a model with nonconvex adjustment costs of investment in which low investment firms have excess capital capacity and hence can fully benefit from positive aggregate shocks without undertaking costly investment, implying these firms are riskier than high investment firms which operate near full capacity.

Li, Livdan, and Zhang (2009) and Liu, Whited, and Zhang (2009) show that the neoclassical *q*-theory of investment predicts a negative relation between investment and future returns. The intuition behind this result is that firms will invest when their cost of capital is low. Thus, a low discount rate implies more projects attain a positive net present value (NPV) and hence will trigger investment by firms. Therefore, according to the *q*-theory, firms with low systematic risk will invest more. Moreover, firms which receive discount rate shocks that reduce their cost of capital will also respond by undertaking investment. Thus, a fall in risk and average returns during periods of investment is consistent with the prediction of the *q*-theory.

Real option models (see, for example, McDonald and Siegel, 1986; Majd and Pindyck, 1987; Pindyck, 1988; and Carlson, Fisher, and Giammarino, 2006) also predict that firms undertaking investment projects experience a fall in their systematic risk because undertaking real investment exercises a risky real option.

Alternative interpretations of the investment-return relation are based on behavioral type explanations that include investor overreaction, management overinvestment, and market timing. This latter argument for the negative relation is based on the notion that mangers are timing the market and invest when their stocks are overpriced and hence, the negative abnormal returns reflect a correction for the overpricing of the stocks. Stein (1996) derives a capital budgeting model and shows that when managers are interested in maximizing short-term stock prices or when their firms are financially constrained, they will optimally undertake investment when their stocks are overpriced. Baker, Stein, and Wurgler (2003) present a model in which firms that need external equity to finance their marginal investments will exhibit high sensitivity of investment to nonfundamental movements in stock prices. Lamont and Stein (2006, p. 148) argue that "… a manager whose stock is overvalued will certainly issue more shares but whether the proceeds of the issue go into new physical capital as opposed to simply being invested in T-bills is less obvious and depends on considerations of time horizons and financial constraint (Stein, 1996)."

Titman, Wei, and Xie (2004) argue that the investment-return relation is consistent with investors being slow to react to overinvestment by empire building managers. Using Carhart's (1997) four-factor model, Titman, Wei, and Xie (2004) uncover negative benchmark-adjusted returns following investment, especially for firms that have greater investment discretion, that is, firms with higher cash flows and lower debt ratios. They also show that this relation is significant only in time periods when hostile takeovers are less prevalent.

Cooper, Gulen, and Schill (2008) show that standard models of risk, such as the three, and four-factor models of Fama and French (1993) and Carhart (1997), as well as the conditional capital asset pricing model (CAPM), have difficulty in explaining the variation in returns associated with asset growth. They argue that investors overreact to asset growth, where the growth in the assets is not necessarily overinvestment, and that the negative abnormal returns after investment are a correction for the overreaction.

2.2. Testable hypotheses

Our paper aims to examine the extent to which risk drives the investment-return relation. The risk-based explanations offered for this relation motivate our testable hypotheses. We use the Chen, Roll, and Ross (1986) factors as common risk factors driving the pricing kernel. Thus, according to the risk-based explanations, we should observe a spread in the loadings with respect to these factors that accounts for the average return spread across low and high investment (asset growth) portfolios. Hence, our first hypothesis is:

H1: The Chen, Roll, and Ross factors are priced risk factors, and the dispersion in the loadings with respect to these factors across low and high investment portfolios accounts for the spread of average returns across these portfolios.

Our next hypothesis pertains to risk dynamics around high investment and around disinvestment periods. The risk-based explanations offered for the investment-return relation, namely the *q*-theory and the real option models, both predict a fall (rise) in risk following large investment (disinvestment) periods. Therefore, our second hypothesis is:

H2: The expected returns are lower in the periods following large investment than in the periods prior to the investment, and are higher in the periods following large disinvestment than the periods prior to the disinvestment.

Finally, the extant literature shows that investment factors have been able to capture much of the cross-sectional variation in average stock returns. If these factors are state variables in the context of Merton's (1973) intertemporal capital asset pricing model (ICAPM), then there should exist a positive relation between the factors and future economic growth. The existence of such a positive relation implies that the factors covary with news regarding the state of the economy, and they earn low returns when bad news arrives (see Fama, 1981 for a discussion regarding the market portfolio). Therefore, our third testable hypothesis is:

H3: There is a positive relation between the return on the investment (asset growth) factors and future macroeconomic activity.

3. Data and variable construction

We use all NYSE, Amex, and Nasdaq nonfinancial firms listed on the Center for Research in Security Prices (CRSP) monthly stock return files and the Compustat annual industrial firms file from January 1960 through December 2009. We exclude firms in regulated industries with four-digit standard industrial classification (SIC) codes between 4000 and 4999 and financial firms with SIC codes between 6000 and 6999. Only firms with ordinary common equity (security type 10 or 11 in CRSP) are used in constructing the sample. To reduce survivorship bias, firms are not included in the sample until they are on the Compustat database for three years. A further requirement to be included in the sample is that a firm has 36 months of stock return data. These requirements reduce the influence of small firms in the initial stages of their development. Following the conventions in Fama and French (1992), stock returns from July of year t to June of year $t+1$ are matched with accounting information from the fiscal year ending in calendar year $t-1$ in Compustat.

We focus on three real investment-based variables known to capture the cross-section of average stock returns. Our first measure, the investment-to-assets ratio (which we intermittently refer to as I/A), is the annual change in gross property, plant, and equipment plus the annual change in inventories divided by the lagged book value of assets. This measure is employed in Lyandres, Sun, and Zhang (2008) and in Chen, Novy-Marx, and Zhang (2010). We form an I/A return factor, generated by subtracting the top decile I/A portfolio return from the bottom decile I/A portfolio return. In our sample, the equal-weighted I/A factor earns a substantial premium of 0.93% per month, whereas the value-weighted I/A factor earns a smaller premium of 0.52% per month.

The second measure of investment is the year-on-year percentage change in total assets, which we denote AG (for asset growth). This measure is used by Cooper, Gulen, and Schill (2008) who show that it is a strong determinant of the cross-section of average stock returns. The equal-weighted asset growth factor, defined as the difference between the return on the bottom decile AG portfolio and the return on the top decile AG portfolio, earns a considerable premium of 1.15% per month. The value-weighted asset growth portfolio, defined similarly, earns a smaller premium of 0.46% per month. Finally, following Xing (2008), our third measure of investment is the growth rate of capital expenditures (denoted IG, which stands for investment growth). The equal-weighted IG factor earns an average premium of 0.47% per month, whereas the value-weighted IG portfolio earns a premium of 0.39% per month. Hereafter, we intermittently refer to I/A, AG, and IG by the general term investment.

We now turn to the allocation of stocks into portfolios. At the end of June in year t, stocks are allocated into portfolios based on information published in their financial statements from the fiscal year ending in calendar year $t-1$. Portfolios of stocks are then formed from July of year t through June of year $t+1$. We form ten equal-weighted portfolios as well as ten value-weighted portfolios based on either I/A, AG, or IG.

Following Liu and Zhang (2008), we obtain data on the five Chen, Roll, and Ross (1986) factors, which we intermittently refer to as the CRR factors, as follows. The growth rate of industrial production, MP, is defined as $MP_t = \log(IP_t) - \log(IP_{t-1})$, where IP_t is the index of industrial production in month t from the Federal Reserve Bank of St. Louis.[4] Unexpected inflation (UI) and the change in expected inflation (DEI) are calculated in the same way as in Chen, Roll, and Ross (1986) and are derived from the total seasonally adjusted consumer price index (CPI) obtained from the Federal Reserve Bank of St. Louis. We define the term premium, UTS, as the yield spread between the long-term (ten-year) and the one-year Treasury bonds from the Federal Reserve Bank of St. Louis. The default premium, URP, is the yield spread between Moody's Baa and Aaa corporate bonds from the Federal Reserve Bank of St. Louis.

Cochrane (2005, p. 125) and Ferson, Siegel, and Xu (2006), among others, recommend using mimicking portfolios when the risk factors are not traded assets. Using mimicking portfolios delivers sharper estimates of portfolios' loadings and therefore less biased estimates of risk premiums. For example, in their study of an international multifactor asset pricing model, where the factors include macroeconomic variables, Ferson and Harvey (1994, p. 794) write that: "Measurement errors in the economic data may reduce the correlation of the global risk measures with the country returns. We therefore conduct an additional set of tests using maximum correlation portfolios for the economic risk factors ..." and "If there is measurement error which is unrelated to returns, then the measurement error is captured in the residual when the maximum correlation portfolios are formed.", implying that the mimicking portfolios do not contain the measurement errors. Vassalou (2003) argues that "One nice property of the use of mimicking portfolios to proxy economic variables is the following. The information captured in the portfolio about the economic variable is that which is reflected in the asset returns, and which can therefore affect the prices of assets. There is sometimes much more information about the economic variable which is not captured by the mimicking portfolio, but that is because this additional information may not be relevant for asset returns. Furthermore, the use of mimicking portfolios avoids problems related to measurement errors of economic variables." We follow Breeden, Gibbons, and Litzenberger (1989), Ferson and Harvey (1991, 1993, 1994), Chan, Karceski, and Lakonishok (1998), Vassalou (2003), and Ang, Hodrick, Xing, and Zhang (2006), among others, and form mimicking portfolios for the five CRR factors.

Among the CRR factors, three are non-traded assets while two are traded assets. To put all factors on equal footings, we construct mimicking portfolios for all five.[5] Importantly, untabulated results show that our risk premium estimates using the mimicking portfolios are the same as the risk premium estimates when using the five CRR factors themselves. Moreover, the investment portfolios' loadings with respect to the five mimicking portfolios are similar to their loadings with respect to the actual five CRR factors. Thus, all of our results using the mimicking portfolios are very similar to the results when using the macroeconomic factors themselves, however, the use of the factor mimicking portfolios provides sharper estimates of the factor loadings across portfolios. We form the mimicking portfolios from ten equal-weighted

[4] Following Chen, Roll, and Ross (1986) and Liu and Zhang (2008), we lead the MP variable by one month to align the timing of macroeconomic and financial variables.

[5] Chan, Karceski, and Lakonishok (1998) also form mimicking portfolios for the five Chen, Roll, and Ross (1986) factors.

book-to-market portfolios, ten equal-weighted size portfolios, ten value-weighted momentum portfolios, and ten equal-weighted asset growth portfolios.[6] The size, book-to-market, and momentum portfolios are taken from Kenneth French's Web site, whereas the ten asset growth portfolios are calculated from our measure of asset growth defined above.

We follow Lehmann and Modest (1988, Section 4.2) and form the mimicking portfolios as follows.[7] We first regress the return on each of the 40 test assets on the five CRR factors, that is, we undertake 40 time-series regressions producing a (40×5) matrix B of slope coefficients against the five factors. Let V be the (40×40) covariance matrix of error terms for these regressions (assumed to be orthogonal), then the weights on the mimicking portfolios are given by: $w=(B'V^{-1}B)B'V^{-1}$. Note that w is a 5×40 matrix, and the mimicking portfolios are given by wR' where R is a $T\times40$ matrix. This product yields a $(5\times T)$ matrix, of which each row represents a mimicking portfolio return over the sample period. This procedure produces unit-beta mimicking portfolios. That is, the mimicking portfolio for a specific factor has a beta of unity with respect to that factor and a beta of zero with respect to all other factors.

4. Can macroeconomic risk explain the negative investment - return relation?

This section presents evidence on the variation in the Chen, Roll, and Ross (1986) risk factors' loadings across real investment portfolios, estimates the risk premiums on the mimicking portfolios for the five CRR factors, and examines to what extent the spread in expected returns across low and high investment portfolios can account for the average return spread across these portfolios.

4.1. Macroeconomic risk exposure: investment-to-assets portfolios

In Panel A of Table 1, we report the mean monthly returns and the loadings with respect to the mimicking portfolios for the CRR factors of the ten equal-weighted portfolios sorted by the investment-to-assets ratio. The first row of Panel A shows that the average returns of low I/A firms are substantially higher than those of high I/A firms. The difference is 0.93% per month, or 11.75% in annual terms, and is statistically significant.

Preliminary evidence regarding the ability of systematic risk to explain the spread in average returns is presented in the second to sixth rows of Panel A. The portfolios' loadings on the CRR factors generally decline with I/A and assuming that the CRR factors are priced risk factors, this implies that low I/A firms are riskier than high I/A firms. For instance, as seen in the second row of Panel A, the loadings on the mimicking portfolio for MP decline as I/A increases; the loading of the low I/A portfolio is 0.64 (with a t-statistic of 3.91). The loadings then decline rapidly for higher I/A portfolios ending with a loading of 0.35 (with a t-statistic of 2.21) for the high I/A portfolio. The difference between these two loadings is economically large and statistically significant.[8]

The loadings with respect to the mimicking portfolio for UI exhibit a U-shape and are actually higher for the high I/A portfolio than for the low I/A portfolio. The loadings with respect to the mimicking portfolio for DEI initially increase from -3.46 for the low I/A portfolio to -2.91 for portfolio 5, before declining again to -4.10 for the high I/A portfolio.

The loadings with respect to the mimicking portfolio for the term spread fall substantially from 0.62 for the low I/A portfolio to 0.41 for the high I/A portfolio. The difference in the loadings on the mimicking portfolios for UTS is economically and statistically significant (the hypothesis that the loadings of the low and high I/A portfolios on UTS are the same is rejected). Finally, the loadings with respect to the mimicking portfolio for the default spread, UPR, generally decline (though non-monotonically) from 1.34 for the low I/A portfolio to 1.19 for the high I/A portfolio, although the difference is not statistically significant.[9]

The largest differences in the factor loadings between low and high I/A portfolios are recorded for the MP and UTS mimicking portfolios. Both of these factors are based on well-known business cycle variables. The growth rate of industrial production is a macroeconomic variable that clearly varies with business conditions. Therefore, our evidence that low investment firms' exposure to this factor is substantially higher than the exposure of high investment firms is an economically significant finding. There is an extensive evidence that the term spread (but not the default spread) is a strong predictor of output growth. A downward sloping yield curve almost always precedes recessions. The forecasting ability of the term spread for aggregate output is shown in, among others, Stock and Watson (1989), Chen (1991), Estrella and Hardouvelis (1991), and Estrella (2005). Moreover, Lettau and Ludvigson (2002) show that the term spread is a strong predictor of aggregate investment growth.

