Journal of Financial Economics 145 (2022) 706–724

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

The cross-section of investment and profitability: Implications for asset pricing☆

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ARTICLE INFO

Article history:
Received 21 May 2021
Revised 21 June 2022
Accepted 22 June 2022
Available online 7 July 2022

JEL classification:
G10
G12

Keywords:
Investment CAPM
Cross-section of stock returns
q-Factors
Investment premium
Profitability premium
Out-of-sample test

ABSTRACT

Asset pricing predictions from the investment CAPM depend on the cross-sectional relation between investment and profitability. In samples of U.S. stocks featuring high cross-sectional investment-profitability correlation, both investment and profitability premiums are weak. Consistent with the *conditional* predictions from the investment CAPM, triple sorts on size, investment, and profitability as in Hou et al. (2015)'s *q*-factors resurrect the premiums in the high-correlation samples. We find similar results using cash-based profitability, consistent with the dynamic investment CAPM. Our work has important implications for constructing asset pricing factors and interpreting out-of-sample asset pricing test results, in particular the insignificance of historical investment and profitability premiums.

1. Introduction

The investment CAPM predicts that a firm's expected return is increasing in its expected profitability and decreasing in its investment rate (Hou et al., 2015; Zhang, 2017). Empirical tests of the investment CAPM exploit the cross-sectional variation in investment and profitability and find strong support for expected return variation in those dimensions. For instance, an empirical *q*-factor model motivated by the investment CAPM largely subsumes other recently proposed factor premiums (see Hou et al., 2019).

We show that the cross-sectional relation between investment and profitability is crucial for interpreting empirical tests of the investment CAPM. To see this, note that the static version of the investment CAPM per Hou et al. (2015) predicts a *triangular* relationship between a firm's investment rate, expected profitability, and expected returns. Expected returns are decreasing in in-

☆ Bill Schwert was the editor for this article. We are grateful to an anonymous referee for helpful comments and suggestions. We also thank Kenneth Ahern, Frederico Belo, Jules van Binsbergen, Nick Bloom, Alexandre Corhay, Zhi Da, Patty Dechow, Ian Dew-Becker, Stefano Giglio, Jerry Hoberg, Christopher Jones, Shelley Li, Christian Opp, Sang Byung Seo, Richard Sloan, Anjan Thakor, Selale Tuzel, Jessica Wachter, Mao Ye, and especially Juhani Linnainmaa, as well as participants at the AFA Annual Meeting, the SFS Cavalcade, the MFA Annual Meeting, the ITAM Finance Conference, the Minnesota Junior Finance Conference, CKGSB, UIUC, USC Marshall School of Business, and USC Leventhal School of Accounting for comments and suggestions. We thank Sunil Wahal, Juhani Linnainmaa, and Michael Roberts for sharing historical data on investment, profitability, and returns. An earlier version of this paper was circulated under the title "The Great Divorce between Investment and Profitability: Implications for Asset Pricing."

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https://doi.org/10.1016/j.jfineco.2022.06.003
0304-405X/

vestment holding profitability constant and increasing in profitability holding investment constant. These *conditional* predictions suggest that unconditional sorts may not be capable of detecting investment and profitability premiums. In particular, when investment and profitability are highly positively correlated, the cross-sectional variation in investment is primarily driven by the variation in expected profitability instead of discount rates. As a result, even though investment negatively predicts returns within the profitability buckets, unconditional sorts on investment may not identify this predictability. In sum, the investment CAPM suggests an economic reason for weak unconditional investment and profitability premiums when the cross-sectional investment-profitability correlation is high. In contrast, conditional sorts that orthogonalize investment and profitability, as in the empirical design of Hou et al. (2015)'s *q*-factors, can mitigate the impact of the correlation and detect the predicted premiums.

To test our predictions, we construct two samples of U.S. firms with significantly positive and negative cross-sectional relations between investment (I/A) and profitability (Roe). We classify industries featuring high I/A-Roe correlation as the High-*Corr* sample and industries featuring low I/A-Roe correlation as the Low-*Corr* sample.

We first examine unconditional investment and profitability premiums in these samples. To do so, we compute portfolio returns based on 2-by-3 size-I/A and size-Roe sorts separately within the High-*Corr* and Low-*Corr* samples. Consistent with the predictions from the investment CAPM, investment and profitability factors constructed using these double-sorted portfolios earn significantly lower average returns in the High-*Corr* sample compared to their full sample counterparts and the benchmark *q*-factors of Hou et al. (2015). The investment premium in the High-*Corr* sample is insignificant and less than one fifth of that for the benchmark *q*-factors, and the profitability premium, while statistically significant, is about three fifth of that for the *q*-factors. In contrast, in the Low-*Corr* sample, both premiums are statistically significant and indistinguishable from their full sample counterparts and the benchmark *q*-factors. The difference in premiums between High-*Corr* and Low-*Corr* is striking in that the fundamental investment and profitability spreads do not differ between these two samples.

Next, we investigate whether conditional sorts, which we view as the correct method to test the investment CAPM, mitigate the impact of the high investment-profitability correlation on factor premiums. We apply the empirical design of Hou et al. (2015)'s *q*-factors and conduct 2-by-3-by-3 independent sorts on size, I/A, and Roe. We confirm that both investment and profitability factors based on triple sorts earn significant average returns in the High-*Corr* sample. Both premiums are no longer statistically different from the benchmark *q*-factors that use the full sample. This is consistent with our prediction that triple sorts help detect premiums by properly addressing the correlation between investment and profitability.

We repeat our cross-industry analysis using the investment (CMA) and profitability (RMW) factors of Fama and French (2015). Specifically, we form High-*Corr* and Low-*Corr* samples using Fama and French (2015)'s investment (INV) and profitability (OP) measures. We observe that CMA and RMW, which are constructed based on 2-by-3 sorts on size-INV and size-OP, both earn insignificant average returns in the High-*Corr* sample. Meanwhile, factors based on triple sorts on size, INV, and OP earn significant average returns. This finding has important implications for constructing asset pricing factors. In particular, note that Fama and French (2015) construct CMA and RMW based on double sorts instead of triple sorts. Hence, insignificant CMA and RMW factors, such as those in our High-*Corr* sample, are not sufficient to reject the importance of investment and profitability for expected returns.

After understanding the impact of the investment-profitability correlation on premiums in the static investment CAPM, we extend our analysis to the dynamic setting in Hou et al. (2021). The dynamic investment CAPM predicts that expected returns are also increasing in expected investment growth. Following our prior argument, a highly positive correlation between investment and expected growth can also weaken the *unconditional* relation between these characteristics and expected returns. Hou et al. (2021) construct an expected growth factor based on predictions of investment-to-asset changes and identify Ball et al. (2016)'s cash-based operating profitability (Cop) as the most important determinant. Intuitively, Cop can provide a summary statistic of firms' intangible investments and financial flexibility that are both related to expected growth. Consequently, we use Cop as a proxy for expected growth and repeat our tests in two samples featuring highly positive and negative correlations between I/A and Cop. Consistent with the dynamic investment CAPM, factors based on 2-by-3 sorted size-I/A and size-Cop portfolios earn significantly lower returns compared to their full sample counterparts in the High-$Corr_{\text{Cop}}$ sample. The premiums in the Low-$Corr_{\text{Cop}}$ sample are highly significant. Triple sorts mitigate the impact of the positive I/A-Cop correlation, resulting in significant I/A and Cop factors that are no longer distinguishable from their full sample counterparts.

Next, we ask whether a full orthogonalization of investment, profitability, and expected growth further mitigates the impact of the investment-profitability correlation on premiums. We conduct quadruple sorts (2-by-3-by-3-by-3) on size, I/A, Roe, and Cop within the High-*Corr* and Low-*Corr* samples based on the I/A-Roe correlation. We find that all three premiums earn significant average returns within both High-*Corr* and Low-*Corr* samples, and five out of six premiums pass the high $t > 3$ hurdle per Harvey et al. (2016).

Finally, we leverage insights from our cross-industry tests to address an ongoing concern about the out-of-sample robustness of investment and profitability premiums. Linnainmaa and Roberts (2018) and Wahal (2019) show that both CMA and RMW factors of Fama and French (2015) earn insignificant average returns in the pre-Compustat era.[1] We use historical data from Wahal (2019) and reveal that Fama and French (2015)'s in-

[1] Data limitations, specifically a lack of monthly updated Roe that captures expected profitability, hinder the exact empirical design of Hou et al. (2015)'s *q*-factors in the pre-Compustat period.

vestment (INV) and operating profitability (OP) are highly positively correlated in the cross-section during the early decades and negatively correlated in the recent decades. We then construct CMA and RMW using triple sorts on size, INV, and OP. Once again, we find that investment and profitability premiums become significant once the correlation between INV and OP is properly addressed.

Our evidence suggests that the insignificance of CMA and RMW in the out-of-sample test moving back in time does not necessarily imply that the in-sample premiums are the result of data snooping. In fact, because of the highly positive correlation between investment and profitability in the early decades, the insignificant unconditional premiums and the significant conditional investment and profitability premiums are fully consistent with the investment CAPM.

Our paper contributes to the literature studying the empirical implementations of the investment CAPM. Hou et al. (2015) propose the q-factor model guided by the static investment CAPM which is derived from the first principal of investment. The q-factor model includes investment and profitability factors, in addition to market and size factors.[2] Hou et al. (2021) extend the framework to a dynamic setting and introduce the q^5-factor model by further including an expected growth factor. These factor models subsume other previously proposed factors, such as Fama and French (2015)'s CMA and RMW (see Hou et al., 2019), and help explain prominent quantitative security analysis strategies motivated by Graham and Dodd (1934) (see Hou et al., 2022). We uncover a nuanced insight from the investment CAPM that the cross-sectional investment-profitability relation affects the significance of investment and profitability premiums. Our findings highlight that investment and profitability factors based on triple sorts, that is, the q-factors, offer a proper test for the investment CAPM. Factors based on double sorts, such as Fama and French (2015)'s CMA and RMW, may have insignificant average returns when the investment-profitability correlation is high even though the investment CAPM is valid.