[6] For the asset growth, size, and book-to-market portfolios, the spread in average returns is higher when using equal-weighted portfolios than when using value-weighted portfolios. However, the opposite is the case for the spread between the top decile momentum portfolio (winner stocks) and the bottom decile momentum portfolio (loser stocks). In our sample, the spread is 1.36% per month for the value-weighted portfolios and 0.99% per month for the equal-weighted portfolios. In light of this, we use value-weighted momentum portfolios when forming the mimicking portfolios and when estimating the factor risk premiums in Section 4.4.1 below. The results when using equal-weighted momentum portfolios are similar to the results when using value-weighted momentum portfolios and are available from the authors upon request.

[7] Grinblatt and Titman (1989) and Eckbo, Masulis, and Norli (2000), among others, also apply the Lehmann and Modest (1988) methodology of forming mimicking portfolios.

[8] All the t-statistics, and the p-values that test the null hypothesis of a zero difference in the loadings on a given factor between the low and high investment portfolios, are based on standard errors that are adjusted for heteroskedasticity and autocorrelation.

[9] The variation in the portfolio loadings with respect to the original CRR factors is very similar to the results presented in all Panels of Tables 1–3 unless otherwise stated. Untabulated results are available on request.

Table 1
Summary statistics and macroeconomic exposure for portfolio returns formed on the investment-to-assets ratio.

Panel A presents average portfolio returns and loadings with respect to mimicking portfolios of the five Chen, Roll, and Ross (1986) (CRR) factors for ten equal-weighted portfolios formed on the investment-to-assets ratio, *I*/*A*. The loadings are estimated from monthly regressions of portfolio returns on the five mimicking portfolios for the CRR factors. *MP* is the growth rate of industrial production, *UI* is unexpected inflation, *DEI* is the change in expected inflation, *UTS* is the term spread, and *UPR* is the default spread. $\bar{r}$ denotes average portfolio returns. The 2nd to the 6th rows are the loadings with respect to the mimicking portfolios for the five factors. Panel B presents average portfolio returns and loadings with respect to mimicking portfolios of the CRR factors for ten value-weighted portfolios formed on *I*/*A*. The sample is monthly from January 1960 to December 2009. The column *p* (*dif*) reports the *p*-value for the hypothesis test that the difference in average returns or loadings between the low and high *I*/*A* portfolios is zero. The *t*-statistics (in parentheses) and the *p*-values are adjusted for heteroskedasticity and autocorrelations.

Panel A: Investment-to-assets portfolios: Equal-weighted portfolios

Decile	Low	2	3	4	5	6	7	8	9	High	*p*(*dif*)
$\bar{r}$	1.71	1.60	1.47	1.34	1.33	1.34	1.22	1.18	1.03	0.78	0.00
MP	0.64 (3.91)	0.52 (3.82)	0.45 (3.33)	0.36 (2.73)	0.32 (2.64)	0.32 (2.68)	0.30 (2.51)	0.30 (2.26)	0.33 (2.25)	0.35 (2.21)	0.00
UI	3.71 (5.80)	3.23 (6.22)	3.04 (5.79)	2.92 (5.68)	2.51 (5.50)	2.65 (6.18)	2.58 (5.98)	2.77 (5.17)	3.01 (6.25)	3.81 (6.98)	0.79
DEI	−3.46 (−7.37)	−3.24 (−8.87)	−3.18 (−8.37)	−3.13 (−8.51)	−2.91 (−8.80)	−3.05 (−9.49)	−3.01 (−9.63)	−3.20 (−8.27)	−3.47 (−10.03)	−4.10 (−10.18)	0.03
UTS	0.62 (5.90)	0.50 (6.76)	0.50 (6.29)	0.45 (6.24)	0.41 (6.03)	0.39 (5.19)	0.41 (5.99)	0.40 (5.07)	0.40 (4.81)	0.41 (4.44)	0.00
UPR	1.34 (3.60)	1.16 (3.88)	1.15 (4.26)	1.21 (4.74)	1.07 (4.47)	1.14 (4.57)	1.16 (4.78)	1.24 (4.57)	1.24 (4.59)	1.19 (4.21)	0.22

Panel B: Investment-to-assets portfolios: Value-weighted portfolios

Decile	Low	2	3	4	5	6	7	8	9	High	*p*(*dif*)
$\bar{r}$	1.30	1.04	1.05	0.95	0.89	0.90	0.92	0.93	0.81	0.78	0.01
MP	0.37 (2.48)	0.23 (1.70)	0.21 (1.91)	0.16 (1.14)	0.20 (2.06)	0.28 (2.54)	0.24 (2.43)	0.17 (1.31)	0.13 (0.94)	0.22 (1.45)	0.01
UI	1.79 (5.19)	1.44 (4.26)	1.31 (3.76)	1.39 (3.71)	0.85 (2.83)	1.13 (3.03)	1.42 (3.48)	1.46 (2.92)	1.63 (2.98)	2.30 (3.48)	0.37
DEI	−2.44 (−8.77)	−2.18 (−7.92)	−2.13 (−6.72)	−2.11 (−6.58)	−1.74 (−6.72)	−1.85 (−6.00)	−2.10 (−6.76)	−2.20 (−5.96)	−2.44 (−6.05)	−2.98 (−5.86)	0.27
UTS	0.40 (6.69)	0.30 (3.73)	0.29 (5.21)	0.20 (2.65)	0.22 (3.64)	0.21 (3.12)	0.23 (3.17)	0.18 (2.73)	0.14 (1.92)	0.20 (2.14)	0.00
UPR	0.85 (3.66)	0.69 (4.34)	0.72 (4.50)	0.72 (5.82)	0.57 (4.06)	0.61 (5.00)	0.65 (4.86)	0.56 (3.78)	0.55 (3.06)	0.81 (5.10)	0.74

Thus, similar to the market portfolio, the term spread is a leading indicator of economic activity and falls prior to recessions. Therefore, our finding that the loadings of low investment firms with respect to the *UTS* factor are substantially higher than the loadings of high investment firms suggests that low investment firms are riskier in the sense that they are more sensitive to the business cycle.

Panel B of Table 1 presents the results for the value-weighted *I*/*A* portfolios. The first row of Panel B shows that the average monthly return falls from 1.30% for the low *I*/*A* portfolio to 0.78% for the high *I*/*A* portfolio. The difference between the returns on the low and high *I*/*A* portfolios is statistically significant. Thus, there is a considerable spread in average returns across the value-weighted *I*/*A* portfolios of 0.52% per month, although it is substantially smaller than the spread achieved when using the equal-weighted portfolios.

The second row of Panel B shows that the loadings on the mimicking portfolio for *MP* decline rapidly, from 0.37 for the low *I*/*A* portfolio to 0.16 for portfolio 4, and then increase. Notwithstanding this increase, the loading of the high *I*/*A* portfolio is 0.22, which is substantially lower than the loading of the low *I*/*A* portfolio. The hypothesis that the *MP* loading of the value-weighted low *I*/*A* portfolio is equal to the *MP* loading of the value-weighted high *I*/*A* portfolio is rejected.

The loadings with respect to the other mimicking portfolios decline with *I*/*A* with the exception of the loadings on *UI*. The most notable difference is observed for the loadings with respect to the mimicking portfolio of *UTS* which is twice as large for the low *I*/*A* portfolio than for the high *I*/*A* portfolio and the difference between these two loadings is statistically significant.

Considering the two panels in Table 1, we obtain consistent findings indicating that the decline in average return as investment falls is also associated with a decline in factor loadings as measured by the CRR factors. The loadings on the industrial production factor and the term structure factor, two key business cycle variables, exhibit the largest falls. The results are robust to the use of the factor mimicking portfolios and the original CRR factors and to the formation of portfolios that employ both equal weights and value weights.

4.2. Macroeconomic risk exposure: asset growth portfolios

Panel A of Table 2 shows that there is a monotonic decrease in average returns when moving from the low to the high equal-weighted *AG* portfolio. The spread in average returns between the low and high *AG* portfolios is 1.15% per month and the hypothesis that the difference is zero is rejected, consistent with findings in Cooper, Gulen, and Schill (2008). The second row of Panel A shows that the loadings with respect to the mimicking portfolio for *MP* decline with *AG* from 0.64 for the low *AG* portfolio to 0.30 for the high *AG* portfolio and that the difference between these two loadings is statistically significant. The

Table 2

Summary statistics and macroeconomic exposure for portfolio returns formed on asset growth.

Panel A presents average portfolio returns and loadings with respect to mimicking portfolios of the five Chen, Roll, and Ross (1986) (CRR) factors for ten equal-weighted portfolios formed by asset growth, *AG*. The loadings are estimated from monthly regressions of portfolio returns on the five mimicking portfolios for the CRR factors. *MP* is the growth rate of industrial production, *UI* is unexpected inflation, *DEI* is the change in expected inflation, *UTS* is the term spread, and *UPR* is the default spread. $\bar{r}$ denotes average portfolio returns. The 2nd to the 6th rows are the loadings with respect to the mimicking portfolios for the five factors. Panel B presents average portfolio returns and loadings with respect to mimicking portfolios of the CRR factors for ten value-weighted portfolios formed on *AG*. The sample is monthly from January 1960 to December 2009. The column *p*(*dif*) reports the *p*-value for the hypothesis test that the difference in average returns or loadings between the low and high *AG* portfolios is zero. The *t*-statistics (in parentheses) and the *p*-values are adjusted for heteroskedasticity and autocorrelations.

Panel A: Asset growth portfolios: Equal-weighted portfolios

Decile	Low	2	3	4	5	6	7	8	9	High	*p*(*dif*)
$\bar{r}$	1.78	1.60	1.46	1.38	1.42	1.28	1.27	1.19	1.01	0.63	0.00
MP	0.64	0.65	0.42	0.33	0.40	0.33	0.33	0.20	0.29	0.30	0.00
	(3.11)	(4.69)	(3.23)	(2.88)	(3.54)	(2.87)	(2.73)	(1.51)	(2.07)	(1.70)	
UI	4.50	3.23	3.10	2.29	2.34	2.69	2.72	2.41	3.08	3.97	0.07
	(5.68)	(5.42)	(6.74)	(6.03)	(5.73)	(7.33)	(6.59)	(5.52)	(5.21)	(6.01)	
DEI	−3.83	−3.20	−3.23	−2.70	−2.71	−3.16	−3.14	−3.00	−3.46	−4.35	0.02
	(−6.71)	(−7.46)	(−9.27)	(−9.77)	(−9.07)	(−12.52)	(−10.67)	(−9.63)	(−8.25)	(−8.70)	
UTS	0.66	0.54	0.51	0.48	0.42	0.42	0.40	0.40	0.34	0.35	0.00
	(6.00)	(6.43)	(6.49)	(7.15)	(6.07)	(6.48)	(5.98)	(5.46)	(3.97)	(3.55)	
UPR	1.57	1.17	1.02	1.06	1.20	1.28	1.12	1.07	1.18	1.24	0.02
	(3.84)	(3.88)	(3.74)	(4.46)	(5.33)	(5.81)	(4.34)	(4.28)	(4.16)	(4.14)	

Panel B: Asset growth portfolios: Value-weighted portfolios

Decile	Low	2	3	4	5	6	7	8	9	High	*p*(*dif*)
$\bar{r}$	1.12	1.04	1.01	1.04	0.95	0.94	1.02	0.93	0.94	0.66	0.05
MP	0.32	0.35	0.21	0.17	0.24	0.19	0.23	0.16	0.21	0.12	0.10
	(1.77)	(2.35)	(1.73)	(1.21)	(2.22)	(1.76)	(2.14)	(1.42)	(1.53)	(0.71)	
UI	2.18	1.75	1.51	0.75	1.18	1.27	0.95	1.31	1.84	2.39	0.68
	(6.17)	(5.89)	(5.30)	(2.78)	(3.82)	(3.86)	(2.97)	(2.77)	(2.91)	(3.71)	
DEI	−2.69	−2.44	−2.19	−1.56	−1.82	−1.98	−1.71	−2.16	−2.65	−3.22	0.21
	(−9.22)	(−10.63)	(−9.15)	(−6.37)	(−7.04)	(−8.27)	(−6.10)	(−5.65)	(−5.52)	(−6.65)	
UTS	0.41	0.32	0.34	0.23	0.25	0.22	0.19	0.18	0.11	0.17	0.00
	(5.20)	(4.50)	(5.74)	(4.03)	(3.98)	(4.20)	(2.91)	(2.64)	(1.23)	(1.57)	
UPR	1.04	0.74	0.70	0.66	0.66	0.62	0.61	0.54	0.63	0.77	0.14
	(4.29)	(3.81)	(5.04)	(5.36)	(6.29)	(4.93)	(4.84)	(3.64)	(3.28)	(4.30)	

loadings on *UI* also fall with *AG*, albeit non-monotonically, as do the loadings on *DEI*. The loading of the low *AG* portfolio with respect to the *UTS* factor (0.66, *t*-statistic of 6.00) is almost twice as large as the corresponding loading of the high *AG* portfolio (0.35, *t*-statistic of 3.55) and the difference between the two loadings is statistically significant. The loadings on *UPR* also fall with *AG*, from 1.57 for the low *AG* portfolio to 1.24 for the high *AG* portfolio.

Similar to our evidence regarding the loadings of the *I*/*A* portfolios, it appears that low asset growth firms are more sensitive to the business cycle than high asset growth firms. This is reflected in the loadings with respect to two factors that are closely related to the business cycle, namely the growth rate of industrial production and the term spread.

Panel B of Table 2 reports results which employ value-weighted *AG* portfolios. The average return spread across the value-weighted *AG* portfolios is 0.46% per month which is slightly smaller than the average return spread across the value-weighted *I*/*A* portfolios (0.52% per month). The *p*-value that the spread across the value-weighted low and high *AG* portfolios is zero is 0.05. The loadings with respect to the mimicking portfolios for *MP* decline substantially with *AG* from 0.32 for the low *AG* decile to 0.12 for the high *AG*. The loadings on *UTS* fall sharply from 0.41 for the low *AG* portfolio to 0.17 for high *AG* portfolio. The loadings with respect to the *UPR* factor fall from 1.04 for the low *AG* portfolio to 0.77 for the high *AG* portfolio although the difference in the loadings is not statistically significant. Overall, the findings in Panel B are also consistent with the conjecture that low *AG* firms are riskier than high *AG* firms.

Our evidence regarding the *AG* portfolios indicates that the macroeconomic risk exposure of low asset growth portfolios is higher than that of the high asset growth portfolios. This suggests that at least part of the asset growth effect in stock returns can potentially be explained by variation in systematic risk across firms with different asset growth characteristics. These findings are consistent with those reported in Table 1 that employ *I*/*A* as the investment measure.

4.3. Macroeconomic risk exposure: investment growth portfolios

Xing (2008) presents evidence that firms with a low growth rate of investment (measured as capital expenditures) earn substantially higher average returns than firms with a high growth rate of investment. In this section, we present evidence on the variation in macroeconomic factor loadings across investment growth portfolios.