Our work also speaks to the economic interpretation of out-of-sample test results of cross-sectional premiums. A recent debate centers on whether in-sample premiums remain significant out of sample (e.g., Mclean and Pontiff, 2016; Fama and French, 2017; Linnainmaa and Roberts, 2018; Wahal, 2019, and Jensen et al., 2021). Poor out-of-sample performance of investment and profitability factors, according to traditional inference, indicates that the in-sample premiums are a statistical artifact and discourages researchers from exploring the economic channels behind the premiums. We demonstrate that the investment CAPM, that is the theoretical foundation underlying the investment and profitability factors, helps us interpret the out-of-sample test results economically. In particular, the absence of significant CMA and RMW factors in certain samples does not reject investment and profitability's relation to expected returns. In fact, the investment CAPM predicts weak unconditional investment and profitability premiums when the fundamental investment-profitability relation is positive but strong premiums otherwise. Therefore, the insignificance of the premiums in high-correlation samples is just as consistent with the investment CAPM as their significance in other samples. In sum, our work highlights that the economic conditions (e.g., the investment-profitability correlation) under which an out-of-sample test is performed should be inspected, because they can affect whether or not we expect to find significant out-of-sample results.

The paper is organized as follows. Sections 2 and 3 present the results demonstrating the importance of the investment-profitability correlation channel in the investment CAPM in static and dynamic settings, respectively. Section 4 discusses the historical evolution of the investment-profitability correlation, and its implications for factors from the perspective of the investment CAPM. Section 5 concludes.

2. The static investment CAPM

2.1. Conceptual framework

In this section, we discuss the correlation between investment and profitability and what it implies for the cross-section of expected returns. Consider a static, two-period version of the investment CAPM as in Hou et al. (2015). The first principle for investment implies that the conditional expected equity return of firm j, $\mathbb{E}_0[R_{j,1}]$, is given by

$$\mathbb{E}_0[R_{j,1}] = \frac{\mathbb{E}_0[\Pi_{j,1}]}{1 + a(I_{j,0}/A_{j,0})}, \tag{1}$$

where $\mathbb{E}_0[\Pi_{j,1}]$ is expected profitability, $I_{j,0}/A_{j,0}$ is the investment rate, and $a > 0$ is a capital adjustment cost parameter.

The investment CAPM in Eq. (1) predicts that equilibrium stock prices should adjust such that firms with higher investment or lower expected profitability earn lower expected returns *holding all else equal* in the cross-section. The intuition behind this return predictability is the net present value rule in corporate finance (Zhang, 2017): Given expected profitability, a firm invests less because a higher cost of capital lowers the value of additional investment. Similarly, consider two firms with identical investment but different expected profitability. The firm with higher expected profitability must have a higher discount rate such that the net present values of new capital can be equated and both firms decide to expand their capital by the same rate.

According to the investment CAPM in Eq. (1), discount rates vary cross-sectionally to the extent that the ratio of expected profitability to investment varies. This implies that the cross-sectional correlation between investment and expected profitability, which is the focus of this

[2] A large body of empirical studies focuses on the relation between investment and expected stock returns and the relation between profitability and expected returns. For the relation between investment and expected stock returns, see Titman et al. (2004), Fama and French (2006), Cooper et al. (2008), Xing (2008), and Kumar and Li (2016), among others. For the relation between profitability and expected stock returns, see Novy-Marx (2013), Ball et al. (2015), and Ball et al. (2016), among others.

paper, has important implications for the empirical applications of the investment CAPM. In particular, a high positive cross-sectional correlation between $\mathbb{E}_0[\Pi_{j,1}]$ and $1 + a(I_{j,0}/A_{j,0})$ can weaken the *unconditional* relation between expected returns and each of the two characteristics. In the investment CAPM, a firm invests more because it has higher expected profitability and/or a lower discount rate. If investment and expected profitability are highly correlated in the cross-section, higher investment tends to be driven by higher expected profitability rather than lower discount rates. As a result, the direct relation between investment and returns (and the direct relation between expected profitability and returns) will be weaker when the investment-profitability correlation is high. This leads to our first empirical prediction that the unconditional investment and profitability premiums are lower when the cross-sectional investment-profitability correlation is higher.

Notably, the investment-profitability correlation channel predicts an important role for orthogonalizing investment and expected profitability when forming factor portfolios in empirical tests. Equation (1) shows that higher (lower) investment (expected profitability) predicts lower expected returns *conditional* on expected profitability (investment). Hence, failure to control for the other channel when testing each of the investment and profitability channels can lead to a false rejection of the investment CAPM. This leads to our second empirical prediction that the conditional investment and profitability premiums are more likely to be significant than the unconditional premiums when the investment-profitability correlation is high.

Next, we empirically examine the implications of the cross-sectional correlation between investment and profitability for the investment CAPM. In particular, we create samples of U.S. firms in industries featuring high and low cross-sectional investment-profitability correlations. We then construct unconditional and conditional investment and profitability factors in these samples and analyze their behavior.

2.2. Data

We closely follow Hou et al. (2019) and Hou et al. (2021) for the sample selection, including an extension of the sample back to January 1967, and the definitions of investment (I/A) and profitability (Roe). Importantly, we use updated earnings in monthly sorts on Roe to be consistent with the theory in Section 2.1, because Roe from monthly sorts can serve as a good proxy for expected profitability (Hou et al., 2019). Appendix A.1 defines the variables in detail.

Our empirical procedure closely replicates the original q-factors of Hou et al. (2015), Hou et al. (2019), and Hou et al. (2021) published in the data library (http://global-q.org). We find that our investment factor $R_{\mathrm{I/A}}$ has a correlation of 98.9%, and our profitability factor R_{Roe} has a correlation of 99.1% with the original q-factors from January 1967 to June 2018. The monthly average investment factor return $R_{\mathrm{I/A}}$ is 0.36% ($t = 4.29$) in our sample compared to 0.37% ($t = 4.52$) for the original factor, and the monthly average profitability factor return R_{Roe} is 0.53% ($t = 5.30$) compared to 0.54% ($t = 5.32$) for the original factor. Given the high correlation, we refer to our replicated $R_{\mathrm{I/A}}$ and R_{Roe} as q-factors in our analyses unless otherwise stated.

2.3. High-Corr and low-Corr samples

To study the impact of the correlation between investment and profitability on factor premiums, we group firms into samples that differ in that correlation and exploit the variation across industries.

We first compute the within-industry correlation between I/A and Roe every month, where industries are categorized at the 2-digit SIC level. Figure 1 plots the distribution of the I/A-Roe correlation in each decade from 1970s to 2010s, where each industry-month observation is weighted by the number of firms within that industry-month. The kernel density in Fig. 1 reveals a rich variation in the within-industry correlation in each decade. Notably, there is a significant mass of observations where the I/A-Roe correlation is positive, potentially making the identification of investment and profitability premiums challenging per our first prediction outlined in Section 2.1.

In each month, we group firms based on the investment-profitability correlation of the 2-digit SIC industry they belong to. In particular, we place the top tercile of firms in the high-correlation (High-*Corr*) sample and the bottom tercile of firms in the low-correlation (Low-*Corr*) sample. See Appendix A.1 for details about the sample construction.

Next, we run panel regressions of I/A on Roe controlling for year-month fixed effects within the High-*Corr* and Low-*Corr* samples. Panel A of Table 1 confirms that our grouping strategy indeed generates a significantly positive cross-sectional relation between I/A and Roe in the High-*Corr* sample and a significantly negative cross-sectional relation in the Low-*Corr* sample.

2.4. Sorts within the high-Corr and low-Corr samples

The first prediction in Section 2.1 suggests that the unconditional relation between expected returns and I/A (and Roe) may be muted within the High-*Corr* sample. To test this prediction, we sort portfolios based on I/A and Roe within the High-*Corr* and Low-*Corr* samples.

We start by constructing 2-by-3 size-I/A and 2-by-3 size-Roe sorts within the High-*Corr* and Low-*Corr* samples. Controlling for size in factor construction follows standard practice in empirical asset pricing and is motivated by the stronger cross-sectional effects among small firms (Fama and French, 2008). We use independent sorts throughout. At the end of each June, we use the median New York Stock Exchange (NYSE) size within each sample to split stocks into two groups: small and big. Independently, at the end of each June, we break each sample into 3 I/A groups, using the NYSE breakpoints for the low 30%, middle 40%, and high 30% of I/A. In addition, independently, at the beginning of each month, we split each sample into 3 Roe groups, using the NYSE breakpoints for the low 30%, middle 40%, and high 30% of Roe (see Hou et al., 2015). The intersection of the independent size and I/A

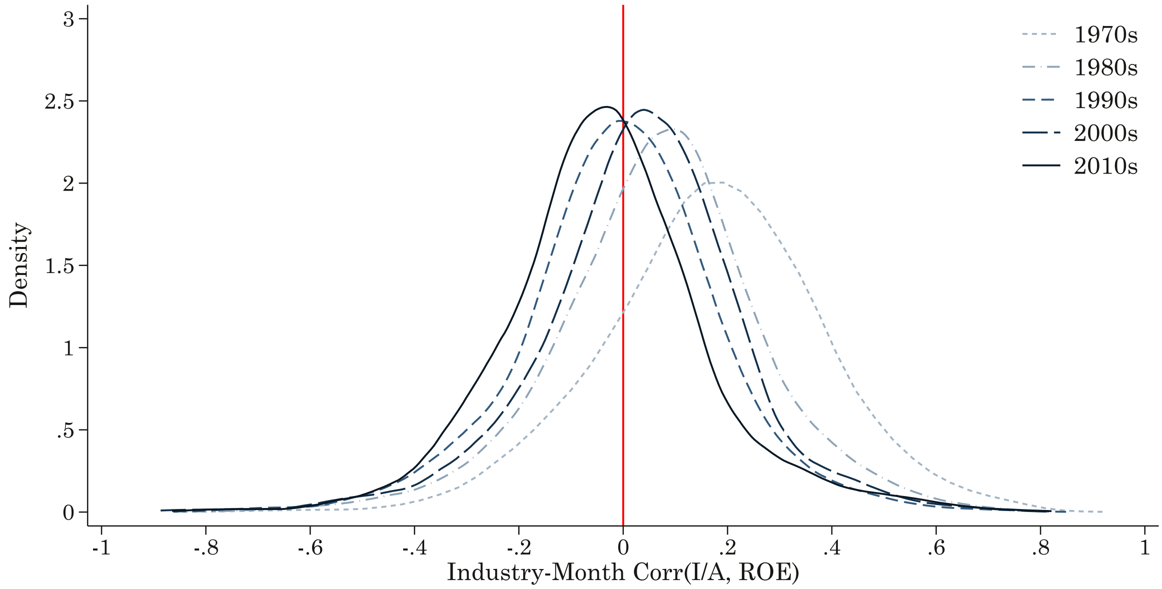

Fig. 1. Distribution of the Monthly Within-Industry I/A-Roe Correlation. This figure plots the kernel density of the monthly within-industry correlation between investment (I/A) and profitability (Roe). The bandwidth for the kernel density is 0.05. In each month, we assign each firm the I/A-Roe correlation within the firm's 2-digit SIC industry. We then plot the distribution of firm-month observations for this correlation in each decade. The sample period is from January 1967 to June 2018, and months before 1970 are grouped with months in the 1970s. See Section 2.3 for details and Appendix A.1 for variable definitions.

Table 1
Relation between Investment and Profitability in the High-*Corr* and Low-*Corr* Samples.

	(1) High-*Corr* sample	(2) Low-*Corr* sample
	Panel A: Firm level	
Roe	0.43***	-0.71***
	(0.06)	(0.10)
	Panel B: Double-sorted portfolio level	
Roe	1.47**	-1.64*
	(0.66)	(0.76)
	Panel C: Triple-sorted portfolio level	
Roe	0.33	-1.58
	(0.97)	(1.45)

This table reports the regression coefficients of investment (I/A) on profitability (Roe), controlling for time (year-month) fixed effects in High-*Corr* and Low-*Corr* samples. I/A is annual growth rate of total assets, and Roe is the quarterly return on equity constructed following Hou et al. (2015). The High-*Corr* sample includes 2-digit SIC industries with an I/A-Roe correlation in the top tercile in the month, and Low-*Corr* includes those in the bottom tercile. See Section 2.3 for details. Panel A reports the firm-level results. Panels B reports the results in which I/A and Roe are value weighted and aggregated to twelve 2-by-3 sorted portfolios (six size-I/A portfolios, plus six size-Roe portfolios). Panel C reports the results in which I/A and Roe are value weighted and aggregated to eighteen 2-by-3-by-3 sorted portfolios based on size, I/A, and Roe. Standard errors, reported in parentheses, are double clustered by year and firm (in Panel A and by year and portfolio in Panels B and C. The sample period is from January 1967 to June 2018. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

sorts results in 6 size-I/A portfolios, and the intersection of the independent size and Roe sorts results in 6 size-Roe portfolios. Appendix A.1 provides further details about the construction of the portfolios.

To verify that the firm-level investment-profitability relation carries over to the portfolio level, we compute I/A and Roe for each of the 12 portfolios by value-weighting I/A and Roe using last month's market capitalization. We then regress I/A on Roe at the portfolio level using month fixed effects. Panel B of Table 1 confirms that portfolio-level I/A and Roe are positively correlated within the High-*Corr* sample. The negative investment-profitability relation within the Low-*Corr* sample holds at the portfolio level as well.

The 2-by-3 double sorting method is common in the empirical literature. For instance, Fama and French (2015) construct the value, investment, and profitability factors by double sorting on size and each of

Table 2
Relation between Investment and Profitability Factors in the High-*Corr* and Low-*Corr* Samples.

	(1) High-*Corr* sample	(2) Low-*Corr* sample
	Panel A: Double-sorted factors	
R_{Roe}	-0.38***	-0.05
	(0.03)	(0.04)
	Panel B: Triple-sorted factors	
R_{Roe}	-0.02	0.02
	(0.03)	(0.03)

This table reports the regression coefficients of the investment factor ($R_{\mathrm{I/A}}$) on the profitability factor (R_{Roe}) in High-*Corr* and Low-*Corr* samples. See Section 2.3 for variable definitions and the sample construction. Panel A reports the results using double-sorted factors, where $R_{\mathrm{I/A}}$ is based on returns of 2-by-3 size-I/A-sorted portfolios, and R_{Roe} is based on returns of size-Roe-sorted portfolios. Panel B reports the results using triple-sorted factors, where $R_{\mathrm{I/A}}$ and R_{Roe} are returns based on 2-by-3-by-3-sorted portfolios on size, I/A, and Roe. Newey-West standard errors with 3 months lag are reported in parentheses. The sample period is from January 1967 to June 2018. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

the characteristics, respectively. When empirically designing the q-factor model, Hou et al. (2015) use triple sorts on size, I/A, and Roe in an attempt to orthogonalize the investment and profitability factors. Therefore, we next ask how much triple sorts change the relation between investment and profitability at the portfolio level. For this purpose, we construct 18 portfolios sorted 2-by-3-by-3 on size, I/A, and Roe from independent sorts on each characteristic. The construction of these 18 portfolios follows the methodology outlined in Hou et al. (2015), except that we construct them separately in the High-*Corr* and Low-*Corr* samples. We then value-weight I/A and Roe in each portfolio to obtain the characteristics at the portfolio level.

Panel C of Table 1 shows that triple sorts eliminate the positive relation between I/A and Roe. We observe that the loading of I/A on Roe using 18 triple-sorted portfolios is no longer distinguishable from zero within the High-*Corr* sample.

2.5. *q*-Factors in the high-*Corr* and low-*Corr* samples

We construct investment and profitability factors, $R_{\mathrm{I/A}}$ and R_{Roe}, based on double and triple sorts described in Section 2.4 and investigate their behavior within the High-*Corr* and Low-*Corr* samples. Panel A of Table 2 shows that double-sorted $R_{\mathrm{I/A}}$ and R_{Roe} are significantly and negatively correlated in the High-*Corr* sample. The negative relation is consistent with the positive I/A-Roe correlation in this sample, as $R_{\mathrm{I/A}}$ is short high I/A stocks, while R_{Roe} is long high Roe stocks. In contrast, there is no significant correlation between $R_{\mathrm{I/A}}$ and R_{Roe} in the Low-*Corr* sample.

Next, we construct triple-sorted $R_{\mathrm{I/A}}$ and R_{Roe} based on the 18 2-by-3-by-3 portfolios sorted on size, I/A, and Roe. Panel B of Table 2 shows that triple sorting mitigates the correlation between $R_{\mathrm{I/A}}$ and R_{Roe} in the High-*Corr* sample, consistent with the intuition that triple sorting orthogonalizes factors in the q-factor model of Hou et al. (2015).

Next, we test the main predictions of the investment CAPM discussed in Section 2.1. Recall from our first prediction that the unconditional investment and profitability premiums can be weak when investment and profitability are highly correlated as in the High-*Corr* sample. Our second prediction is that the conditional investment and profitability premiums are less affected by the high investment-profitability correlation.

We test the first prediction using double-sorted $R_{\mathrm{I/A}}$ and R_{Roe} in the High-*Corr* and Low-*Corr* samples. Panel A of Table 3 reports the results. As the investment-profitability correlation channel predicts, the double-sorted investment factor, $R_{\mathrm{I/A}}$, earns a low average return of 0.06% per month ($t = 0.57$) in the High-*Corr* sample. This average is 0.17% ($t = 1.97$) lower than the double-sorted $R_{\mathrm{I/A}}$ using the full sample. More strikingly, it is lower by 0.29% per month ($t = 3.13$) compared to the benchmark triple-sorted $R_{\mathrm{I/A}}$ in the q-factors. In contrast, the average double-sorted $R_{\mathrm{I/A}}$ in the Low-*Corr* sample earns an average return of 0.24% per month ($t = 2.04$) and is statistically significant. This average return is only 1 basis point different from the double-sorted full sample $R_{\mathrm{I/A}}$. It is lower by 0.12% than the benchmark $R_{\mathrm{I/A}}$, but the difference is not statistically significant ($t = 1.56$). In sum, the double-sorted investment factor, $R_{\mathrm{I/A}}$, suffers from the high investment-profitability correlation in the High-*Corr* sample, contrasting the case in the Low-*Corr* sample.

The double-sorted R_{Roe} in the High-*Corr* sample earns a significant average return of 0.34% ($t = 2.57$) as shown in Panel A of Table 3. Hence, the investment-profitability correlation channel does not completely eliminate the strong R_{Roe} factor. However, a weakening effect persists, and the average double-sorted R_{Roe} in the High-*Corr* sample is lower than its full sample counterpart by 0.15% ($t = 1.77$) and the benchmark R_{Roe} from the q-factor model by 0.18% ($t = 2.11$). Conversely, the double-sorted R_{Roe} in the Low-*Corr* sample earns 0.55% per month, which is not lower than its full sample counterpart or the benchmark R_{Roe} from the q-factor model.

One may wonder whether the double-sorted factors have different fundamental spreads in the High-*Corr* and Low-*Corr* samples that may explain the distinct premiums in these samples. We show that this is not the case in Panel A1 of Table IA.1 in the Internet Appendix. Specifically, the fundamental spread for I/A is 0.45 (standard error = 0.02) in the High-*Corr* sample and 0.49 (standard er-

Table 3
Investment and Profitability Premiums in the High-*Corr* and Low-*Corr* Samples.