The first row of Panel A of Table 3 shows that average returns decline with investment growth for the equal-weighted portfolios, resulting in an average excess return

Table 3
Summary statistics and macroeconomic exposure for portfolio returns formed on investment growth.

Panel A presents average portfolio returns and loadings with respect to mimicking portfolios of the five Chen, Roll, and Ross (1986) (CRR) factors for ten equal-weighted portfolios formed by investment growth, *IG*. The loadings are estimated from monthly regressions of portfolio returns on the five mimicking portfolios for the CRR factors. *MP* is the growth rate of industrial production, *UI* is unexpected inflation, *DEI* is the change in expected inflation, *UTS* is the term spread, and *UPR* is the default spread. $\bar{r}$ denotes average portfolio returns. The 2nd to the 6th rows are the loadings with respect to the mimicking portfolios for the five factors. Panel B presents average portfolio returns and loadings with respect to mimicking portfolios of the CRR factors for ten value-weighted portfolios formed on *IG*. The sample is monthly from January 1960 to December 2009. The column *p*(*dif*) reports the *p*-value for the hypothesis test that the difference in average returns or loadings between the low and high *IG* portfolios is zero. The *t*-statistics (in parentheses) and the *p*-values are adjusted for heteroskedasticity and autocorrelations.

Panel A: Investment growth portfolios: Equal-weighted portfolios

Decile	Low	2	3	4	5	6	7	8	9	High	*p*(*dif*)
$\bar{r}$	1.56	1.35	1.43	1.34	1.33	1.25	1.30	1.20	1.12	1.09	0.00
MP	0.58 (3.78)	0.50 (3.67)	0.42 (3.13)	0.37 (3.10)	0.32 (2.76)	0.32 (2.69)	0.31 (2.34)	0.30 (2.29)	0.33 (2.12)	0.42 (2.52)	0.00
UI	3.64 (5.52)	3.15 (5.68)	2.85 (5.94)	2.72 (6.22)	2.51 (6.21)	2.56 (6.13)	2.81 (6.52)	2.92 (6.30)	3.22 (6.05)	3.83 (5.98)	0.23
DEI	−3.32 (−7.07)	−3.23 (−7.87)	−3.12 (−8.89)	−3.12 (−10.29)	−3.00 (−9.97)	−2.98 (−9.59)	−3.27 (−10.61)	−3.38 (−9.96)	−3.51 (−9.24)	−3.83 (−8.28)	0.00
UTS	0.56 (6.46)	0.50 (5.98)	0.46 (5.72)	0.45 (5.90)	0.43 (6.09)	0.39 (5.78)	0.43 (5.53)	0.42 (4.98)	0.42 (5.03)	0.43 (4.91)	0.00
UPR	1.25 (3.61)	1.26 (4.23)	1.24 (4.78)	1.13 (4.42)	1.12 (4.94)	1.13 (4.39)	1.14 (4.50)	1.19 (4.70)	1.19 (4.30)	1.22 (3.86)	0.58

Panel B: Investment growth portfolios: Value-weighted portfolios

Decile	Low	2	3	4	5	6	7	8	9	High	*p*(*dif*)
$\bar{r}$	1.15	0.84	1.03	0.95	0.98	0.94	0.82	0.99	0.75	0.76	0.02
MP	0.22 (1.28)	0.29 (2.25)	0.24 (2.12)	0.21 (1.71)	0.28 (3.09)	0.22 (1.75)	0.18 (1.48)	0.19 (1.52)	0.10 (0.68)	0.10 (0.52)	0.10
UI	2.23 (4.35)	1.92 (4.35)	1.59 (3.89)	1.30 (3.42)	0.98 (2.53)	1.20 (2.93)	1.32 (3.40)	1.46 (2.88)	2.17 (3.78)	3.23 (4.77)	0.02
DEI	−2.97 (−7.70)	−2.58 (−7.10)	−2.28 (−7.22)	−2.03 (−6.06)	−1.75 (−5.30)	−1.81 (−5.71)	−2.04 (−7.27)	−2.31 (−5.76)	−3.02 (−6.79)	−4.15 (−8.06)	0.00
UTS	0.35 (4.00)	0.28 (4.79)	0.25 (4.49)	0.21 (2.90)	0.21 (3.75)	0.20 (2.95)	0.18 (2.71)	0.22 (2.62)	0.18 (1.83)	0.26 (2.73)	0.06
UPR	0.87 (3.32)	0.93 (5.94)	0.72 (5.98)	0.63 (5.02)	0.53 (4.29)	0.60 (4.95)	0.69 (5.00)	0.62 (3.88)	0.70 (3.61)	0.85 (3.25)	0.86

of the low *IG* portfolio over the high *IG* portfolio of 0.47% per month. The hypothesis that the spread in average returns across the low *IG* and high *IG* portfolios is zero is rejected. This spread is around half the size of those obtained on the *I*/*A* and *AG* portfolios. As seen in the following rows of Table 3, the pattern of the variation in the loadings across the *IG* portfolios is rather similar to that for the *I*/*A* portfolios and for the *AG* portfolios, with substantial falls in the loadings with respect to the mimicking portfolios for *MP* and for *UTS*.

Panel B of Table 3 reports results using value-weighted *IG* portfolios. The average value-weighted returns on the *IG* portfolios are reported in the first row of Panel B. The first thing to note is that, unlike the case of the *I*/*A* and *AG* portfolios where the premium on the low minus high portfolio falls substantially when moving from equal weights to value weights, the premium on the low minus high *IG* portfolio falls by only around 20% (from 0.47% per month for the equal-weighted portfolios to 0.39% per month for the value-weighted portfolios). The premium when using the value-weighted portfolios is statistically significant.

The remaining rows of Panel B report the loadings of the value-weighted *IG* portfolios with respect to the mimicking portfolios for the CRR factors. The variation in the loadings is quite similar to the variation in the loadings of the value-weighted *I*/*A* and *AG* portfolios, with a more moderate decline in the loadings on the mimicking portfolio for *UTS*.[10]

Overall, with the exception of loadings of the value-weighted *IG* portfolios with respect to the original CRR factors, the patterns in factor loadings across low and high *IG* portfolios are similar to those for the *I*/*A* and *AG* portfolios and suggest that low *IG* firms are riskier than high *IG* firms.

4.4. Explaining the investment effect with the CRR loadings

The previous section provided evidence that low investment firms have, in general, higher loadings with respect to the Chen, Roll, and Ross (1986) factors than high investment firms. In this section, we examine to what extent the variation in the loadings between low and high investment portfolios can explain the average return spreads across the investment portfolios. Specifically, after estimating the CRR factor risk premiums, we assess the extent to which the average return spread between the low and high investment portfolios can be accounted for by the expected return spread that is implied by the product of the loadings of

[10] Untabulated results show that, unlike for the other portfolios, most of loadings for these portfolios actually increase with *IG* when employing the original CRR factors although none of the increases in the loadings are statistically significant.

Table 4
Risk premium estimates.
We estimate the risk premiums for the mimicking portfolios for the five Chen, Roll, and Ross (1986) factors, including industrial production (*MP*), unexpected inflation (*UI*), change in expected inflation (*DEI*), term spread (*UTS*), and default spread (*UPR*) using the two-stage Fama and MacBeth (1973) cross-sectional regression methodology. In the first stage, we estimate factor loadings using full-sample regressions, extending-window regressions, and 60-month rolling-window regressions. The extending windows always start in January 1960 and end in month *t*. We perform the second-stage cross-sectional regressions of portfolio returns from *t* to *t*+1 on factor loadings estimated using information up to month *t*. In the extending-window and rolling-window estimations, we start the second-stage regressions in January 1965 to ensure that we always have 60 monthly observations in the first-stage rolling window and extending-window regressions. We use 40 testing portfolios: ten equal-weighted size portfolios, ten equal-weighted book-to-market portfolios, ten value-weighted momentum portfolios, and ten equal-weighted asset growth portfolios. We report results from the second-stage cross-sectional regressions including the intercepts ($\hat{\gamma}_0$), risk premiums ($\hat{\gamma}$), and average second-stage cross-sectional regression $\overline{R}^2$s. The intercepts and the risk premiums are in percentage per month. The Shanken (1992)-corrected *t*-statistics are reported in parentheses.

	$\hat{\gamma}_0$	$\hat{\gamma}_{MP}$	$\hat{\gamma}_{UI}$	$\hat{\gamma}_{DEI}$	$\hat{\gamma}_{UTS}$	$\hat{\gamma}_{UPR}$	$\overline{R}^2$ (%)
Full sample in first stage	0.53 (2.26)	1.08 (3.75)	0.08 (0.58)	0.15 (1.11)	0.94 (3.36)	−0.26 (−3.95)	46
Extending window in first stage	0.67 (2.80)	0.87 (3.30)	0.02 (0.11)	0.18 (1.44)	1.00 (3.47)	−0.21 (−3.19)	45
Rolling window in first stage	0.73 (3.65)	0.84 (3.54)	0.05 (0.39)	0.17 (1.31)	0.52 (2.70)	−0.14 (−2.24)	48

these portfolios with respect to the CRR factors and the factors' estimated risk premiums.

4.4.1. Estimation of the risk premiums on the CRR factors

We estimate the risk premiums associated with the five mimicking portfolios for the CRR factors using the two-step Fama and MacBeth (1973) cross-sectional regression methodology.[11] The test assets used to estimate the risk premiums are portfolios of stocks that display a wide spread in average returns. To this end, we use 40 test assets including ten size, ten book-to-market, ten momentum (the 30 portfolios used by Liu and Zhang, 2008 and by Bansal, Dittmar, and Lundblad, 2005), as well as ten portfolios based on asset growth.[12] Our motivation for including the asset growth portfolios as test assets is based on our interest in the asset growth effect in stock returns and the finding in Cooper, Gulen, and Schill (2008) that asset growth is the strongest determinant of average stock returns.

Following Black, Jensen, and Scholes (1972), Fama and French (1992), Lettau and Ludvigson (2001), and Liu and Zhang (2008), we use the full sample to estimate factor loadings in the first-stage estimation. As Liu and Zhang (2008) note, if the true factor loadings are constant, the full-sample estimates should be more precise than estimates based on rolling regressions and extending windows. Indeed, untabulated results show that the first-step loadings are estimated much more precisely when employing the full-sample regressions. The standard errors for the full-sample loadings are about one-third of the corresponding standard errors for the rolling-window loadings across the test assets.

Due to the fact that the attenuation bias is less severe, using an extending window or full-sample in the first-step regressions is expected to yield higher and less biased risk premium estimates than when using a rolling window. As robustness checks, we also employ an extending window and a rolling window in the first-stage estimation of portfolio factor loadings. The rolling-window estimation uses 60 months of returns. The extending window always starts in January 1960 and ends in month *t*, in which we perform the second-step cross-sectional regressions of portfolio excess returns from *t* to *t*+1 on factor loadings estimated using information up to month *t*. The first extending window uses 60 months of returns.

The first row of Table 4 presents the results for the case in which the first-stage estimation uses the full sample. Most of the estimated risk premiums are positive. The industrial production factor commands the largest risk premium at 1.08% per month. The premium is statistically significant with a Shanken (1992)-corrected *t*-statistic of 3.75. The second largest premium is associated with the term spread factor and is estimated at 0.94% per month, with a Shanken-corrected *t*-statistic of 3.36. The default spread factor earns, surprisingly, a negative (but small) premium of −0.26% per month. The unexpected inflation and the change in expected inflation factors earn small and statistically insignificant risk premiums.

The average $\overline{R}^2$ across the cross-sectional regressions is 46% which is comparable to findings in other studies.[13] The constant in the regression is quite large (0.53%) suggesting that while the factors can explain a large proportion of the cross-sectional variation in the average returns of the tests assets as reflected in the $\overline{R}^2$, the model does poorly in simultaneously pricing the zero-beta rate. This finding is common among models that use macroeconomic factors (see, for example, Jagannathan and Wang, 1996; Lettau and Ludvigson, 2001), and has been related to the possible effect

[11] The estimated risk premiums obtained using the original CRR factors are identical to those reported in the tables that use the mimicking portfolios. We do not report them for reasons of brevity. They are available from the authors on request.

[12] As when forming the mimicking portfolios, we use equal-weighted size, book-to-market, and asset growth portfolios and value-weighted momentum portfolios.

[13] Liu and Zhang (2008), for example, use 30 portfolios that are single-sorted by book-to-market, size, and past six-months returns as test assets. They find that the average $\overline{R}^2$ in Fama and MacBeth (1973) cross-sectional regressions is 53%, where the factors are the three Fama and French (1993) factors and the first-stage estimation uses the full sample.

greater sampling error in the estimated betas has on the upward bias in the zero-beta estimates when using macroeconomic factors (see Lettau and Ludvigson, 2001 for a detailed discussion of this issue). While our use of estimated betas with respect to mimicking portfolios, and not with respect to the macroeconomic factors themselves, reduces the sampling error of the beta estimates, the formation of the mimicking portfolios involves estimating the loadings of each of the 40 test assets with respect to the macroeconomic factors, which in itself introduces sampling error. Interestingly, the intercept from the Fama-French three-factor model, which is 0.81% using a slightly different sample, is considerably larger than the intercept estimated here of 0.53% (see Liu and Zhang, 2008, Table 5, panel C).

When using the extending window, reported in the second row of Table 4, the industrial production factor premium falls to 0.87% per month, and the estimated *UTS* risk premium is now the largest, at 1.00% per month. The average $\overline{R}^2$ across the cross-sectional regressions is 45%.

The final row of Table 4 reports the results when using a rolling window in the first stage. The risk premium associated with the *MP* factor is by far the largest at 0.84%.

Table 5

Average return spreads and expected return spreads.

This table reports the loadings with respect to the mimicking portfolios of the five Chen, Roll, and Ross (1986) (CRR) factors for the low (bottom decile) and high (top decile) investment portfolios. Also reported is the difference in average monthly returns between these two portfolios ($\overline{r}_L - \overline{r}_H$), the difference in the expected returns ($E(\overline{r}_L) - E(\overline{r}_H)$), and the ratio of the difference in expected returns to the difference in average returns ($(E(\overline{r}_L) - E(\overline{r}_H))/(\overline{r}_L - \overline{r}_H)$). Monthly expected returns are calculated as the product of the loadings from regressing the monthly returns of a portfolio on the mimicking portfolios for the five CRR factors, and the average monthly factor premiums estimated based on the full sample in the first stage. The row entitled *dif* reports the difference in the factor loadings between the low and high investment portfolios. The final row *p*(*dif*) reports the *p*-value of the null hypothesis that the difference in factor loadings is zero. The final column *t*(*dif*) reports a *t*-statistic that tests the null hypothesis that $(E(\overline{r}_L) - E(\overline{r}_H))/(\overline{r}_L - \overline{r}_H) = 1$. Panel A reports the results using equal-weighted portfolios formed by *I/A*, Panel B reports the results using value-weighted portfolios formed by *I/A*, Panel C reports the results using equal-weighted portfolios formed by *AG*, Panel D reports the results using value-weighted portfolios formed by *AG*, Panel E reports the results using equal-weighted portfolios formed by *IG*, and Panel F reports the results using value-weighted portfolios formed by *IG*. The sample period is January 1960 through December 2009. The *t*-statistics (in parentheses and in the last column) and the *p*-values are adjusted for heteroskedasticity and autocorrelation.