	High-*Corr* sample		Low-*Corr* sample	
	Mean	[*t*-stat.]	Mean	[*t*-stat.]
	Panel A: Double-sorted factor premiums			
Monthly premium				
$R_{I/A}$	0.06	[0.57]	0.24**	[2.04]
R_{Roe}	0.34**	[2.57]	0.55***	[4.44]
Premium relative full sample factors				
$R_{I/A}$	-0.17**	[-1.97]	0.01	[0.12]
R_{Roe}	-0.15*	[-1.77]	0.05	[0.62]
Premium relative to q-factors				
$R_{I/A}$	-0.29***	[-3.13]	-0.12	[1.56]
R_{Roe}	-0.18**	[-2.11]	0.02	[0.20]
	Panel B: Triple-sorted factor premiums			
Monthly premium				
$R_{I/A}$	0.24**	[2.31]	0.35***	[3.30]
R_{Roe}	0.49***	[3.88]	0.44***	[3.87]
Premium relative to q-factors				
$R_{I/A}$	-0.12	[-1.36]	0.00	[0.06]
R_{Roe}	-0.04	[-0.41]	-0.09	[-1.21]

This table reports average monthly percentage returns of the investment factor, $R_{I/A}$, and profitability factor, R_{Roe}, in *High-Corr* and *Low-Corr* samples. See Section 2.3 for variable definitions and the sample construction. Panel A reports the results using double-sorted factors, where $R_{I/A}$ is based on 2-by-3 size-I/A sorts and R_{Roe} is based on 2-by-3 size-Roe sorts. *q*-factors from Hou et al. (2015) are based on triple sorts on size, I/A, and Roe. Panel B reports the results using triple-sorted factors, where $R_{I/A}$ and R_{Roe} are based on 2-by-3-by-3 sorts on size, I/A, and Roe. *t*-statistics are Newey-West adjusted with 3 months lag. The sample period is from January 1967 to June 2018. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

ror = 0.03) in the Low-*Corr* sample. Hence, the spreads are close in level and not statistically distinct from each other. Similarly, the fundamental spread for Roe is 0.09 (standard error = 0.01) in both the High-*Corr* and Low-*Corr* samples.

Do triple sorts mitigate the impact of the high investment-profitability correlation on $R_{I/A}$ and R_{Roe}? Panel B of Table 3 reports the average returns of triple-sorted $R_{I/A}$ and R_{Roe} in the High-*Corr* and Low-*Corr* samples. Triple sorts resurrect the investment factor, $R_{I/A}$, in the High-*Corr* sample with an average monthly return of 0.24% ($t = 2.31$). This is lower than the benchmark $R_{I/A}$ by 0.12%, but the difference is no longer statistically significant ($t = 1.36$). Triple sorts also increase the average profitability factor return, R_{Roe}, to 0.49% per month ($t = 3.88$) in the High-*Corr* sample. In Panel A2 of Table IA.1 in the Internet Appendix, we confirm that the fundamental investment and profitability spreads do not increase as a result of triple sorting. Hence, the operating channel is the investment-profitability correlation rather than the sample dispersion of sorting variables. The investment and profitability premiums in both High-*Corr* and Low-*Corr* samples are not statistically different from the benchmark *q*-factors that use the full sample of stocks.

The evidence in Table 3 confirms the informativeness of the investment-profitability correlation for empirical tests of the investment CAPM. In a high correlation sample, failure to orthogonalize investment and profitability leads to significant shrinkage in the corresponding premiums. Hence, the low returns of the double-sorted investment and profitability factors in the High-*Corr* sample do not suggest the failure of the investment CAPM. Rather, this evidence supports the mechanism underlying the investment CAPM that is discussed in Section 2.1. In summary, we highlight a key message that the predictions of the investment CAPM are conditional: expected returns decline in investment holding expected profitability constant and expected returns increase in expected profitability holding investment constant.

2.6. Implications for Fama-French factors

As a robustness check, we also investigate the correlation between investment and profitability for the investment (CMA) and profitability (RMW) factors of Fama and French (2015). While CMA and RMW are constructed using sorts on proxies for investment and profitability, they do not have a theoretical foundation like the first principle of investment. Also, they differ empirically in several ways from Hou et al. (2015)'s *q*-factors (see Appendix A.2 for variable definitions). For instance, RMW is based on annually updated operating profitability, which is arguably disadvantageous as a proxy for expected profitability compared to the most recent quarterly updated Roe used in the *q*-factor model. Another difference particularly relevant for our study is that CMA and RMW are based on 2-by-3 double sorts on size-investment and size-profitability, whereas the *q*-factors are based on triple-sorted portfolios. Importantly, Hou et al. (2019) show that $R_{I/A}$ and R_{Roe} from the *q*-factor model fully subsume CMA and RMW.

With these caveats in mind, we perform our cross-industry tests using the characteristics and portfolios underlying the CMA and RMW factors of Fama and French (2015). That is, we first compute the cross-sectional correlation between investment (INV) and operating prof-

Table 4
Results Using Fama-French Investment and Profitability Measures.

Panel A: Relation between investment and profitability		
	(1) High-*Corr* sample	(2) Low-*Corr* sample
	A1: Firm level	
OP	0.14***	-0.40***
	(0.02)	(0.06)
	A2: Double-sorted portfolio level	
OP	0.34*	-0.68**
	(0.17)	(0.26)
	A3: Triple-sorted portfolio level	
OP	-0.01	-0.52
	(0.30)	(0.45)
Panel B: Relation between investment and profitability factors		
	High-*Corr* sample	Low-*Corr* sample
	B1: Double-sorted factors	
RMW	-0.31***	0.15***
	(0.04)	(0.04)
	B2: Triple-sorted factors	
RMW	0.17***	0.18***
	(0.04)	(0.05)

Panel C: Investment and profitability premiums				
	High-*Corr* sample		Low-*Corr* sample	
	Mean	[*t*-stat.]	Mean	[*t*-stat.]
	C1: Double-sorted factors			
Monthly premium				
CMA	0.14	[1.35]	0.25**	[2.09]
RMW	0.08	[0.70]	0.31***	[2.86]
Premium relative to FF factors				
CMA	-0.13*	[-1.66]	-0.03	[-0.44]
RMW	-0.21**	[-2.56]	0.02	[0.26]
	C2: Triple-sorted factors			
Monthly premium				
CMA	0.24**	[2.34]	0.27**	[2.44]
RMW	0.20*	[1.74]	0.26***	[2.81]
Premium relative to full sample factors				
CMA	-0.09	[-1.16]	-0.06	[-0.91]
RMW	-0.11	[-1.46]	-0.05	[-0.77]
Premium relative to FF factors				
CMA	-0.04	[-0.45]	-0.00	[-0.07]
RMW	-0.09	[-1.06]	-0.03	[-0.40]

Panels A–C report the results in Tables 1–3, respectively, using Fama and French (2015) investment and profitability characteristics (INV and OP) and factors (CMA and RMW). See Section 2.6 for variable definitions and the sample construction. FF factors are based on 2-by-3 size-INV and 2-by-3 size-OP sorts. The sample period is from January 1967 to June 2018. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

itability (OP) in all 2-digit SIC industries. We then assign firms into the High-*Corr* and Low-*Corr* samples based on their industries' INV-OP correlation. While we maintain the sample at the firm-month level, to be consistent with our analyses in Section 2.3, it is rebalanced annually because the underlying characteristics used for the CMA and RMW factor construction are only updated annually in Fama and French (2015). See more sample details in Appendix A.2.

Panel A1 of Table 4 shows results from firm-level panel regressions of INV on OP controlling for year-month fixed effects. We double cluster standard errors by firm and portfolio-year to address the repeated values of firm INV and OP across months within a portfolio-year. Indeed, the loading of INV on OP is significantly positive in the High-*Corr* sample and significantly negative in the Low-*Corr* sample.[3] Panel A2 of Table 4 confirms that the significant INV-OP relation also holds at the level of 12 portfolios constructed using 2-by-3 sorts on size-INV and size-

[3] Figure IA.1 in the Internet Appendix plots the distribution of the within-industry INV-OP correlation, which exhibits substantial variation.

OP. Finally, the positive relation between INV and OP is essentially reduced to zero in the High-*Corr* sample in case of triple sorts resulting in 18 portfolios from 2-by-3-by-3 sorts on size, INV, and OP (Panel A3 of Table 4). In the Low-*Corr* sample, the negative coefficient of INV on OP loses its statistical significance when moving from double-sorted to triple-sorted portfolios as test assets.

Consistent with the significantly positive fundamental investment-profitability correlation in the High-*Corr* sample, we observe in Panel B1 of Table 4 that the double-sorted CMA and RMW factors are significantly negatively correlated in the High-*Corr* sample. Panel B2 of Table 4 shows that once again triple sorting, as done when constructing the q-factor, successfully eliminates the negative correlation between CMA and RMW in the High-*Corr* sample.

Panel C1 of Table 4 shows that both CMA and RMW in the High-*Corr* sample earn insignificant average returns when constructed based on double sorts as in Fama and French (2015). The CMA factor earns an average return of 0.14% per month (t = 1.35), which is lower than the benchmark CMA factor constructed using all firms by 0.13% (t = 1.66). The RMW factor earns an average of 0.08% per month (t = 0.70) and is lower by 0.21% (t = 2.56) compared to the benchmark RMW. In contrast, the average CMA and RMW factors in the Low-*Corr* sample are higher and significant at 0.25% (t = 2.09) and 0.31% (t = 2.86), respectively.

Finally, Panel C2 of Table 4 shows that versions of both CMA and RMW based on triple-sorted portfolios earn higher and more significant average returns in the High-*Corr* sample as opposed to their double-sorted counterparts. The CMA factor earns an average return of 0.24% (t = 2.34) and the RMW factor earns an average return of 0.20% (t = 1.74). The differences between these returns and their full sample double- and triple-sorted counterparts are not statistically significant. In Panel B of Table IA.1 in the Internet Appendix, we show that the fundamental spread in INV and OP does not increase when going from double to triple sorting; this result is similar to the one for I/A and Roe. In sum, triple sorting helps resurrect the investment and profitability premiums using INV and OP consistent with our findings in Section 2.5 on q-factors. In the Low-*Corr* sample, both average CMA and RMW based on triple sorts remain significant.

The results from this exercise confirm our intuition on the importance of the investment-profitability correlation: investment and profitability factors are likely to be weak in samples with a high cross-sectional correlation unless the characteristics are orthogonalized. Notably, they also highlight a crucial difference between q-factors and Fama-French factors. The original CMA and RMW factors of Fama and French (2015) are based on double sorts on size-INV and size-OP, respectively. We show that the significance of these factors is not robust to high cross-sectional correlation between investment and profitability. However, the investment CAPM offers guidance in this regard as discussed in Section 2.1: the negative (positive) relation between expected returns and investment (profitability) holds conditional on profitability (investment). The empirical design of Hou et al. (2015)'s q-factors follows this theoretical foundation and uses triple sorts in $R_{\mathrm{I/A}}$ and R_{Roe} factors. This mitigates the impact of the investment-profitability correlation channel on factor premiums and helps isolate the significant relation between investment, profitability, and expected returns.

3. The dynamic investment CAPM

Our analysis so far highlights a key message that the investment CAPM predicts conditional return premiums because expected returns, investment, and expected profitability form a triangular relation in the static investment CAPM. In this section, we examine whether the insight of conditional return predictability extends to the dynamic investment CAPM model.

3.1. Conceptual framework

The extension of the investment CAPM to a dynamic setting as in Liu et al. (2009) motivates a third factor in addition to investment and profitability: expected growth (Hou et al., 2021). The first principle of investment in an infinite-horizon model implies that the conditional expected equity return of firm j at time t, $\mathbb{E}_t[R_{j,t+1}]$, is given by

$$\mathbb{E}_t[R_{j,t+1}] = \frac{\mathbb{E}_t[\Pi_{j,t+1}] + \mathbb{E}_t[(a/2)(I_{j,t+1}/A_{j,t+1})^2] + (1-\delta)\mathbb{E}_t[1 + a(I_{j,t+1}/A_{j,t+1})]}{1 + a(I_{j,t}/A_{j,t})}, \tag{2}$$

where $\mathbb{E}_t[\Pi_{j,t+1}]$ is expected profitability, $I_{j,t}/A_{j,t}$ is the investment rate, $a > 0$ is a capital adjustment cost parameter, and δ is the depreciation rate of capital.

The term $\mathbb{E}_t[1 + a(I_{j,t+1}/A_{j,t+1})]$ divided by $1 + a(I_{j,t}/A_{j,t})$ in Eq. (2) motivates the expected growth factor in the q^5-factor model of Hou et al. (2021). This term essentially represents the marginal value of additional assets in the next period, namely, q. Intuitively, higher expected q should heighten current investment holding the discount rate and expected profitability constant. By the same token, two firms with identical current investment and expected profitability can have different expected q if the firm with the higher expected q is also facing a higher discount rate, thus preventing the firm from investing more.

Expected growth and current investment can be very different both empirically and conceptually. For instance, a large part of firm spending is allocated to intangible investment, which has market value (Peters and Taylor, 2017). Intangible investments, such as R&D, represent expenses, rather than capital expenditure, related to conservative accounting principles and are therefore not included in $I_{j,t}/A_{j,t}$ in Eq. (2). However, acquisition of intangible assets arguably raises a firm's growth prospects, and intangible investments therefore can be incorporated into the expected growth factor. This intuition suggests that tangible and intangible investments should be treated differently in asset pricing. While the investment CAPM predicts a positive relation between intangible investments and expected returns through the expected growth channel, expected returns are declining in tangible investment (Hou et al., 2022).

3.2. Cross-industry tests with cash-based profitability

Hou et al. (2021) construct an expected growth factor motivated by the investment CAPM formulated in Eq. (2). In predictive regressions of investment-to-asset changes on firm characteristics, they find that the cash-based operating profitability (Cop) of Ball et al. (2016) is the major component in explaining expected growth. In particular, consistent with the link between intangibles and expected growth discussed above, Cop includes R&D expenses. Furthermore, Cop also may be a good proxy for expected growth as it captures the availability of internal funds that can be used for future investments (Hou et al., 2021).

3.2.1. The correlation between investment and cash-based profitability

The dynamic investment CAPM in Eq. (2) suggests that the correlation between investment and expected growth has analogous implications to the investment-profitability correlation because expected investment also appears in the numerator of the expected return. For instance, a highly positive cross-sectional correlation can lower average factor returns for investment and expected growth. Specifically, the investment CAPM predicts that investment and expected growth would counteract one another in case of a positive cross-sectional correlation between the characteristics.

As a result, we study factors in samples that differ in the correlation between I/A and Cop, where Cop serves as a proxy for expected growth as elaborated above. We follow Ball et al. (2016) for the calculation and Hou et al. (2021) for the timing alignment of Cop in the data (see Appendix A.1 for details). We follow the same industry-based methodology used in Section 2.3, except that we use Cop instead of Roe to construct the High-$Corr_{\mathrm{Cop}}$ and Low-$Corr_{\mathrm{Cop}}$ samples. Figure 2 plots the distribution of the I/A-Cop correlation in each decade from 1970s to 2010s for each industry-month weighted by the number of firms within that industry-month. The kernel densities show the rich variation in the within-industry correlation in each decade. A remarkable difference between the I/A-Roe correlation in Fig. 1 and the I/A-Cop correlation in Fig. 2 is that the latter is tilted toward negative values, whereas the I/A-Roe correlation tends to be centered around zero. This observation manifests itself in the High-$Corr_{\mathrm{Cop}}$ sample, which consists of stocks in the top tercile of the I/A-Cop correlation. Panel A of Table 5 shows that the loading of I/A on Cop in panel regressions using firm-level data is essentially zero in the High-$Corr_{\mathrm{Cop}}$ sample. We also construct 2-by-3-sorted size-I/A and size-Cop portfolios within the High-$Corr_{\mathrm{Cop}}$ sample and find that the lack of a significant correlation between I/A and Cop obtains at the portfolio level as well (Panel B of Table 5).

Why is the I/A-Cop tilted toward lower values compared to the I/A-Roe correlation? The answer lies in the growth of current assets. The growth in current assets (e.g., accounts receivable, inventory, prepaid expenses) are subtracted from operating profits to arrive at Cop because Cop represents cash-based profits only. In contrast, the current asset growth items contribute to total asset growth and hence I/A positively. Current assets and working capital exhibit significant variation and are important for the cross-section of expected returns (Cooper et al., 2020; Gonçalves et al., 2020). This variability manifests in a lower I/A-Cop correlation compared to the I/A-Roe correlation.

Despite the overall lower level of the I/A-Cop correlation, a substantial fraction of firms (but less than one-third of the whole sample) are in industries with a positive I/A-Cop correlation (see Fig. 2). Consequently, we use a Positive-$Corr_{\mathrm{Cop}}$ sample, including all firm-month observations from industries with a positive I/A-Cop correlation instead of the High-$Corr_{\mathrm{Cop}}$ sample. The number of firm-month observations in the Positive-$Corr_{\mathrm{Cop}}$ sample is 64% of the number of observations in the High-$Corr_{\mathrm{Cop}}$ sample. We continue to use the Low-$Corr_{\mathrm{Cop}}$ sample that includes firms in the bottom tercile of the industry-level I/A-Cop correlation distribution.

Panel A of Table 5 confirms that the loading of I/A on Cop is significantly positive in the Positive-$Corr_{\mathrm{Cop}}$ sample at the firm level. And Panel B of Table 5 shows that the positive loading remains significant at the double-sorted portfolio level. In contrast, the coefficient of I/A on Cop is significantly negative in the Low-$Corr_{\mathrm{Cop}}$ sample using data both at the firm level and at the level of 12 2-by-3 portfolios.

Next, we construct 2-by-3-by-3 portfolios sorted on size, I/A, and Cop, resulting in 18 portfolios. Panel C of Table 5 shows that triple sorts eliminate the significance of the cross-sectional positive correlation between I/A and Cop in the Positive-$Corr_{\mathrm{Cop}}$ sample and cut the magnitude of the coefficient of I/A on Cop to one-fifth of its value when double sorting. For Low-$Corr_{\mathrm{Cop}}$ industries, the negative loading is also insignificant using 18 portfolios resulting from triple sorts. That these patterns are similar to the ones presented in Section 2.4 on the relation between I/A and Roe begs the question of whether the I/A-Cop correlation affects the corresponding premiums.

3.2.2. I/A and cop factors in positive-$Corr_{\mathrm{Cop}}$ and low-$Corr_{\mathrm{Cop}}$ samples

We construct investment and cash-based operating profitability factors, $R_{\mathrm{I/A}}$ and R_{Cop}, based on double and triple sorts described in Section 3.2 and investigate their behavior within Positive-$Corr_{\mathrm{Cop}}$ and Low-$Corr_{\mathrm{Cop}}$ portfolios.

Panel A1 of Table 6 shows that the double-sorted factors are significantly negatively correlated in the Positive-$Corr_{\mathrm{Cop}}$ sample, consistent with the positive correlation of underlying characteristics because $R_{\mathrm{I/A}}$ is long low-I/A and R_{Cop} is long high-Cop. The coefficient of $R_{\mathrm{I/A}}$ on R_{Cop} is still significantly negative but closer to zero in magnitude when the factors are constructed using triple sorts on size, I/A, and Cop (Panel A2 of Table 6). The double-sorted factors are positively correlated in the Low-$Corr_{\mathrm{Cop}}$ sample, again consistent with the correlation of underlying characteristics, and the correlation disappears once the factors are constructed based on triple sorts.

Panel B1 of Table 6 shows that the double-sorted investment factor, $R_{\mathrm{I/A}}$, earns an average return of only 0.08%

Table 5
Relation between Investment and Cash-Based Operating Profitability.