Panel A: Full sample, investment-to-assets, equal-weighted portfolios

I/A	*MP*	*UI*	*DEI*	*UTS*	*UPR*	$\overline{r}_L - \overline{r}_H$	$E(\overline{r}_L) - E(\overline{r}_H)$	$\frac{E(\overline{r}_L) - E(\overline{r}_H)}{\overline{r}_L - \overline{r}_H}$	*t*(*dif*)
Low	0.64	3.71	−3.46	0.62	1.34				
	(3.91)	(5.80)	(−7.37)	(5.90)	(3.60)				
High	0.35	3.81	−4.10	0.41	1.19	0.93	0.55	0.59	2.72
	(2.21)	(6.98)	(−10.18)	(4.44)	(4.21)				
dif	0.29	−0.10	0.64	0.21	0.15				
p(*dif*)	0.00	0.79	0.03	0.00	0.22				

Panel B: Full sample, investment-to-assets, value-weighted portfolios

I/A	*MP*	*UI*	*DEI*	*UTS*	*UPR*	$\overline{r}_L - \overline{r}$	$E(\overline{r}_L) - E(\overline{r})$	$\frac{E(\overline{r}_L) - E(\overline{r})}{\overline{r}_L - \overline{r}}$	*t*(*dif*)
Low	0.37	1.79	−2.44	0.40	0.85				
	(2.48)	(5.19)	(−8.77)	(6.69)	(3.66)				
High	0.22	2.30	−2.98	0.20	0.81	0.52	0.38	0.73	0.69
	(1.45)	(3.48)	(−5.86)	(2.14)	(5.10)				
dif	0.15	−0.51	0.54	0.20	0.04				
p(*dif*)	0.01	0.37	0.27	0.00	0.74				

Panel C: Full sample, asset growth, equal-weighted portfolios

AG	*MP*	*UI*	*DEI*	*UTS*	*UPR*	$\overline{r}_L - \overline{r}$	$E(\overline{r}_L) - E(\overline{r})$	$\frac{E(\overline{r}_L) - E(\overline{r})}{\overline{r}_L - \overline{r}}$	*t*(*dif*)
Low	0.64	4.50	−3.83	0.66	1.57				
	(3.11)	(5.68)	(−6.71)	(6.00)	(3.84)				
High	0.30	3.97	−4.35	0.35	1.24	1.15	0.69	0.60	2.10
	(1.70)	(6.01)	(−8.70)	(3.55)	(4.14)				
dif	0.34	0.53	0.52	0.31	0.33				
p(*dif*)	0.00	0.07	0.02	0.00	0.02				

Panel D: Full sample, asset growth, value-weighted portfolios

AG	*MP*	*UI*	*DEI*	*UTS*	*UPR*	$\overline{r}_L - \overline{r}$	$E(\overline{r}_L) - E(\overline{r})$	$\frac{E(\overline{r}_L) - E(\overline{r})}{\overline{r}_L - \overline{r}}$	*t*(*dif*)
Low	0.32	2.18	−2.69	0.41	1.04				
	(1.77)	(6.17)	(−9.22)	(5.20)	(4.29)				
High	0.12	2.39	−3.22	0.17	0.77	0.46	0.44	0.96	0.09
	(0.71)	(3.71)	(−6.65)	(1.57)	(4.30)				
dif	0.20	−0.21	0.53	0.24	0.27				
p(*dif*)	0.10	0.68	0.21	0.00	0.14				

Table 5. (*continued*)

Panel E: Full sample, investment growth, equal-weighted portfolios

IG	*MP*	*UI*	*DEI*	*UTS*	*UPR*	$\overline{r}_L-\overline{r}$	$E(\overline{r}_L)-E(\overline{r})$	$\frac{E(\overline{r}_L)-E(\overline{r})}{\overline{r}_L-\overline{r}}$	$t(dif)$
Low	0.58 (3.78)	3.64 (5.52)	−3.32 (−7.07)	0.56 (6.46)	1.25 (3.61)				
High	0.42 (2.52)	3.83 (5.98)	−3.83 (−8.28)	0.43 (4.91)	1.22 (3.86)	0.47	0.35	0.74	1.12
dif	0.16	−0.19	0.51	0.13	0.03				
p(*dif*)	0.00	0.23	0.00	0.00	0.58				

Panel F: Full sample, investment growth, value-weighted portfolios

IG	*MP*	*UI*	*DEI*	*UTS*	*UPR*	$\overline{r}_L-\overline{r}$	$E(\overline{r}_L)-E(\overline{r})$	$\frac{E(\overline{r}_L)-E(\overline{r})}{\overline{r}_L-\overline{r}}$	$t(dif)$
Low	0.22 (1.28)	2.23 (4.35)	−2.97 (−7.70)	0.35 (4.00)	0.87 (3.32)				
High	0.10 (0.52)	3.23 (4.77)	−4.15 (−8.06)	0.26 (2.73)	0.85 (3.25)	0.39	0.31	0.79	0.38
dif	0.12	−1.00	1.18	0.09	0.02				
p(*dif*)	0.10	0.02	0.00	0.06	0.86				

Also consistent with the previous estimations, there is a large risk premium estimated for *UTS*, at 0.52%, although it is considerably smaller than when using the full sample in the first-stage estimation or when using the extending window. The risk premium on the *UPR* factor is still negative, but smaller, at −0.14%. The estimated risk premiums on *UI* and *DEI* are 0.05 and 0.17, respectively, and both are statistically indistinguishable from zero.

The results presented above indicate that the mimicking portfolios for the CRR risk factors provide a good description of the cross-section of expected returns. Whether we employ full sample, extending windows, or rolling windows in the cross-sectional estimations, the *MP* and *UTS* factors command the largest risk premiums.

4.4.2. Test design and empirical results

Having estimated the risk premiums associated with the five Chen, Roll, and Ross (1986) factors, we now turn to testing whether the negative cross-sectional relation between investment and future returns can be accounted for by the spread in the portfolios' systematic risk. For this purpose, we calculate the fraction of average return spread that can be accounted for by the spread in expected returns.

Expected returns are calculated as the product of the estimated factor risk premiums reported in Table 4 and the portfolio loadings with respect to these factors reported in Tables 1–3. That is, as in Liu and Zhang (2008), we estimate for portfolio *P* the following equation:

$$r_{Pt}=\alpha+\beta_{MP}MP_t+\beta_{UI}UI_t+\beta_{DEI}DEI_t+\beta_{UTS}UTS_t+\beta_{UPR}UPR_t+\varepsilon_{Pt}, \quad (1)$$

where r_{Pt} is the portfolio return. Next, we calculate portfolio *P*'s expected return as

$$E(r_P)=\hat{\beta}_{MP}\hat{\gamma}_{MP}+\hat{\beta}_{UI}\hat{\gamma}_{UI}+\hat{\beta}_{DEI}\hat{\gamma}_{DEI}+\hat{\beta}_{UTS}\hat{\gamma}_{UTS}+\hat{\beta}_{UPR}\hat{\gamma}_{UPR}, \quad (2)$$

where the $\hat{\beta}$s are the estimated factor loadings and the $\hat{\gamma}$s are the estimated risk premiums.

Panel A of Table 5 presents the results for equal-weighted portfolios of low (bottom decile) and high (top decile) *I/A* firms where the first-stage estimation of the factor premiums uses the full sample. The first through fifth columns show the loadings of the portfolios with respect to the five factors and the differences between the loadings on each factor. The third row reports the difference in the loadings between the low and high *I/A* portfolios, and the fourth row reports the *p*-value corresponding to the null hypothesis that the difference in the loadings is zero. The sixth column presents the average return spread between the low *I/A* decile portfolio and the high *I/A* decile portfolio (second row). The seventh column presents the expected return spread. The penultimate column shows the ratio of expected return spread to average return spread. A ratio of one implies that all of the average return spread is accounted for by the spread in expected returns. The final column, entitled *t*(*dif*) reports a *t*-statistic that corresponds to the null hypothesis that the difference between the average return spread and the expected return spread is zero.

Panel A shows that there are large differences in the loadings of the low *I/A* and high *I/A* equal-weighted portfolios with respect to the *MP* and *UTS* factors. Given the large risk premiums earned by these two factors, there is a substantial spread in expected returns across these two portfolios of 0.55% per month. The average return difference between the low and high *I/A* portfolios is 0.93% per month. Thus, the fraction of the average return spread that is accounted for by the spread in expected returns is 59%. Consequently, a substantial part of the average return difference across *I/A* portfolios can be attributed to an expected return difference implied by exposure to macroeconomic variables. The final column reports that the difference between the average return spread and the expected return spread is statistically significant, with a *t*-statistic of 2.72. This implies that while a large fraction of the average return spread can be accounted for by the spread in expected returns, the model cannot fully account for the average return difference across extreme *I/A* portfolios. However, the evidence that the bulk of the average return spread of *I/A* portfolios can be accounted for by macroeconomic risk exposure lends support for the risk-based explanations for the real investment effect, namely the q-theory of investment and the real option models.

Panel B of Table 5 presents the results for value-weighted I/A portfolios. In this case, 73% of the average return spread can be explained by the expected return spread and the difference between the average return and the expected return spread of these portfolios is statistically insignificant. This implies that we cannot reject the null hypothesis that all of the average return spread across the two portfolios can be accounted for by the spread in expected returns.

Panel C of Table 5 presents the results for the equal-weighted asset growth portfolios and shows that 60% of the spread in average returns can be accounted for by the spread in expected returns. As the t-statistic of the difference between the average return spread and the expected return spread implies, not all of the spread in average returns across the low and high equal-weighted AG portfolios is explained by the spread in these portfolios' expected returns.

Results for the value-weighted asset growth portfolios are presented in Panel D of Table 5. In this case, we find that 96% of the spread in average returns between the low value-weighted AG portfolio and the high value-weighted AG portfolio can be accounted for by a spread in the exposure to macroeconomic risk. Thus, practically all of the spread in average returns can be explained by the expected return spread implied by the CRR factors.

The results for the equal-weighted investment growth portfolios are presented in Panel E. As much as 74% of the spread in average returns is explained by the spread in expected returns, and the difference between the average return spread and the expected return spread is statistically insignificant.

In Panel F of Table 5 we report the results for the value-weighted investment growth portfolios. As in the case of the value-weighted I/A and AG portfolios, the average return spread on the IG value-weighted portfolios can be explained by the spread in expected returns implied by the CRR factors, where the ratio between these two is 79%.

In general, the results in Table 5 are consistent with the predictions of real option models and the q-theory of investment. In the data, we find that the average return spread between firms that have low investment and firms that have high investment is largely accounted for by the spread in expected return based on a pricing kernel that employs the CRR factors. Over the three measures of investment, the average spread in returns accounted for by systematic risk, as measured by the CRR factors, is over 60% when considering equal-weighted portfolios. The corresponding figure is over 80% when considering value-weighted portfolios.

4.5. Robustness checks

In this section, we assess the robustness of our results concerning the fraction of average return spread that is explained by the spread in expected returns. We calculate expected returns based on an extending window and on a rolling window in the first stage of the Fama and MacBeth (1973) estimation procedure.

The results in Panel A of Table 6 using the extending window for equal-weighted portfolios are similar to the full-sample results provided in Table 5. The top row of the panel shows that 58% of the average return spread between the low and high equal-weighted I/A portfolios is explained by the expected return spread. The following row shows that the expected return spread between the two extreme equal-weighted AG portfolios is 0.64% per month, implying that 56% of the average return spread is explained by the expected return spread. The final row of the panel shows that 74% of the average return spread between the low and high equal-weighted IG portfolios is accounted for by the expected return spread.

Table 6

Average return spreads and expected returns spreads: robustness.

This table reports the difference in average monthly returns between the low (bottom decile) and high (top decile) investment portfolios ($\bar{r}_L-\bar{r}_H$), the difference in their expected returns ($E(\bar{r}_L)-E(\bar{r}_H)$), and the ratio of the difference in expected returns to the difference in average returns ($E(\bar{r}_L)-E(\bar{r}_H))/(\bar{r}_L-\bar{r}_H)$. Monthly expected returns are calculated as the product of the loadings from regressing the monthly returns of a portfolio on the mimicking portfolios for the five CRR factors, and the estimated monthly factor premiums. In the final column, $t(dif)$ reports a t-statistic that tests the null hypothesis that $(E(\bar{r}_L)-E(\bar{r}_H))/(\bar{r}_L-\bar{r}_H)=1$. Panel A reports the results using equal-weighted portfolios formed by I/A, AG, and IG and an extending window to estimate the factor loadings in the first-stage Fama and MacBeth (1973) estimation. Panel B reports the results using value-weighted portfolios formed by I/A, AG, and IG and an extending window to estimate the factor loadings in the first-stage Fama and MacBeth estimation. Panel C reports the results using equal-weighted portfolios formed by I/A, AG, and IG and a rolling window to estimate the factor loadings in the first-stage Fama and MacBeth estimation. Panel D reports the results using value-weighted portfolios formed by I/A, AG, and IG and a rolling window to estimate the factor loadings in the first-stage Fama and MacBeth estimation. The sample period is January 1960 through December 2009. The t-statistics (in the last column) are adjusted for heteroskedasticity and autocorrelations.

	$\bar{r}_L-\bar{r}$	$E(\bar{r}_L)-E(\bar{r})$	$\frac{E(\bar{r}_L)-E(\bar{r})}{\bar{r}_L-\bar{r}}$	$t(dif)$
Panel A: Extending window, equal-weighted				
I/A	0.93	0.54	0.58	2.79
AG	1.15	0.64	0.56	2.33
IG	0.47	0.35	0.74	1.12
Panel B: Extending window, value-weighted				
I/A	0.52	0.41	0.79	0.54
AG	0.46	0.45	0.98	0.04
IG	0.39	0.40	1.03	−0.06
Panel C: Rolling window, equal-weighted				
I/A	0.93	0.44	0.47	3.51
AG	1.15	0.52	0.45	2.88
IG	0.47	0.27	0.57	1.87
Panel D: Rolling window, value-weighted				
I/A	0.52	0.29	0.56	1.13
AG	0.46	0.34	0.74	0.51
IG	0.39	0.30	0.77	0.57

Panel B of Table 6 presents the results when using the extending window for value-weighted portfolios. In this case, a large fraction of the average return spread (79% for the *I/A* portfolios, 98% for the *AG* portfolios, and 103% for the *IG* portfolios) is accounted for by the expected return spread. Consistent with the tests based on the full sample, the tests based on an extending window also indicate that risk plays a central role in the negative investment-return relation.