	(1) High-$Corr_{Cop}$	(2) Positive-$Corr_{Cop}$	(3) Low-$Corr_{Cop}$
		Panel A: Firm level	
Cop	-0.02	0.38***	-1.98***
	(0.09)	(0.02)	(0.24)
		Panel B: Double-sorted portfolio level	
Cop	0.01	0.40*	-1.67**
	(0.30)	(0.23)	(0.62)
		Panel C: Triple-sorted portfolio level	
Cop	-0.07	0.08	-0.86
	(0.59)	(0.51)	(0.88)

This table reports the regression coefficients of investment (I/A) on cash-based operating profitability (Cop) controlling for time (year-month) fixed effects in High-$Corr_{Cop}$, Positive-$Corr_{Cop}$, and Low-$Corr_{Cop}$ samples. I/A is annual growth rate of total assets, and Cop is computed following Ball et al. (2016) and Hou et al. (2021). The High-$Corr_{Cop}$ sample includes 2-digit SIC industries with an I/A-Cop in the top tercile in the month, and the Low-$Corr_{Cop}$ includes those in the bottom tercile. The Positive-$Corr_{Cop}$ sample is based on the High-$Corr_{Cop}$ sample but further requires the correlation between I/A and Cop to be positive. See Section 3.2 for details. Panel A reports the firm-level results. Panels B reports the results in which I/A and Cop are value weighted and aggregated to twelve 2-by-3 sorted portfolios (six Size-I/A portfolios and six Size-Cop portfolios). Panel C reports the results in which I/A and Cop are value weighted and aggregated to eighteen 2-by-3-by-3 sorted portfolios based on size, I/A, and Cop. Standard errors, reported in parentheses, are double clustered by year and firm in Panel A and by year and portfolio in Panels B and C. The sample period is from January 1967 to June 2018. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6
Investment and Cash-Based Operating Profitability Factors.

Panel A: Relation between I/A and Cop factors		
	(1) Positive-$Corr_{Cop}$	(2) Low-$Corr_{Cop}$
	A1: Double-sorted factors	
R_{Cop}	-0.27***	0.23***
	(0.04)	(0.04)
	A2: Triple-sorted factors	
R_{Cop}	-0.08**	-0.01
	(0.04)	(0.05)

Panel B: I/A and Cop factor premiums				
	Positive-$Corr_{Cop}$		Low-$Corr_{Cop}$	
	Mean	[t-stat.]	Mean	[t-stat.]
	B1: Double-sorted factor premiums			
Monthly premium				
$R_{I/A}$	0.08	[0.96]	0.42***	[3.34]
R_{Cop}	0.31**	[2.41]	0.67***	[5.85]
Premium relative to full sample factors				
$R_{I/A}$	-0.18*	[-1.71]	0.16**	[2.53]
R_{Cop}	-0.24**	[-2.14]	0.11	[1.63]
	B2: Triple-sorted factor premiums			
Monthly premium				
$R_{I/A}$	0.29**	[2.28]	0.34***	[2.86]
R_{Cop}	0.36***	[2.73]	0.58***	[5.65]
Premium relative to full sample factors				
$R_{I/A}$	0.03	[0.24]	0.08	[1.18]
R_{Cop}	-0.16	[-1.38]	0.07	[1.00]

Panel A reports the regression coefficients of monthly returns of the investment factor ($R_{I/A}$) on the Cop factor (R_{Cop}) in Positive-*Corr* and Low-*Corr* samples. Panel B reports average monthly percentage factor returns for both samples. See Section 3.2 for variable definitions and the sample construction. Double-sorted $R_{I/A}$ is based on returns of 2-by-3 size-I/A-sorted portfolios, and double-sorted R_{Cop} is based on returns of 2-by-3 size-Cop-sorted portfolios. Triple-sorted $R_{I/A}$ and R_{Cop} are based on returns of 2-by-3-by-3 sorts on size, I/A, and Cop. t-statistics are Newey-West adjusted with 3 months lag. The sample period is from January 1967 to June 2018. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

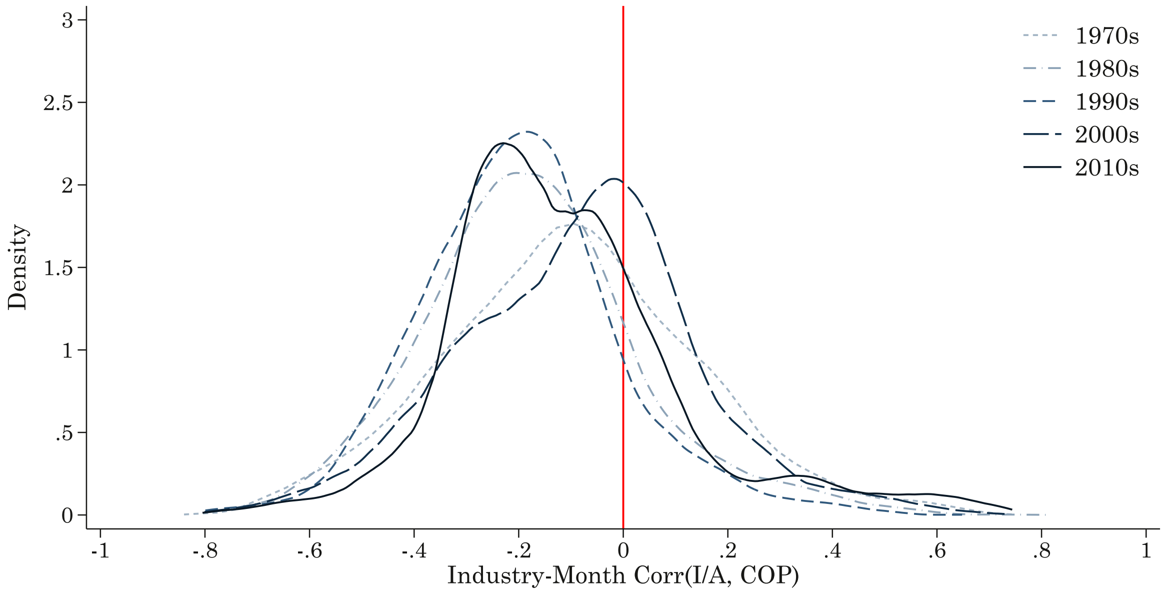

Fig. 2. Distribution of Monthly Within-Industry I/A-Cop Correlation. This figure plots the kernel density of the monthly within-industry correlation between investment (I/A) and cash-based operating profitability (Cop). The bandwidth for the kernel density is 0.05. In each month, we assign each firm the I/A-Cop correlation within the firm's 2-digit SIC industry. We then plot the distribution of firm-month observations for this correlation in each decade. The sample period is from January 1967 to June 2018, and months before 1970 are grouped with months in the 1970s. See Section 3.2 for details and Appendix A.1 for variable definitions.

per month ($t = 0.96$) in the Positive-$Corr_{\text{Cop}}$ sample, which is in sharp contrast to the average return of 0.42% ($t = 3.34$) in the Low-$Corr_{\text{Cop}}$ sample. This suggests that a positive correlation between investment and expected growth weakens the double-sorted investment premium as predicted by the investment CAPM in Eq. (2). The average $R_{\text{I/A}}$ in the Positive-$Corr_{\text{Cop}}$ sample is lower than its full sample counterpart by 0.18% ($t = 1.71$). In contrast, the average $R_{\text{I/A}}$ in the Low-$Corr_{\text{Cop}}$ sample is higher than its full sample counterpart by 0.16% ($t = 2.53$).

The double-sorted Cop factor, R_{Cop}, in the Positive-$Corr_{\text{Cop}}$ sample earns an average return of 0.31% per month ($t = 2.41$), which, despite its significance, is significantly lower than its full sample counterpart by 0.24% ($t = 2.14$). The Cop premium in the Low-$Corr_{\text{Cop}}$ sample is higher: the average R_{Cop} is 0.67% per month ($t = 5.85$), which is higher than its full sample counterpart by 0.11% ($t = 1.63$).

Panel B2 of Table 6 shows that triple sorts greatly mitigate the impact of the positive I/A-Cop correlation on the investment premium: The average $R_{\text{I/A}}$ constructed using triple-sorted portfolios earns an average return of 0.29% per month ($t = 2.28$) in the Positive-$Corr_{\text{Cop}}$ sample. Triple-sorted $R_{\text{I/A}}$ in both High-*Corr* and Low-*Corr* samples are statistically indistinguishable from their full sample counterparts. The average R_{Cop} also slightly improves as a result of triple sorting and earns an average return of 0.36% ($t = 2.73$) in the Positive-$Corr_{\text{Cop}}$ sample and 0.58% ($t = 5.65$) in the Low-$Corr_{\text{Cop}}$ sample. Moreover, triple-sorted R_{Cop} in neither sample is statistically different from the full sample counterpart as shown in Panel B2 of Table 6. Similar to the previous cases, the fundamental spreads in I/A and Cop do not change significantly from double sorting to triple sorting (see Panel C of Table IA.1 in the Internet Appendix).

These results suggest that the correlation channel is also important in the dynamic investment CAPM, where the cross-sectional investment-expected growth relation becomes relevant. For empirical tests of the dynamic investment CAPM, it is crucial to orthogonalize investment and expected growth. A double-sorted investment factor may falsely reject the relevance of investment for expected returns in a high I/A-Cop correlation sample. And a double-sorted expected growth premium seems weaker than it actually is in such a sample. These results reinforce our overall emphasis on controlling for other determinants of expected returns when testing the investment CAPM. Factor constructions based on double-sorted portfolios in the spirit of Fama and French (1993) and Fama and French (2015) can mask the relevance of theoretically grounded determinants of expected returns.

3.2.3. *Quadruple-sorted factors*

Our analyses in Section 2 support the prediction from the static investment CAPM that triple-sorted investment and profitability factors earn higher average returns than the double-sorted factors when the investment-profitability correlation is high. In this section, we ask whether further controlling for expected growth in the dynamic investment CAPM improves the investment and profitability premiums. To answer this question, we construct quadruple-sorted factors $R_{\text{I/A}}$, R_{Roe}, and R_{Cop}. Table 7 shows the average returns from the quadruple-sorted factors in the High-*Corr* and Low-*Corr* samples from Section 2.3.

As shown in Table 7, all factors earn statistically significant average returns. The average $R_{\text{I/A}}$ in the High-*Corr* industry is 0.31% per month ($t = 3.06$), a further improvement from the triple-sorted $R_{\text{I/A}}$ of 0.24% ($t = 2.31$) and

Table 7
Quadruple-Sorted Investment, Profitability, and Cop Premiums.

	High-*Corr* sample		Low-*Corr* sample	
	Mean	*t*-stat.	Mean	*t*-stat.
$R_{\mathrm{I/A}}$	0.31***	[3.06]	0.41***	[3.84]
R_{Roe}	0.51***	[3.89]	0.50***	[4.16]
R_{Cop}	0.36***	[3.61]	0.26***	[2.68]

This table reports the average monthly percentage returns of the quadruple-sorted investment factor, $R_{\mathrm{I/A}}$, profitability factor, R_{Roe}, and Cop factor, R_{Cop}, in *High-Corr* and *Low-Corr* samples. The High-*Corr* sample includes 2-digit SIC industries with an I/A-Roe correlation in the top tercile in the month, and Low-*Corr* includes those in the bottom tercile. See Section 2.3 for more details of sample construction. The factors are constructed using returns of 2-by-3-by-3-by-3 sorts on size, I/A, Roe, and Cop. *t*-statistics are Newey-West adjusted with 3 months lag. The sample period is from January 1967 to June 2018. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

a drastic uplift from the double-sorted $R_{\mathrm{I/A}}$ of 0.06% ($t = 0.57$). The average $R_{\mathrm{I/A}}$ in the Low-*Corr* sample also goes up from 0.35% ($t = 3.30$) using triple sorting to 0.41% ($t = 3.84$) using quadruple sorting controlling for Cop. Finally, both the average R_{Roe} and R_{Cop} are statistically significant in both High-*Corr* and Low-*Corr* samples, suggesting a distinct role for Cop in explaining expected returns as suggested by Ball et al. (2016) and Hou et al. (2021).

4. Historical investment and profitability premiums

Using hand-collected pre-Compustat accounting data, recent literature has questioned the robustness of various asset pricing factors. In particular, Linnainmaa and Roberts (2018) construct historical investment and profitability factors following a similar methodology as in Fama and French (2015). They find that the historical CMA and RMW earn low and insignificant average returns suggesting that the investment and profitability premiums in the Compustat sample are an artifact of data snooping. Wahal (2019) similarly shows that the pre-Compustat data features no reliable relation between investment and returns, and argues that low power in empirical tests is unlikely to be the culprit given the large size of the data set.

We evaluate the historical out-of-sample evidence on the investment and profitability premiums from the perspective of the investment CAPM. Since the investment CAPM provides a theoretical foundation for the investment and profitability premiums, it offers guidance on whether one should expect to observe significant premiums depending on the cross-sectional relation between investment and profitability. Consequently, we investigate whether the lack of significant investment and profitability premiums can be explained by a high cross-sectional investment-profitability correlation in the historical data.

4.1. Data

For the pre-Compustat period, we download the data used in Wahal (2019).[4] The data provide investment and profitability characteristics at the firm level from 1941 to 1962 (see Appendix A.2 for details). We combine this historical data with the Compustat data to obtain a long panel of investment and profitability for firms with fiscal year ending from 1941 to 2017. To ensure the robustness of our results using the historical data, we repeat the analysis with the data used in Linnainmaa and Roberts (2018), which is independently collected, and report results in Table IA.3 in the Internet Appendix.[5]

Investment and profitability in the historical data set are only available at the annual frequency. Therefore, we cannot exactly follow the construction of R_{Roe} in the *q*-factor model of Hou et al. (2015) as it is based on monthly sorts on Roe.[6] The motivation for using monthly sorts is the theoretical prediction of the investment CAPM that expected returns depend on expected (not past) profitability, which is better proxied by the most recently available data. With this caveat in mind, we study how the investment-profitability correlation channel affects investment and profitability premiums in historical and modern periods using Fama and French (2015) characteristics.

Based on the observation in Linnainmaa and Roberts (2018) that the profitability premium is weak until 1980s, we split the sample into two periods: early decades from 1941 to 1979 and later decades from 1980 to 2017. In this section, we use the entire universe of stocks in all tests and focus on the evolution of the investment-profitability correlation going from the early to the later decades.

4.2. Investment-profitability correlation in early and later decades

Panel A of Table 8 shows that the cross-sectional relation between investment and profitability is positive in the early decades and weakly negative in the later decades, while controlling for year-month fixed effects.[7] The change in the relation between INV and OP is statistically signif-

[4] Wahal (2019) hand-collects historical firm-level accounting information from Moody's Manuals. We thank Sunil Wahal for making the data publicly available at https://research.wpcarey.asu.edu/investment-engineering/historical-profitability-and-investment-2/.

[5] We are grateful to Juhani Linnainmaa and Michael Roberts for providing the historical factors.

[6] The historical data from Wahal (2019) only include accounting variables used to construct the Fama and French (2015) investment and profitability measures. Therefore, we focus on the investment-profitability correlation.

Table 8
Relation between Fama-French Investment and Profitability in Early and Later Decades.

	(1) Early decades	(2) Later decades	(3) All
	Panel A: Firm level		
OP	0.22***	-0.09**	0.22***
	(0.03)	(0.04)	(0.03)
OP × *Later*			-0.31***
			(0.05)
	Panel B: Double-sorted portfolio level		
OP	0.33***	-0.28	0.33***
	(0.10)	(0.28)	(0.10)
OP × *Later*			-0.61**
			(0.26)
	Panel C: Triple-sorted portfolio level		
OP	0.02	-0.38	0.02
	(0.16)	(0.44)	(0.16)
OP × *Later*			-0.40
			(0.32)

This table reports the regression coefficients of Fama-French investment rate (INV) on profitability (OP) controlling for time (year-month) fixed effects. Early decades represent the period from July 1942 and June 1981. Later decades represent the period from July 1981 and June 2018. *Later* is a dummy variable indicating the later decades. INV and OP are computed following Fama and French (2015) and Wahal (2019). Panel A reports firm-level results. Panels B reports the results in which INV and OP are value weighted and aggregated to twelve 2-by-3 sorted portfolios (six size-INV portfolios and six size-OP portfolios). Panel C reports the results in which INV and OP are value weighted and aggregated to eighteen 2-by-3-by-3 sorted portfolios based on size, INV, and OP. See Appendix A.2 for variable definitions and the sample selection. Standard errors, reported in parentheses, are double clustered at the year and firm levels in Panel A and at year and portfolio level in Panels B and C. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

icant as can be seen in the full sample regression with an interaction term of OP and a dummy variable for later decades.[8] Figure 3 illustrates the different relation between INV and OP in the early and later decades at the portfolio level. For both small-cap and large-cap firms, the value-weighted investment of high-profitability portfolios is higher in early decades. That this pattern reverses in the later decades is another manifestation of the decoupling between INV and OP.

The CMA and RMW factors of Fama and French (2015) use double-sorted portfolios on size-INV and size-OP. We compute value-weighted INV and OP for 12 portfolios used in the construction of those factors and test whether the firm-level correlations are also evident at the portfolio level. Panel B of Table 8 shows that the answer is yes. The loading of INV on OP is significantly positive in early decades but is significantly reduced in the later decades.

Even though we are not able to adopt all features of *q*-factors in the historical data, we can conduct triple sorts on size, INV, and OP. This is an important feature of Hou et al. (2015)'s *q*-factors guided by the investment CAPM. As shown in Section 2.5, triple sorts mitigate the impact of the investment-profitability correlation. Hence, we construct 18 portfolios using 2-by-3-by-3 sorts on size, INV, and OP and compute their value-weighted INV and OP. Panel C of Table 8 shows that triple sorts indeed eliminate the significant positive cross-sectional relation between INV and OP in early decades. The relation in later decades, which was not significant to start with, is quite invariant to the sorting method.

What is the asset pricing implication of the fact that the cross-sectional correlation between investment and profitability is significantly positive in early decades, but not in later decades? Panel A of Table 9 shows that CMA and RMW factors constructed following Fama and French (2015) in early decades are weak and earn average returns that are not significantly different from zero. This result is consistent with Linnainmaa and Roberts (2018) and Wahal (2019). While the investment-profitability correlation channel predicts this relation, we go one step further by examining whether the conditional investment and profitability premiums can be significant as predicted by the investment CAPM. Panel B of Table 9 shows that triple sorts improve the investment and profitability factors. CMA and RMW earn an average return of 0.16% ($t = 2.01$) and 0.17% ($t = 2.33$), respectively, in early decades when constructed using triple-sorted portfolios as in Hou et al. (2015)'s $R_{\mathrm{I/A}}$ and R_{Roe}.

[7] We double cluster standard errors by firm and *portfolio year* in all panels of Table 8 to address the repeated values of investment and profitability for the same firm or portfolio within a portfolio year.

[8] One may wonder whether our findings conflict with those from the corporate finance literature, which find a positive sensitivity of investment to cash flows (e.g., Fazzari et al., 1988; Kaplan and Zingales, 1997). We show that they do not. Corporate finance studies typically control for firm fixed effects, which represent unobserved and time-invariant firm heterogeneity. However, cross-sectional asset pricing factors are constructed using raw sorting variables instead of firm-demeaned variables. Table IA.2 in the Internet Appendix shows that investment and profitability remain positively related in both early and later periods once we control for firm fixed effects.