Panels C and D present the robustness results when the first step in the Fama-MacBeth procedure is estimated using a rolling window. Panel C examines equal-weighted portfolios and Panel D examines value-weighted portfolios. Panel C shows that a relatively smaller part of the average return spread across equal-weighted portfolios is accounted for by the spread in the expected returns (47% for the *I/A* portfolios, 45% for the *AG* portfolios, and 57% for the *IG* portfolios). This result is consistent with the findings reported in Liu and Zhang (2008) who show that when using the full sample in the first-stage estimation, 91% of momentum profits are explained by expected momentum profits implied by the loadings of winners and losers on the five Chen, Roll, and Ross (1986) factors. In contrast, when using a rolling-window estimation in the first-stage, expected momentum profits are only 18% of actual momentum profits (see Panel B of Table 6 in their paper).

Panel D presents the results for the value-weighted portfolios. In this case, 56% of the average return spread between the low and high *I/A* value-weighted portfolios is accounted for by the spread in expected returns. This fraction rises to 74% for the *AG* portfolios and to 77% for the *IG* portfolios. In these cases, we can not reject the null hypothesis that the differences in the average and expected returns are zero.

This set of robustness tests, which employ an extending and a rolling window to estimate the factor loadings, leads to results that are consistent with the findings that use the whole sample in the first-stage Fama-MacBeth estimation.

5. Risk dynamics and investment

The q-theory of investment predicts that firms' risk and expected returns fall during periods of investment for the following reasons (see Li, Livdan, and Zhang, 2009). First, firms invest more when their marginal q is high. Therefore, shocks that lower the discount rate will raise q and therefore trigger investment, implying that in the period following investment, risk and expected returns are lower than in the period prior to the investment. Second, decreasing returns to scale means that more investment leads to a lower marginal product of capital, which in turn means lower expected returns. Real option models predict that risk falls during investment periods because when a firm undertakes investment, it is exercising a risky real option. Thus, both theories predict lower systematic risk and hence expected returns following investment periods in comparison to the preceding period. Similarly, the theories predict a rise in systematic risk and expected returns following disinvestment periods (as we explain in Section 5.2 below). This section examines the dynamics of systematic risk around periods of high investment and around periods of disinvestment.

5.1. Risk dynamics and large positive investment

In order to examine the dynamics of systematic risk around large investment periods, we define two portfolios: the pre-investment portfolio and the post-investment portfolio. In year t the pre-investment period portfolio is the portfolio of firms whose *I/A* (*AG*, *IG*) will be in the top decile *I/A* (*AG*, *IG*) of all firms in either year $t+4$, $t+3$, or year $t+2$ (or in any two of the three years, or in all three years). The pre-investment portfolio does not include firms who are in the top decile of investment in year $t+1$ because systematic risk can decline already in the year before investment for the following reason. If the firm receives a discount rate shock that reduces its cost of capital, or if it decides to exercise a real option, investment in some cases could take place a period later due to investment planning (e.g., Lamont, 2000) or due to time to build (Kydland and Prescott, 1982). Therefore, in order to clearly distinguish between the pre-investment period, in which the firm has not yet received a discount rate shock, and the post-investment period, we exclude these firms from the pre-investment portfolio. The post-investment portfolio in year t is a portfolio of the firms whose investment places them in the top decile of investment in year $t-1$.

In Table 7, we report the factor loadings in the pre- and post-investment periods along with changes in the factor loadings and expected returns around investment periods. As seen in Panel A of the table, the loadings with respect to *MP*, *UTS*, and *DEI* decline during high *I/A* years and, as is evident from the t-statistics reported in the final row of Panel A, these declines are statistically significant. The loading with respect to the *MP* factor falls by 25% from 0.40 to 0.30. The loading on the *DEI* factor falls by 0.51, from -3.42 to -3.93, and the loading on the *UTS* factor falls from 0.38 to 0.34. The overall change in the loadings translates into a decline in expected returns of 0.20% per month, which is 2.43% per annum. In economic terms, there is a considerable fall in the cost of equity capital for high investing firms.

Panel B examines the risk dynamics for the value-weighted *I/A* portfolios. The loading on *MP* actually increases slightly after the investment period although the increase is not statistically significant. The loading on *UPR* also rises and this increase is statistically significant. The loadings with respect to *DEI* and *UTS* fall following the investment period, significantly so in the case of *UTS*. The overall change in the loadings around the investment period implies that expected returns fall by 0.10% per month (1.21% in annualized expected returns).

The risk dynamics for the equal-weighted high *AG* (top decile) portfolio are examined in Panel C. The loading on *MP* falls substantially from 0.40 in the pre-investment period to 0.26 in the post-investment period and the fall is statistically significant. The loading on *UTS* falls as well, by an economically and statistically significant size (from 0.36 to 0.29), while the loading with respect to *UI* rises by 0.41 and this rise is statistically significant. The overall change in the loadings translates into a fall in expected returns of 0.30% per month which is equivalent to 3.66% in annual terms. Similar to the fall in expected returns for the equally weighted *I/A* portfolios reported in Panel A, this is a considerable fall in the equity cost of capital.

Table 7
Risk dynamics around investment.

This table reports results from regressing monthly returns of an equal-(value)-weighted portfolio of firms whose investment-to-assets ratio, *I/A* (asset growth, *AG*, investment growth, *IG*) is in the top decile of all firms' *I/A* (*AG*, *IG*) in any of years t+4, t+3, or year t+2 (the pre-investment portfolio) on the mimicking portfolios for the five Chen, Roll, and Ross (1986) factors and the monthly returns of an equal-(value)-weighted portfolio of firms whose *I/A* (*AG*, *IG*) is in the top decile *I/A* (*AG*, *IG*) in year $t-1$ (the post-investment period) on the mimicking portfolios for the five CRR factors. $E(r)$ is the investment period portfolio expected return as calculated by the product of the loadings with respect to the mimicking portfolios for the five CRR factors with the corresponding estimated risk premiums (based on the full sample in the first-stage estimation). Similarly, $E(r_{pre})$ is the implied expected returns for the pre-investment portfolio. Post-Pre records the difference in the post-investment and pre-investment factor loadings. The final row $t(dif)$ reports a t-statistic that tests the null hypothesis that the difference in factor loadings is zero. Panel A reports the results using equal-weighted portfolios when *I/A* is the measure of investment. Panel B reports the results using value-weighted portfolios when *I/A* is the measure of investment. Panel C reports the results using equal-weighted portfolios when *AG* is the measure of investment. Panel D reports the results using value-weighted portfolios when *AG* is the measure of investment. Panel E reports the results using equal-weighted portfolios when *IG* is the measure of investment. Panel F reports the results using value-weighted portfolios when *IG* is the measure of investment. The sample period is January 1960 through December 2009. t-Statistics are in parentheses.

Panel A: Highest investment-to-assets, equal-weighted portfolios

	MP	*UI*	*DEI*	*UTS*	*UPR*	$E(r)-E(r_{pre})$
Pre-investment	0.40	3.11	−3.42	0.38	1.17	
	(4.47)	(8.03)	(−9.66)	(5.84)	(7.07)	
Post-investment	0.30	3.57	−3.93	0.34	1.19	−0.20
	(3.27)	(9.05)	(−10.87)	(5.02)	(7.08)	
Post−Pre	−0.10	0.46	−0.51	−0.04	0.02	
t (dif)	−3.52	3.77	−4.49	−2.23	0.49	

Panel B: Highest investment-to-assets, value-weighted portfolios

	MP	*UI*	*DEI*	*UTS*	*UPR*	$E(r)-E(r_{pre})$
Pre-investment	0.13	1.69	−2.43	0.17	0.61	
	(1.63)	(4.89)	(−7.69)	(2.99)	(4.13)	
Post-investment	0.14	1.69	−2.51	0.12	0.79	−0.10
	(1.63)	(4.52)	(−7.36)	(1.84)	(4.95)	
Post−Pre	0.01	−0.00	−0.08	−0.05	0.18	
t (dif)	0.25	−0.02	−0.49	−1.96	2.36	

Panel C: Highest asset growth, equal-weighted portfolios

	MP	*UI*	*DEI*	*UTS*	*UPR*	$E(r)-E(r_{pre})$
Pre-investment	0.40	3.50	−3.67	0.36	1.16	
	(4.01)	(8.06)	(−9.23)	(4.93)	(6.26)	
Post-investment	0.26	3.91	−4.36	0.29	1.20	−0.30
	(2.58)	(9.05)	(−11.01)	(3.92)	(6.51)	
Post−Pre	−0.14	0.41	−0.69	−0.07	0.04	
t (dif)	−4.59	2.94	−5.43	−3.29	0.66	

Panel D: Highest asset growth, value-weighted portfolios

	MP	*UI*	*DEI*	*UTS*	*UPR*	$E(r)-E(r_{pre})$
Pre-investment	0.13	1.71	−2.51	0.13	0.70	
	(1.61)	(4.73)	(−7.60)	(2.15)	(4.53)	
Post-investment	0.08	2.20	−3.10	0.10	0.72	−0.14
	(0.81)	(5.18)	(−7.96)	(1.34)	(3.99)	
Post−Pre	−0.05	0.49	−0.59	−0.03	0.02	
t (dif)	−1.17	2.40	−3.04	−1.03	0.26	

Panel E: Highest investment growth, equal-weighted portfolios

	MP	*UI*	*DEI*	*UTS*	*UPR*	$E(r)-E(r_{pre})$
Pre-investment	0.51	3.65	−3.66	0.44	1.26	
	(5.13)	(8.55)	(−9.34)	(6.12)	(6.90)	
Post-investment	0.38	3.83	−3.87	0.39	1.22	−0.19
	(3.87)	(9.09)	(−10.03)	(5.54)	(6.80)	
Post−Pre	−0.13	0.18	−0.21	−0.05	−0.04	
t (dif)	−4.55	1.40	−1.86	−2.30	−0.73	

Panel F: Highest investment growth, value-weighted portfolios

	MP	*UI*	*DEI*	*UTS*	*UPR*	$E(r)-E(r_{pre})$
Pre-investment	0.21	2.98	−3.77	0.21	0.76	
	(2.11)	(6.96)	(−9.61)	(2.94)	(4.19)	
Post-investment	0.03	2.98	−3.95	0.20	0.82	−0.25
	(0.27)	(6.54)	(−9.47)	(2.60)	(4.21)	
Post−Pre	−0.18	0.00	−0.18	−0.01	0.06	
t (dif)	−3.62	0.01	−0.99	−0.36	0.59	

The results for the value-weighted *AG* portfolio are presented in Panel D. The loading with respect to *MP* falls from 0.13 to 0.08, although the difference is not statistically significant. The loading on *DEI* falls substantially from -2.51 to -3.10 and the difference is statistically significant. The loading on *UTS* falls by 0.03, albeit the difference between the loading in the pre- and post-investment periods is not statistically significant. The overall change in the loadings implies that expected returns fall by 0.14% per month which is equivalent to 1.69% per annum.

Panel E of Table 7 examines the risk dynamics for an equal-weighted portfolio surrounding high *IG* periods. As seen, the loading with respect to *MP* falls from 0.51 before the high investment growth period to 0.38 after the high investment growth year. The difference is statistically significant with a *t*-statistic of 4.55. The loadings on *UTS*, *DEI*, and *UPR* drop as well although the fall in the latter is not statistically significant, and the fall in the loading on *DEI* is marginally statistically significant. The loading on *UI* increases by 0.18 but the change in the loading with respect to this factor is not statistically significant. Expected returns fall by 0.19% per month following periods of high investment growth, which is 2.30% in annual terms.

Finally, Panel F presents the results for a value-weighted portfolio around high investment growth periods. The loading on *MP* of the high *IG* value-weighted portfolio falls from 0.21 in the period preceding high investment growth years to 0.03 in the year after the high investment growth years and the difference is statistically significant. The loadings on *DEI* and *UTS* fall slightly, whereas the loading on *UPR* increases slightly, although it should be noted that none of these changes are statistically significant. Due to the change in the loadings, expected returns fall by 0.25%, which is a considerable fall of 3.04% in annual terms.

In summary, Table 7 shows that there is a substantial fall in the expected returns and hence the cost of equity capital around large investment periods. In the cases where investment is measured by the investment-to-assets ratio and asset growth, the fall is somewhat larger for the equal-weighted portfolios than for the value-weighted portfolios. This is not the case when investment is measured by investment growth. This finding is consistent with the earlier results that the differences in the spread in average returns are much smaller between value- and equal-weighted portfolios when considering investment growth. Over the three investment measures, the average fall in the cost of equity capital is almost 3% per annum for the equal-weighted portfolios. For the value-weighted portfolios it is almost 2% per annum. These findings provide support for the predictions of the *q*-theory and the real option models. The fall in expected returns during periods of high investment is due mainly to a decline in portfolio loadings with respect to the industrial production and term spread factors, two factors that are tightly linked to the business cycle.

5.2. Risk dynamics and disinvestment

The real option models and the *q*-theory described above pertain to the relation between positive investment and risk. However, the intuition can be carried over to the relation between disinvestment and risk in a straightforward manner. Shocks that increase a firm's discount rate will increase its cost of capital and, consequently, the NPV of some of its existing projects will become negative. In this case, the *q*-theory predicts that firms will disinvest. Therefore, following disinvestment periods there is an increase in systematic risk and hence expected returns. Similarly, the real option models predict that risk increases during disinvestment because the option to disinvest is a real put option and disinvesting constitutes exercising this option.

We examine the dynamics of systematic risk during periods of disinvestment as follows. We compare the loadings with respect to the mimicking portfolios for the five CRR factors of two portfolios. The first portfolio consists, in year t, of all firms who will disinvest (i.e., have negative capital growth or negative total asset growth) in either year $t+4$, $t+3$, or in year $t+2$ (or in any two of the three years, or in all three years). This portfolio is termed the pre-disinvestment portfolio. The second portfolio consists in year t of all firms whose capital growth (asset growth) is negative in year $t-1$. This portfolio is termed the post-disinvestment portfolio.

Panel A of Table 8 shows the results when disinvestment is defined as negative capital growth. In this case, all the factor loadings of the equal-weighted portfolio of disinvesting firms rise during periods of negative capital growth. Particularly noticeable are the increases in the loadings with respect to the *MP* factor (from 0.46 to 0.55 which is statistically significant) and the *UTS* factor (from 0.45 to 0.52 which is statistically significant). The *UI* factor loading also records a statistically significant increase, however, recall that this factor commands a very small risk premium. Considering the changes in all the factor loadings between the pre- and post-disinvestment period, the expected returns rise by 0.19% per month (2.30% annualized).

The results for the value-weighted portfolio of firms undergoing periods of capital disinvestment are presented in Panel B. The loadings with respect to *MP*, *DEI*, and *UTS* rise slightly, while the loadings on *UI* and *UPR* fall. The sum effect of these changes in the factor loadings results in expected returns rising by 0.08% per month or 0.96% in annual terms, in the post-disinvestment period.

The risk dynamics during negative asset growth periods for the equal-weighted portfolio are presented in Panel C. All of the loadings with respect to the CRR factors rise during disinvestment periods. Moreover, the differences between the loadings in the pre-disinvestment period and the post-disinvestment period are all statistically significant. Overall, the change in the loadings entails a substantial increase in expected returns of 0.28% per month which is equivalent to a rise of 3.41% in annual terms.

Panel D shows that for a value-weighted portfolio formed according to asset disinvestment, expected returns also rise after disinvestment. The loadings on four of the five factors increase after negative asset growth periods. In the case of the loadings on *UTS* and *DEI*, these increases are statistically significant (marginally so for the loading on *UTS*). Considering the changes across the loadings before and after disinvestment, we find that expected returns rise by 0.12% per month, or 1.50% per annum.

Table 8
Risk dynamics around disinvestment.

This table reports results from regressing monthly returns of an equal-(value)-weighted portfolio of firms whose capital (asset) growth is negative in any of years t+4, t+3, or year t+2 (the pre-disinvestment portfolio) on the mimicking portfolios of the five Chen, Roll, and Ross (1986) (CRR) factors and the monthly returns of an equal-(value)-weighted portfolio of firms whose capital (asset) growth is negative in year $t-1$ (the post-disinvestment period) on the mimicking portfolios for the five CRR factors. $E(r)$ is the disinvestment period portfolio expected return as calculated by the product of the loadings with respect to the mimicking portfolios for the five CRR factors and the corresponding estimated risk premiums (based on the full sample in the first-stage estimation). Similarly, $E(r_{pre})$ is the implied expected returns for the pre-disinvestment portfolio. Post-Pre records the difference in the post-disinvestment and pre-disinvestment factor loadings. In the final row, $t(dif)$ reports a t-statistic that tests the null hypothesis that the difference in factor loadings is zero. Panel A reports the results using equal-weighted portfolios based on capital disinvestment. Panel B reports the results using value-weighted portfolios based on capital disinvestment. Panel C reports the results using equal-weighted portfolios based on asset disinvestment. Panel D reports the results using value-weighted portfolios based on asset disinvestment. The sample period is January 1960 through December 2009. t-Statistics are in parentheses.

Panel A: Capital disinvestment, equal-weighted portfolios

	MP	*UI*	*DEI*	*UTS*	*UPR*	$E(r)-E(r_{pre})$
Pre-disinvestment	0.46	3.44	−3.66	0.45	1.22	
	(4.96)	(8.53)	(−9.91)	(6.57)	(7.10)	
Post-disinvestment	0.55	3.66	−3.56	0.52	1.26	0.19
	(5.84)	(8.96)	(−9.50)	(7.60)	(7.19)	
Post−Pre	0.09	0.22	0.10	0.07	0.04	
t (*dif*)	3.72	2.15	1.02	4.38	0.69	

Panel B: Capital disinvestment, value-weighted portfolios

	MP	*UI*	*DEI*	*UTS*	*UPR*	$E(r)-E(r_{pre})$
Pre-disinvestment	0.29	2.19	−2.88	0.28	0.77	
	(3.70)	(6.50)	(−9.32)	(4.89)	(5.34)	
Post-disinvestment	0.29	1.68	−2.41	0.30	0.71	0.08
	(3.78)	(5.03)	(−7.84)	(5.39)	(4.95)	
Post−Pre	0.00	−0.51	0.47	0.02	−0.06	
t (*dif*)	0.09	−2.95	2.98	0.90	−0.82	

Panel C: Asset disinvestment, equal-weighted portfolios

	MP	*UI*	*DEI*	*UTS*	*UPR*	$E(r)-E(r_{pre})$
Pre-disinvestment	0.43	3.41	−3.63	0.42	1.22	
	(4.66)	(8.44)	(−9.82)	(6.20)	(7.08)	
Post-disinvestment	0.58	3.65	−3.47	0.53	1.32	0.28
	(6.12)	(8.82)	(−9.15)	(7.56)	(7.45)	
Post−Pre	0.15	0.24	0.16	0.11	0.10	
t (*dif*)	6.99	2.57	1.96	6.75	2.38	

Panel D: Asset disinvestment, value-weighted portfolios

	MP	*UI*	*DEI*	*UTS*	*UPR*	$E(r)-E(r_{pre})$
Pre-disinvestment	0.25	1.98	−2.77	0.25	0.75	
	(3.30)	(5.95)	(−9.06)	(4.36)	(5.24)	
Post-disinvestment	0.29	1.74	−2.31	0.30	0.85	0.12
	(3.86)	(5.36)	(−7.75)	(5.48)	(6.11)	
Post−Pre	0.04	−0.24	0.46	0.05	0.10	
t (*dif*)	0.86	−1.35	2.80	1.81	1.34	

The increases in risk and expected returns around disinvestment periods are consistent across both definitions of disinvestment and when considering both equal- and value-weighted portfolios. In light of these findings, we conclude that the dynamics of risk around disinvestment periods are consistent with the predictions of the q-theory and real option models. These findings are in line with the earlier results regarding the falls in expected returns around investment periods.

6. The investment factors and economic growth

In the previous sections of the paper, we have reached two conclusions. First, the cross-section of investment portfolio returns is driven to a large extent by firms' exposure to macroeconomic risk factors. Second, firms' loadings on the risk factors change around large investment and disinvestment periods. In order to substantiate the link between the investment effect in stock returns and the real economy, we examine whether the three investment factors are related to future real economic activity. Fama (1981) shows that there is a positive relation between current returns on the aggregate US stock market and future economic growth. Liew and Vassalou (2000) show that in selected countries the high minus low book-to-market factor (HML) and small minus big market capitalization factor (SMB) are also positively related to future GDP growth. They conclude that these factors are candidates for state variables in a multifactor asset pricing model.

Assessing the predictive ability of characteristic-based factors for real activity is particularly relevant for investment-based factors since a number of papers discussed earlier show that return factors based on low minus high investment portfolios can capture the cross-sectional variation of average stock returns. In view of these findings, it is important to examine whether the investment and asset growth factors are related to the macroeconomy. If these factors are indeed related to the macroeconomy, then it strengthens the interpretation that they are risk factors that investors require a premium for holding.

Whereas Fama (1981) and Liew and Vassalou (2000) focus on how factor returns are related to future GDP growth, we consider four macroeconomic variables: industrial production growth, GDP growth, aggregate corporate earnings growth, and aggregate investment growth. In all cases, we would expect a positive relation between the investment factor returns and future real activity. If low investment firms are riskier than high investment firms (which would lead to a positive premium on the investment factor), then upon the arrival of bad news that a recession is forthcoming, the investment factor earns low returns, implying it covaries with recessions. This is similar to Fama's (1981) finding of a positive relation between the market return and future economic growth, because the stock market responds immediately to economic news.

In order to assess the relation between investment factor returns and future economic activity, we form three zero-investment portfolios and examine whether they can predict future real activity. The first factor is the excess return of the bottom decile investment-to-assets firms over the top decile investment-to-assets firms. The second factor is the excess return of the bottom decile asset growth firms over the top decile asset growth firms. The third factor is the excess return of the bottom decile investment growth firms over the top decile investment growth firms. Both equal- and value-weighted zero-investment portfolios are constructed.

We analyze the predictability of economic activity over the period January 1960 to December 2009. For industrial production and aggregate corporate earnings, we employ monthly data. The industrial production data are the total industrial production index from the Federal Reserve Bank of St. Louis. Aggregate real corporate earnings comes from the Standard and Poors (S&P) data available from Robert Shiller's Web site. We analyze aggregate GDP and Gross Private Domestic Investment at a quarterly frequency, both from the Bureau of Economic Analysis. We calculate the growth rate in real industrial production, real corporate earnings, real GDP, and real investment using the aggregate seasonally adjusted CPI index.

We focus on the predictability of these four macroeconomic aggregates at both business cycle horizons and at longer horizons. We report results over one-month (when available), one-quarter, one-year, and three-year forecasting horizons by estimating

$$y_{t,t+k} = \alpha + \delta \times IR_{t-1,t} + \xi_{t+k}, \tag{3}$$

where $y_{t,t+k}$ (k=1,3,12, or 36) is the growth rate of the macroeconomic variable from month t to month t+k. If the macroeconomic variable is given at a monthly frequency, then $y_{t,t+k} = y_{t,t+1} + y_{t+1,t+2} + \cdots y_{t+k-1,t+k}$. Similarly, if the macroeconomic variable is given at a quarterly frequency, then the growth rate of the macroeconomic variable from time t to time t+k, $y_{t,t+k}$, is calculated as the sum of the quarterly growth rates of the macroeconomic variable in the quarters between time t and time t+k.[14] IR is the zero-investment return on a portfolio that is either the difference between low and high investment-to-assets, asset growth, or investment growth portfolios and ξ is an error term. The regressions that forecast the growth rate in the macroeconomic variables measured at a monthly frequency at time t+1 regress the growth rate of the macroeconomic variable at time t+1 on the return variables at time t. The quarterly regressions for variables that are observed at a monthly frequency are performed by using overlapping observations. This procedure is employed up to the three-year horizon. The same structure is used when the macroeconomic data are observed at a quarterly frequency. Due to the overlapping nature of the regressions, we adjust the standard errors using a Newey and West (1987) correction with a lag structure of two times the forecasting horizon.

We also assess whether the investment factors have predictive power for economic activity in the presence of a set of control variables by estimating:

$$\begin{aligned} y_{t,t+k} = \alpha + \delta \times IR_{t-1,t} + \phi_1 \times MKT_{t-1,t} + \phi_2 \times SMB_{t-1,t} \\ + \phi_3 \times HML_{t-1,t} + \phi_4 \times DY_t + \phi_5 \times TS_t + \phi_6 \\ \times TB_t + \phi_7 \times DIP_{t-1,t} + \xi_{t+k}. \end{aligned}$$

The choice of the control variables is motivated by the findings of Liew and Vassalou (2000). In particular, they show that HML and SMB are related to future GDP growth in a number of countries at an annual frequency. They also control for the aggregate stock market return in excess of the risk-free rate of return, denoted MKT, that Fama (1981) shows to be related to future economic growth. In addition, they consider a set of business cycle variables that may be related to future growth, namely the dividend yield (DY), the term structure of interest rates (TS) defined as the difference between the yield on a ten-year government bond and the one-month T-bill rate, the one-month T-bill rate (TB), and the growth in real industrial production (DIP).[15]

Section 6.1 presents the results for equal-weighted factor portfolios and summarizes the value-weighted factor portfolio results.

[14] We note that investors are concerned with the continuous flow of output from time t to time t+k and not only with the output at time t+k. Therefore, our tests that use monthly (quarterly) data of the macroeconomic variable are examining the ability of the investment factor return at time t to forecast the average monthly (quarterly) growth rate from time t to time t+k. Our method of calculating the growth rate of the macroeconomic variables is similar to that of Liew and Vassalou (2000) who test the ability of the HML and SMB factors to forecast the (geometric) average quarterly growth rate of GDP over the next year (see, for example, Table 5 in their paper). As a robustness check, we also examine the ability of the investment factor return at time t to forecast the direct growth rate of the macroeconomic variable from time t to time t+k (i.e., $((y_{t+k})/y_t)-1$). The results are very similar to the results reported in this section and are available from the authors upon request.

[15] The SMB, HML, and the excess return on the aggregate stock market are downloaded from Ken French's Web page. We are grateful to him for making these data available.

6.1. Predicting macroeconomic variables with equal-weighted investment factors

Table 9 provides evidence on the ability of the three investment factors to predict future real industrial production growth. Panel A is split vertically into two parts, the left-hand side (LHS) reports the results using only the investment-to-assets factor to predict real industrial production growth and the right-hand side (RHS) includes the control variables. On its own, there is evidence that the investment-to-assets factor predicts future industrial production growth. The evidence is particularly strong at the one-month horizon with a point estimate of 0.03 and associated *t*-statistic of 2.50. This relation is also economically strong. For example, a one-standard-deviation increase in the return on the investment-to-assets factor translates into an increase in real industrial production growth of 0.09%, which is equivalent to over 1.1% per annum. A positive coefficient implies that, just like the return on the market portfolio, the investment factor earns a low return before recessions. Thus, the investment factor is procyclical and its premium is likely a risk premium.

At the three-month horizon, the estimated coefficient on the investment-to-assets factor is 0.05 with a *t*-statistic of 2.21. At the shorter horizons, the investment-to-assets factor does contain information regarding future real industrial production growth. However, at the longer horizons of one and three years, the investment-to-assets factor does not have any predictive power.

The RHS of Panel A reports the results when including the control variables. At the one-month horizon, the *I*/*A* factor retains its economic and statistical significance. The coefficient estimate is 0.03 and the *t*-statistic at 2.78. Of the control variables, the T-bill rate and the first lag of real industrial production growth are both statistically significant. The adjusted R^2,$\overline{R}^2$, is 19.7% in the multiple regression, where due to the persistence in real industrial

Table 9

The investment and asset growth factors as predictors of real industrial production growth.

This table presents results from regressing the growth in real industrial production on the prior equal-weighted monthly returns of investment factor portfolios and control variables. The regressions use monthly, quarterly, annual, and three-year horizons. The return factors are: *I*/*A* is the investment-to-assets ratio factor; *AG* is the asset growth factor; and *IG* is the investment growth factor. MKT is the excess return on the CRSP value-weighted index, HML is the return on the high minus low book-to-market factor, SMB is the return on the small minus big market capitalization factor, DY is the dividend yield on the market portfolio, TS is the term structure of interest rates defined as the difference between the yield on a ten-year government bond and the one-month T-bill rate, TB is the one-month T-bill rate, and DIP is the monthly growth in real industrial production. Panel A reports results from predicting the growth rate in real industrial production, IP, with the *I*/*A*, Panel B reports results from predicting the growth rate in real industrial production, IP, with *AG*, Panel C reports results from predicting the growth rate in real industrial production, IP, with *IG*. Data are sampled from January 1960 to December 2009. Newey and West *t*-statistics are in parentheses. $\overline{R}^2$ is the adjusted R^2.

Panel A: Predicting with I/A

Univariate			Multiple									
IP	*I*/*A*	$\overline{R}^2$	IP	*I*/*A*	MKT	SMB	HML	DY	TS	TB	DIP	$\overline{R}^2$
1m	0.03 (2.50)	0.9	1m	0.03 (2.78)	0.01 (0.88)	−0.02 (−1.39)	0.01 (0.86)	−0.00 (−1.45)	0.00 (1.13)	−0.00 (−2.28)	0.34 (5.52)	19.7
3m	0.05 (2.21)	0.4	3m	0.05 (1.77)	0.07 (2.80)	0.00 (0.12)	0.04 (1.15)	−0.00 (−0.72)	0.00 (1.67)	−0.00 (−2.43)	0.87 (5.35)	31.5
1y	0.12 (1.04)	0.2	1y	0.17 (1.60)	0.25 (3.22)	−0.12 (−1.81)	0.05 (0.60)	0.01 (0.76)	0.01 (1.41)	−0.01 (−3.31)	2.02 (5.56)	41.4
3y	0.19 (1.10)	0.0	3y	0.35 (1.96)	0.19 (2.10)	−0.42 (−1.51)	0.06 (0.41)	0.02 (0.26)	0.01 (0.59)	−0.02 (−1.31)	1.35 (1.02)	20.1

Panel B: Predicting with AG

Univariate			Multiple									
IP	*AG*	$\overline{R}^2$	IP	*AG*	MKT	SMB	HML	DY	TS	TB	DIP	$\overline{R}^2$
1m	0.02 (1.71)	0.4	1m	0.02 (1.54)	0.01 (0.76)	−0.02 (−1.09)	0.01 (0.93)	−0.00 (−1.18)	0.00 (1.20)	−0.00 (−2.26)	0.35 (5.50)	18.9
3m	0.04 (2.68)	0.4	3m	0.02 (1.12)	0.06 (2.76)	0.01 (0.21)	0.04 (1.17)	−0.00 (−0.61)	0.00 (1.69)	−0.00 (−2.42)	0.87 (5.38)	31.2
1y	0.03 (0.39)	0.0	1y	0.06 (0.86)	0.24 (3.17)	−0.10 (−1.42)	0.06 (0.75)	0.01 (0.79)	0.01 (1.43)	−0.01 (−3.27)	2.04 (5.38)	40.8
3y	0.03 (0.23)	0.0	3y	0.14 (1.34)	0.18 (1.99)	−0.38 (−1.42)	0.08 (0.54)	0.02 (0.28)	0.01 (0.64)	−0.02 (−1.30)	1.38 (1.03)	19.7

Panel C: Predicting with IG

Univariate			Multiple									
IP	*IG*	$\overline{R}^2$	IP	*IG*	MKT	SMB	HML	DY	TS	TB	DIP	$\overline{R}^2$
1m	0.03 (1.72)	0.3	1m	0.02 (1.41)	0.01 (0.62)	−0.01 (−0.77)	0.01 (0.92)	−0.00 (−1.31)	0.00 (1.28)	−0.00 (−2.21)	0.35 (5.56)	18.9
3m	0.04 (1.36)	0.0	3m	0.03 (1.09)	0.06 (2.71)	0.02 (0.65)	0.04 (1.18)	−0.00 (−0.67)	0.00 (1.74)	−0.00 (−2.42)	0.88 (5.46)	31.2
1y	−0.02 (−0.19)	0.0	1y	0.03 (0.23)	0.23 (3.18)	−0.07 (−1.07)	0.07 (0.88)	0.01 (0.74)	0.01 (1.45)	−0.01 (−3.21)	2.05 (5.56)	40.8
3y	−0.04 (0.15)	0.0	3y	0.04 (0.19)	0.16 (1.74)	−0.30 (−1.32)	0.11 (0.68)	0.02 (0.25)	0.01 (0.66)	−0.02 (−1.29)	1.38 (1.02)	19.6

production growth, most of this comes from the inclusion of the lagged real industrial production growth variable.

Considering the three-month horizon, the I/A factor has an estimated coefficient of 0.05, and the t-statistic is 1.77. At this horizon, the market premium is statistically significant, along with the T-bill rate and the lagged real industrial production growth. Note that the sign of the coefficients on MKT and I/A are positive at both the one- and three-month horizons, as is expected if these factors are related to risk. At the three-month horizon, the $\overline{R}^2$ is 31.5%. Very similar results are reported at the one-year horizon, where the $\overline{R}^2$ rises to 41.4%.

At the three-year horizon, the estimate on the investment-to-assets factor is positive, large and statistically significant, as is the market premium. Note that the estimate on the I/A factor at this horizon was not statistically significant when included on its own. The T-bill rate and the lagged real industrial production growth are no longer statistically significant at this horizon and the $\overline{R}^2$ is 20.1%.

Over all the horizons, supporting Fama's (1981) results that employ GDP growth, the market risk premium has a positive estimate and is statistically significant in predicting real industrial production growth at all but the one-month horizon. The SMB and HML factors do not have an important role in predicting future real industrial production growth. In fact, the SMB factor has a negative sign in our sample period in all but one horizon, in contrast to the positive sign found in Liew and Vassalou (2000) when predicting GDP growth.[16]

Panel B of Table 9 repeats the above exercise using the asset growth factor as the measure of investment. On the LHS of the panel, which reports the univariate regressions, we observe a positive estimate on the asset growth factor at all horizons which is statistically significant at the one- (marginally) and three-month horizons. The RHS of Panel B reports the results using the control variables and shows that the AG factor loses its predictive power. It should be stressed that a finding that any of the investment factors lose some of their predictability in the presence of the control variables should not diminish the interpretation that they contain important information for future economic activity. We are not conducting a horse race to find the business cycle variable that best forecasts economic activity. Rather, any reduction in the extent of predictability by the investment factors when also including the additional controls simply tells us that the information contained in the investment factors about future economic activity is similar to that contained in other business cycle variables. Therefore, it appears that the AG factor contains similar business cycle information as other well-known business cycle variables. In particular, the T-bill rate and the lagged growth in real industrial production are significant at the one-month to one-year horizons, and the market premium is significant at all but the one-month horizon.

On the LHS of Panel C, we consider the ability of the investment growth factor to predict future real industrial production growth. In this case, we record a positive coefficient at the one-month horizon, which is marginally statistically significant, and at the three-month horizon which is not statistically significant. At the one- and three-year horizons, the estimates become negative but are a long way from being statistically significant. The RHS of Panel C records the results when including the control variables. In this case, the IG factor is no longer significant at the one-month horizon. The size and statistical significance of the other variables in predicting the industrial production growth are very similar to those in Panels A and B.

It is apparent that the IG factor has less predictive power for real industrial production growth than the I/A and AG factors. However, it should be recalled that the size of the premium on the investment growth factor is about half the size of the premium on the other two factors. It is perhaps not surprising that a factor that earns a smaller risk premium covaries with macroeconomic activity to a lesser extent than a factor that earns a larger risk premium. In light of this, we may expect that the investment growth factor has less predictive power for future real industrial production growth.

Overall, the findings in Table 9 support the notion that the investment factors, in particular as measured by the I/A and AG factors, are indicators of future economic activity. This finding is consistent with the interpretation that these factors constitute risk factors that vary with the business cycle, and therefore, on average, earn a positive risk premium. Consequently, an investment factor can be thought of as a state variable that measures risk in a Merton (1973) type of intertemporal capital asset pricing model. If this is indeed the case, investors will require a risk premium in order to hold stocks that load onto such a factor.

Table 10 presents the results from predicting future real GDP growth. The LHS of Panel A presents the findings using the investment-to-assets factor as the only predictor. The pattern in coefficient estimates across the horizons is very similar to those in Table 9 that predict the growth in real industrial production. Notably, the I/A factor is statistically significant at the one-quarter and one-year horizon (marginally so at the one-year horizon), but not at the three-year horizon.

When considering the inclusion of the control variables in the RHS of Panel A, the size of the estimate on the I/A factor falls at the one-quarter and one-year horizons as does its level of statistical significance. This would suggest that the information contained in the I/A factor about future real GDP growth is similar to that contained in other business cycle variables. The market premium, the dividend yield, the T-bill rate, and the lagged industrial production all have predictive power at the one-quarter and one-year horizons for real GDP growth. At the three-year horizon, the I/A factor becomes significant in predicting real GDP growth.

Panel B provides evidence on the predictability of real GDP growth using the asset growth factor. In the univariate regressions, the AG factor is marginally statistically significant

[16] Employing an annual frequency, using the same sample period as Liew and Vassalou (which is 1978–1996), and including the investment factor as a regressor, we find that the estimate on the SMB factor is positive but not statistically significant. Furthermore, the size of the estimate is substantially reduced when the investment factor is included in the regression. In this shorter sample, the investment factor still has a positive estimate and it remains statistically significant.

Table 10
The investment and asset growth factors as predictors of real GDP growth.

This table presents results from regressing the growth in real GDP on the prior monthly equal-weighted returns of investment factor portfolios and control variables. The regressions use quarterly, annual, and three-year horizons. The return factors are: *I*/*A* is the investment-to-assets ratio factor; *AG* is the asset growth factor; and *IG* is the investment growth factor. MKT is the excess return on the CRSP value-weighted index, HML is the return on the high minus low book-to-market factor, SMB is the return on the small minus big market capitalization factor, DY is the dividend yield on the market portfolio, TS is the term structure of interest rates defined as the difference between the yield on a ten-year government bond and the one-month T-bill rate, TB is the one-month T-bill rate, and DIP is the quarterly growth in real industrial production. Panel A reports results from predicting the growth rate in real GDP with *I*/*A*, Panel B reports results from predicting the growth rate in real GDP with *AG*, and Panel C reports results from predicting the growth rate in GDP with *IG*. Data are sampled from January 1960 to December 2009. Newey and West *t*-statistics are in parentheses. $\overline{R}^2$ is the adjusted R^2.

Panel A: Predicting with I/A

Univariate			Multiple									
GDP	*I/A*	$\overline{R}^2$	GDP	*I/A*	MKT	SMB	HML	DY	TS	TB	DIP	$\overline{R}^2$
1q	0.02 (2.17)	1.5	1q	0.01 (1.16)	0.03 (3.27)	0.00 (0.01)	0.01 (1.30)	0.00 (2.24)	0.04 (1.04)	−0.06 (−2.00)	0.22 (5.81)	29.2
1y	0.06 (1.74)	1.6	1y	0.05 (1.43)	0.08 (3.47)	−0.03 (−1.01)	0.03 (1.10)	0.02 (3.10)	0.23 (1.10)	−0.39 (−3.34)	0.45 (3.33)	37.2
3y	0.09 (1.40)	0.7	3y	0.13 (2.71)	0.07 (1.40)	−0.16 (−1.62)	0.09 (1.77)	0.04 (1.50)	−0.01 (−0.01)	−0.79 (−1.39)	0.22 (0.55)	15.2

Panel B: Predicting with AG

Univariate			Multiple									
GDP	*AG*	$\overline{R}^2$	GDP	*AG*	MKT	SMB	HML	DY	TS	TB	DIP	$\overline{R}^2$
1q	0.01 (1.76)	0.3	1q	0.00 (0.46)	0.03 (3.23)	0.00 (0.22)	0.02 (1.40)	0.00 (2.35)	0.05 (1.13)	−0.06 (−1.94)	0.22 (5.87)	28.6
1y	0.01 (0.64)	0.0	1y	0.01 (0.53)	0.08 (3.43)	−0.02 (−0.62)	0.05 (1.30)	0.02 (3.03)	0.25 (1.17)	−0.38 (−3.16)	0.46 (3.32)	36.2
3y	−0.00 (−0.00)	0.0	3y	0.04 (1.82)	0.07 (1.36)	−0.13 (−1.59)	0.09 (1.99)	0.04 (1.47)	0.03 (0.02)	−0.77 (−1.29)	0.25 (0.62)	13.5

Panel C: Predicting with IG

Univariate			Multiple									
GDP	*AG*	$\overline{R}^2$	GDP	*IG*	MKT	SMB	HML	DY	TS	TB	DIP	$\overline{R}^2$
1q	0.01 (1.12)	0.0	1q	0.00 (0.29)	0.03 (3.20)	0.01 (0.39)	0.01 (1.41)	0.00 (2.26)	0.05 (1.21)	−0.06 (−1.90)	0.22 (5.90)	28.5
1y	−0.01 (−0.23)	0.0	1y	−0.02 (−0.54)	0.07 (3.55)	−0.01 (−0.44)	0.04 (1.43)	0.02 (2.87)	0.26 (1.23)	−0.36 (−3.03)	0.46 (3.31)	36.1
3y	−0.01 (−0.02)	0.0	3y	0.02 (0.48)	0.07 (1.26)	−0.11 (−1.39)	0.09 (1.78)	0.04 (1.43)	0.06 (0.08)	−0.75 (−1.27)	0.25 (0.61)	13.1

at the one-quarter horizon and is insignificant at longer horizons. In the presence of the control variables, the AG factor is insignificant at the one-quarter and one-year horizons, and is marginally statistically significant at the three-year horizon. In Panel C, we do not find any evidence that the investment growth factor can predict real GDP growth, either when included on its own or in conjunction with the control variables.

In Table 11, we investigate whether the investment factors can predict the future growth rate of real corporate earnings. If the investment factors are related to future real corporate earnings, then this would constitute further evidence that lends support to the interpretation of these factors as common risk factors in stock returns. Panel A reports the results when real earnings growth is predicted by the investment-to-assets factor. The LHS of Panel A employs the *I*/*A* factor alone and shows that there is a positive relation between the *I*/*A* factor and future growth in real corporate earnings, however, it is never statistically significant. The same result is found when including the control variables. However, the market premium, HML premium, and the growth rate in real industrial production do predict future real earnings growth (marginally so in the case of HML).

In Panel B of Table 11, we examine whether the asset growth factor has predictive power for real corporate earnings growth. At the one- and three-month horizons, the *AG* factor records a positive and statistically significant coefficient (marginally so at the three-month horizon). At the one-year horizon the estimate is positive with a *t*-statistic of 1.62. Although the estimated coefficient on the *AG* factor is positive at the three-year horizon, it is not statistically significant. In the RHS of Panel B, we report the results that also include the control variables. The only major impact is that the effect of the *AG* factor is increased somewhat and is now statistically significant at the one-month, three-month, and one-year horizons. In comparison to the findings in Table 10, where the investment-to-assets ratio had more success in predicting future real GDP growth than the asset growth factor, for real earnings growth, the asset growth factor is a stronger predictor than the investment-to-assets factor.

Panel C of Table 11 also reveals that the investment growth factor has predictive power for future real

Table 11
The investment and asset growth factors as predictors of real corporate earnings growth.

This table presents results from regressing the growth in real corporate earnings on the prior equal-weighted returns of investment factor portfolios and control variables. The regressions use monthly, quarterly, annual, and three-year horizons. The return factors are: *I*/*A* is the investment-to-assets ratio factor; *AG* is the asset growth factor; and *IG* is the investment growth factor. MKT is the excess return on the CRSP value-weighted index, HML is the return on the high minus low book-to-market factor, SMB is the return on the small minus big market capitalization factor, DY is the dividend yield on the market portfolio, TS is the term structure of interest rates defined as the difference between the yield on a ten-year government bond and the one-month T-bill rate, TB is the one-month T-bill rate, and DIP is the monthly growth in real industrial production. Panel A reports results from predicting the growth rate in real corporate earnings, RE, with *I*/*A*, Panel B reports results from predicting the growth rate in real corporate earnings, RE, with *AG*, and Panel C reports results from predicting the growth rate in corporate earnings, RE, with *IG*. Data are sampled from January 1960 to December 2009. Newey and West *t*-statistics are in parentheses. $\overline{R}^2$ is the adjusted R^2.

Panel A: Predicting with I/A

Univariate			Multiple									
RE	*I*/*A*	$\overline{R}^2$	RE	*I*/*A*	MKT	SMB	HML	DY	TS	TB	DIP	$\overline{R}^2$
1m	0.02	0.0	1m	0.01	0.27	−0.02	0.30	−0.01	0.00	0.00	0.96	7.3
	(0.30)			(0.08)	(2.73)	(−0.19)	(1.92)	(−0.72)	(1.68)	(0.27)	(2.83)	
3m	0.20	0.0	3m	0.15	0.78	−0.04	0.91	0.00	0.00	0.00	3.28	10.9
	(0.68)			(0.68)	(1.80)	(−0.28)	(1.74)	(0.11)	(0.99)	(0.02)	(2.92)	
1y	1.27	1.3	1y	1.48	0.65	−0.78	−0.49	0.11	0.03	−0.01	9.38	13.2
	(1.38)			(1.56)	(1.17)	(−1.49)	(−1.22)	(1.48)	(1.57)	(−0.74)	(2.41)	
3y	0.56	0.0	3y	0.27	−0.58	−0.02	0.58	0.26	0.10	−0.06	0.75	28.9
	(0.81)			(0.49)	(−1.26)	(−0.03)	(0.94)	(2.07)	(2.04)	(−3.46)	(0.25)	

Panel B: Predicting with AG

Univariate			Multiple									
RE	*AG*	$\overline{R}^2$	RE	*AG*	MKT	SMB	HML	DY	TS	TB	DIP	$\overline{R}^2$
1m	0.11	0.4	1m	0.12	0.28	−0.08	0.27	−0.00	0.00	0.00	0.95	7.7
	(2.03)			(2.08)	(2.74)	(−1.08)	(1.78)	(−0.45)	(1.46)	(0.19)	(2.83)	
3m	0.56	2.2	3m	0.66	0.85	−0.38	0.73	0.01	0.00	−0.00	3.24	13.4
	(1.86)			(2.13)	(1.84)	(−1.78)	(1.14)	(0.41)	(0.70)	(−0.06)	(3.10)	
1y	0.92	1.2	1y	1.45	0.72	−1.12	−0.65	0.14	0.02	−0.01	9.39	13.9
	(1.62)			(2.07)	(1.29)	(−1.86)	(−1.70)	(1.65)	(1.56)	(−0.87)	(2.46)	
3y	0.24	0.0	3y	0.21	−0.56	−0.05	0.57	0.27	0.10	−0.06	0.78	28.9
	(0.36)			(0.35)	(−1.29)	(−0.09)	(0.86)	(1.99)	(2.05)	(−3.46)	(0.25)	

Panel C: Predicting with IG

Univariate			Multiple									
RE	*IG*	$\overline{R}^2$	RE	*IG*	MKT	SMB	HML	DY	TS	TB	DIP	$\overline{R}^2$
1m	0.06	0.0	1m	0.01	0.26	−0.02	0.30	−0.01	0.00	0.00	0.96	7.2
	(0.74)			(0.08)	(2.64)	(−0.20)	(1.87)	(−0.64)	(1.66)	(0.27)	(2.87)	
3m	0.49	0.4	3m	0.35	0.78	−0.03	0.86	0.01	0.00	0.00	3.31	11.2
	(2.68)			(1.78)	(1.75)	(−0.18)	(1.64)	(0.17)	(0.95)	(0.01)	(2.99)	
1y	0.95	0.3	1y	1.36	0.54	−0.40	−0.52	0.12	0.03	−0.01	9.62	12.3
	(1.75)			(2.27)	(1.13)	(−1.26)	(−0.98)	(1.54)	(1.71)	(−0.69)	(2.23)	
3y	0.80	0.0	3y	0.88	−0.58	−0.02	0.45	0.27	0.10	−0.06	0.82	29.1
	(0.84)			(0.96)	(−1.25)	(0.05)	(0.63)	(2.05)	(2.06)	(−3.46)	(0.26)	

earnings growth at the three-month horizon and at the one-year horizon (marginally so at the one-year horizon). The predictability at the three-month horizon is somewhat reduced when including the control variables.

The final predictability results that we examine relate to predicting real aggregate investment growth. As investment is a very procyclical macroeconomic variable, we would expect that the investment factors can predict future investment growth.[17] Panel A of Table 12 reports the results of predicting real investment growth using the *I*/*A* factor. There is a positive and statistically significant relation at every horizon when *I*/*A* is the only predictor. The predictability with the *I*/*A* factor diminishes at the one-quarter and at the one-year horizons (although it is marginally significant at the one-year horizon) when including the control variables. The SMB and HML factors are not statistically significant (except at the one-quarter horizon where the HML is statistically significant and the SMB is marginally statistically significant), while the market factor has a positive sign at all horizons and is statistically significant at the one-quarter and one-year horizons. The dividend yield and T-bill factors are also important in predicting aggregate real investment at the one- and three-year horizons, while the industrial production factor is statistically significant at the one-quarter and one-year horizons. The term spread is significant at the one-year horizon.

The predictability results of real investment growth using the asset growth factor are reported in Panel B

[17] The volatility of aggregate investment is more than twice that of aggregate output and the correlation between output and investment is very high. Thus, aggregate investment is highly procyclical. See, for example, Hansen (1985), Plosser (1989), and Boldrin, Christiano, and Fisher (2001).

Table 12
The asset growth and investment factors as predictors of real aggregate investment growth.

This table presents results from regressing the growth in real aggregate investment on the prior equal-weighted returns of investment factor portfolios and control variables. The regressions use monthly, quarterly, annual, and three-year horizons. The return factors are: *I*/*A* is the investment-to-assets ratio factor; *AG* is the asset growth factor; and *IG* is the investment growth factor. MKT is the excess return on the CRSP value-weighted index, HML is the return on the high minus low book-to-market factor, SMB is the return on the small minus big market capitalization factor, DY is the dividend yield on the market portfolio, TS is the term structure of interest rates defined as the difference between the yield on a ten-year government bond and the one-month T-bill rate, TB is the one-month T-bill rate, and DIP is the quarterly growth in real industrial production. Panel A reports results from predicting the growth rate in real aggregate investment, Invest, with *I*/*A*, Panel B reports results from predicting the growth rate in real aggregate investment, Invest, with *AG*, and Panel C reports results from predicting the growth rate in real aggregate investment, Invest, with *IG*. Data are sampled from January 1960 to December 2009. Newey and West *t*-statistics are in parentheses. $\bar{R}^2$ is the adjusted R^2.

Panel A: Predicting with I/A

Univariate			Multiple									
Invest	*I*/*A*	$\bar{R}^2$	Invest	*I*/*A*	MKT	SMB	HML	DY	TS	TB	DIP	$\bar{R}^2$
1q	0.11 (2.43)	1.5	1q	0.03 (0.54)	0.09 (1.97)	0.13 (1.78)	0.11 (2.11)	0.00 (0.22)	0.24 (1.03)	0.15 (1.02)	1.20 (5.96)	28.2
1y	0.34 (2.20)	3.3	1y	0.23 (1.66)	0.42 (3.22)	−0.08 (−0.68)	0.17 (1.37)	0.07 (3.50)	1.18 (2.11)	−0.94 (−1.97)	1.82 (2.98)	35.9
3y	0.53 (2.51)	3.1	3y	0.53 (3.23)	0.06 (0.33)	−0.23 (−0.88)	0.18 (1.09)	0.16 (2.40)	1.65 (1.06)	−2.77 (−2.22)	−0.74 (−0.64)	21.7

Panel B: Predicting with AG

Univariate			Multiple									
Invest	*AG*	$\bar{R}^2$	Invest	*AG*	MKT	SMB	HML	DY	TS	TB	DIP	$\bar{R}^2$
1q	0.10 (3.13)	2.9	1q	0.04 (1.22)	0.09 (1.98)	0.11 (1.52)	0.11 (2.02)	0.00 (0.41)	0.21 (0.92)	0.14 (0.76)	1.20 (6.00)	28.6
1y	0.18 (1.67)	1.4	1y	0.14 (1.51)	0.43 (3.27)	−0.07 (−0.57)	0.18 (1.45)	0.08 (3.69)	1.18 (2.04)	−0.94 (−2.01)	1.85 (3.04)	35.3
3y	0.24 (1.27)	0.9	3y	0.32 (2.33)	0.07 (0.40)	−0.21 (−0.85)	0.19 (1.18)	0.18 (2.41)	1.67 (1.05)	−2.77 (−2.15)	−0.63 (−0.53)	20.5

Panel C: Predicting with IG

Univariate			Multiple									
Invest	*IG*	$\bar{R}^2$	Invest	*IG*	MKT	SMB	HML	DY	TS	TB	DIP	$\bar{R}^2$
1q	0.13 (2.25)	1.2	1q	0.05 (0.84)	0.09 (1.94)	0.13 (1.97)	0.10 (2.01)	0.00 (0.33)	0.24 (1.05)	0.15 (0.83)	1.20 (6.01)	28.3
1y	0.18 (1.14)	0.0	1y	0.10 (0.74)	0.42 (3.22)	0.00 (0.02)	0.19 (1.41)	0.08 (3.44)	1.28 (2.27)	−0.87 (−1.76)	1.89 (2.97)	34.5
3y	0.39 (1.59)	0.5	3y	0.49 (2.32)	0.04 (0.21)	−0.05 (−0.21)	0.15 (0.87)	0.17 (2.35)	1.85 (1.19)	−2.71 (−2.09)	−0.65 (−0.52)	20.1

of Table 12. We find predictability at the one-quarter and one-year horizons (marginally so at the one-year horizon) when including only the *AG* factor. This disappears when including the control variables. However, the *AG* factor is statistically significant at the three-year horizon when including the control variables. Finally, in Panel C, we report the results using the investment growth factor. The investment growth factor is only statistically significant at the one-quarter horizon when included on its own and only significant at the three-year horizon when the control variables are included. Overall, there is reliable evidence that the growth in real aggregate investment is predictable with investment factor returns.

To summarize the predictability evidence presented in this section, the investment factors, especially the investment-to-assets and the asset growth factors, contain information about future real activity. On some occasions the investment-based factors predictability is diminished by the inclusion of the control variables. However, we should not consider this a failure of the investment factors to reveal information about future economic activity. Rather, it simply tells us that the investment factor contains information similar to that contained in existing business cycle variables.

Coupled with the earlier findings that the cross-section and time series of the investment-based portfolio returns are related to systematic risk based on macroeconomic factors, the evidence in this part of the paper points to the conclusion that the equal-weighted investment factors are tightly linked to the macroeconomy, consistent with their interpretation as common risk factors in stock returns.

In addition to the results presented above that use equal-weighted portfolios, we also repeated the analysis of macroeconomic predictability using the value-weighted factors.[18] The general tenor of the findings remains unchanged. The only noticeable difference is that the results of macroeconomic predictability are generally weaker when using value-weighted investment portfolios. However, we still uncover some predictability, especially for real GDP growth and real aggregate investment growth. The reduction in the extent of the predictability, vis-a-vis the equal-weighted investment

[18] Tabulated results are available on request.

portfolios, may stem from smaller average return spreads associated with value-weighted portfolios.

7. Conclusion

Previous studies find a strong negative cross-sectional relation between real investment (asset growth) and future stock returns. This paper is an attempt to relate this relation to macroeconomic risk and, thereby, measure the extent to which risk-based explanations, namely the *q*-theory and real option models, account for the negative investment (asset growth)-return relation. The paper provides evidence that risk plays an important role in the investment (asset growth)-return relation. However, the goal of the paper is not to completely disentangle the competing explanations for the investment-returns relation, namely the risk-based explanations and the behavioral explanations, a task which is difficult if not impossible. Thus, we cannot rule out the conjecture that mispricing plays some role in the investment-return relation.

We measure systematic risk as stock returns' loadings with respect to the five Chen, Roll, and Ross (1986) factors. The advantage of using these factors, as opposed to using characteristic-related factors, is their strong association with the business cycle which implies they can be interpreted easily as risk factors. We show that the negative investment (asset growth)-return relation is primarily accounted for by differences in systematic risk between low investment (asset growth) and high investment (asset growth) firms.

Consistent with risk-based explanations of the negative investment-return relation offered by the *q*-theory of investment and by real option models, firms' systematic risk falls during periods of high investment (asset growth). Also consistent with risk-based explanations is our finding that firms' systematic risk increases after they disinvest.

The paper also examines whether return factors, defined as the excess returns of low investment firms over high investment firms, are related to future economic activity. We find that the investment factors can predict future real economic activity. Specifically, the return factors are positively related to future real industrial production growth, real GDP growth, real earnings growth, and the growth rate of real aggregate investment. This evidence suggests that investment factors can indeed be interpreted as risk factors that investors demand a risk premium for holding.

The findings in this paper are important since investment-based factors have been shown to explain several asset pricing anomalies, such as the spread in average returns across book-to-market portfolios (Xing, 2008), the long-term SEO underperformance (Lyandres, Sun, and Zhang, 2008) and the magnitude of the accrual anomaly (Wu, Zhang, and Zhang, 2010). Moreover, Chen, Novy-Marx, and Zhang (2010) show that an investment factor, together with the market factor and a productivity factor, explain much of the average return spread across test assets formed on short-term prior returns, failure probability, *O*-score, earnings surprises, accruals, net stock issues, and stock valuation ratios.

Our extensive investigation into the role of real investment factors provides evidence that lends support to the notion that risk plays an important role in the negative investment (asset growth)-return relation.

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