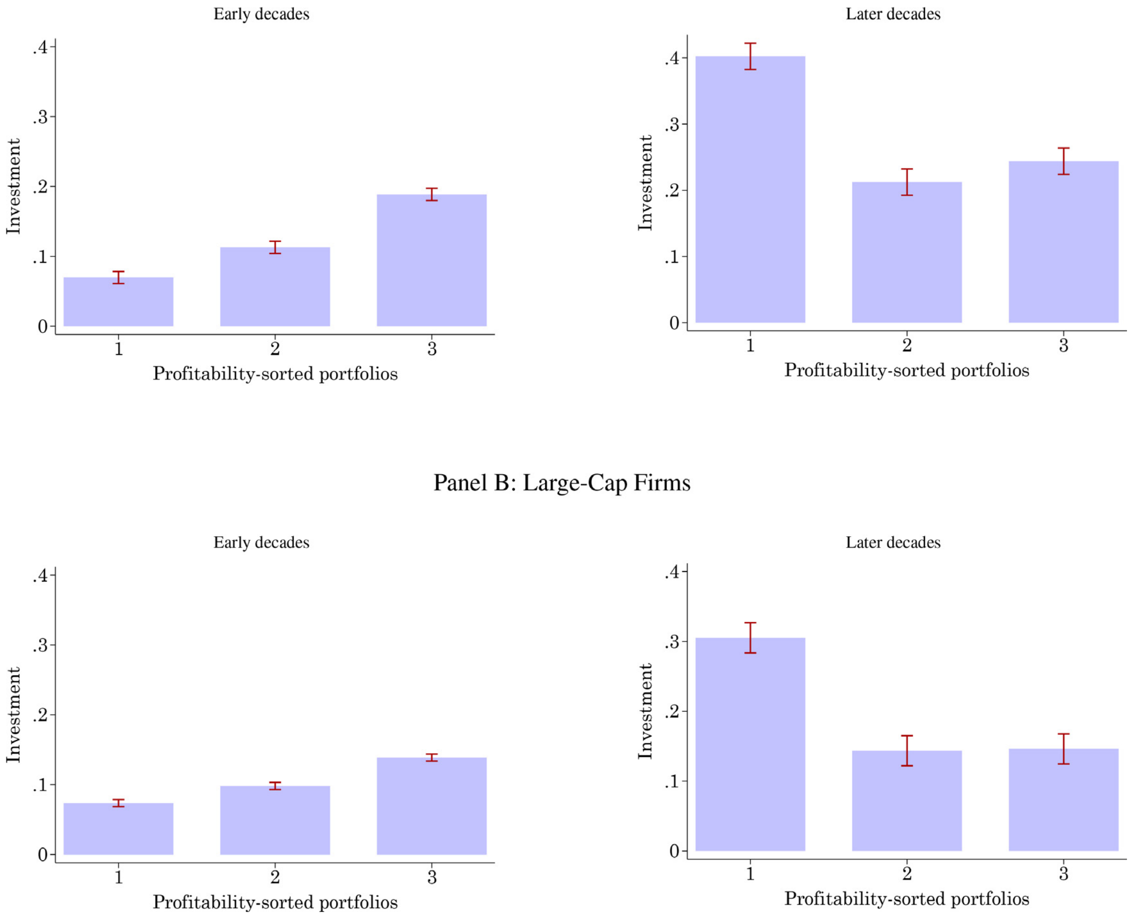

Fig. 3. Value-weighted average investment of profitability-sorted portfolios. This figure plots the value-weighted average investment rate of firms in three portfolios sorted by operating profitability of Fama and French (2015) during the early decades (1941–1979) and the later decades (1980–2017) for small-cap firms in Panel A and large-cap firms in Panel B. The investment rates of all firms are first averaged within each year weighted by market capitalization and then averaged across all years in the early and later decades. The standard error bars represent the time-series standard errors of each portfolio's annual investment rates within the respective sample periods. Data on investment and operating profitability before 1962 are from Wahal (2019). See Section 4.2 for more details and Appendix A.2 for variable definitions.

Table 9
Fama-French Investment and Profitability Premiums in Early and Later Decades.

	Early decades		Later decades	
	Mean	t-stat.	Mean	t-stat.
	Panel A: Double-sorted factor premiums			
CMA	0.11	[1.28]	0.28***	[2.70]
RMW	0.12	[1.45]	0.37***	[3.07]
	Panel B: Triple-sorted factor premiums			
CMA	0.16**	[2.01]	0.32***	[3.14]
RMW	0.17**	[2.33]	0.37***	[3.39]

This table reports the time-series average monthly percentage returns of the investment factor (CMA) and profitability factor (RMW). Early decades represent the period from July 1942 and June 1981. Later decades represent the period from July 1981 and June 2018. Fama-French CMA and RMW are based on 2-by-3 size-INV and 2-by-3 size-OP sorts as in Panel A. Panel B reports results for factors based on 2-by-3-by-3 sorts on size, INV, and OP. See Appendix A.2 for variable definitions and the sample selection. t-statistics are Newey-West adjusted with 3 months lag. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 10
Relation between Profitability, Tangible and Intangible Investments in Early and Later Decades.

Var:	(1) Roe	(2) R&D	(3) INTINV	(4) Cop
Var × *Later*	-0.90***	1.77***	2.26***	-0.35
	(0.08)	(0.57)	(0.53)	(0.24)
Var	0.93***	1.13***	0.63***	-0.53***
	(0.06)	(0.17)	(0.09)	(0.13)

This table reports the regression coefficients of the investment rate (I/A) on profitability (Roe), R&D investment rate, intangible investment rate (INTINV), and cash-based operating profitability (Cop) controlling for time (year-month) fixed effects. All variables are based on Compustat data, and the sample period is from January 1967 to June 2018. *Later* is a dummy variable indicating the period after June 1981 (the cutoff month that separates early and later decades in Section 4). See Appendix A for variable definitions and the sample selection. Standard errors, reported in parentheses, are double clustered by year and firm. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

We interpret these results as a potential resolution of the puzzle that investment and profitability premiums do not appear significant out of sample as documented by Linnainmaa and Roberts (2018) and Wahal (2019). According to traditional inference, poor out-of-sample performance suggests that the in-sample premium is a statistical artifact. Such inference reduces the incentive for researchers to explore the economic channels behind the in-sample premiums. However, economic foundations for empirical asset pricing factors like Hou et al. (2015)'s q-factors also have predictions about conditions under which the factors are expected to operate differently. In particular, the insight from the investment CAPM, that investment (profitability) is associated with expected returns *conditional* on profitability (investment), provides an explanation for the weakness of CMA and RMW factors in the historical data. The double-sorted investment and profitability premiums are not ideal for testing the investment CAPM, and their deficiency is most evident when investment and profitability are highly correlated like in the historical data. Hence, the weakness of historical CMA and RMW factors supports the investment CAPM instead of rejecting it. In addition, triple-sorted CMA (RMW) earns significant average returns in the historical data. While we cannot construct the historical q-factors because of data limitations, we expect the q-factors, which are triple sorted, to work well even in the pre-Compustat era.

Our analyses above highlight that the theory-driven question is not necessarily whether the in-sample premiums are the result of data snooping but why the cross-sectional relation between investment and profitability declined over time. While fully understanding the causes of this trend is beyond the scope of our paper, we highlight potential channels that may contribute to the decoupling between investment and profitability in modern eras.

A potential mechanism is the rise of intangible investment over the last few decades that has received significant attention in the literature (e.g., McGrattan and Prescott, 2010; Crouzet and Eberly, 2020). Intangible investments, such as R&D, raise the future growth prospects and long horizon cash flows of firms, but not necessarily short horizon cash flows. A potential reason for the decoupling of investment and profitability is the complementarity between tangible and intangible capital as proposed by Gourio and Rudanko (2014). The rise of intangibles might have increased the fraction of tangible capital that is complementary to intangibles and is installed to raise long horizon rather than short horizon cash flows. This channel would weaken the relation between investment and short-term expected profitability, while strengthening the relation between tangible and intangible investments.

Table 10 provides suggestive evidence in favor of the intangible investment channel using the Compustat sample. Column 1 of Table 10 confirms the weakening of the relation between I/A and Roe over time. I/A and Roe are significantly positively related in the early period but are close to orthogonal in the later period, after June 1981. At the same time, the relation between I/A and R&D investment is strengthened in the later period as shown in Column 2. This finding is consistent with the hypothesis that tangible and intangible investments are complements, and the rise of intangibles tightens this cross-sectional relation as a result. The strengthening of the relation between intangible and tangible investment also holds when part of SG&A is included in intangible investment following Peters and Taylor (2017) as shown in Column 3 of Table 10.[9]

What does the intangible investment channel imply for the relation between I/A and Cop over time? Different from Roe, Cop includes R&D expenses, which directly measure intangible investments. Hou et al. (2021) consequently show that the q^5 model accounts for intangible investment via the expected growth factor, which uses Cop as a key instrument. Hence, Cop has a profitability component that decoupled from I/A over time and an intangible investment component that became more related to I/A over time. Column 4 of Table 10 suggests that these two effects cancel out: there is no statistically significant change in the I/A-Cop relation in the Compustat period.[10] In sum, the rise of intangibles, along with some degree of complementarity between tangible and intangible investment, can potentially explain the decoupling of I/A and Roe, the strengthened relation between I/A and intangible investments, and the stable I/A-Cop relation over time.

The cross-sectional decoupling of investment and profitability may also be the reflection of increased industry concentration and monopoly power. Gutiérrez and Philip-

[9] Table IA.4 in the Internet Appendix shows that the results are robust to only including firms with non-missing R&D and to using Fama and French (2015)'s operating profitability (OP) measure.

[10] The loading of I/A on Cop is negative in both early and later periods because current asset growth moves I/A and Cop in opposite directions as discussed in Section 3.2.1.

pon (2017) argue that decreasing competition leads to higher markups and lower investment by leading firms. The rise of these high-markup and low-investment firms may have contributed to the decoupling between investment and profitability. Our study focuses on the asset pricing implications of the dynamic investment-profitability relation. We leave deciphering the different mechanisms driving the decoupled investment-profitability relation to future work.

5. Conclusion

In this paper, we uncover two new insights from the triangular cross-sectional relation between investment, expected profitability, and expected returns predicted by the investment CAPM. First, a high cross-sectional investment-profitability correlation weakens the *unconditional* relation between investment and expected returns and between profitability and expected returns. We find strong empirical support for this prediction in industries featuring a high cross-sectional investment-profitability correlation. Second, the investment CAPM predicts *conditional* investment and profitability premiums regardless of the investment-profitability correlation. That is, expected returns decrease in investment holding expected profitability constant, and that expected returns increases in expected profitability holding investment constant. We empirically confirm this prediction by showing that investment and profitability factors based on triple sorts on size, investment, and profitability, as in the empirical design of Hou et al. (2015)'s q-factors, resurrects investment and profitability premiums in samples featuring a high investment-profitability correlation. We also apply our insights to the dynamic investment CAPM and show similar results for the cross-sectional relation between investment and expected growth. Our findings highlight the cross-sectional relations among investment, profitability, and expected growth as important empirical moments for studies of investment, profitability, and expected growth premiums.

Our insights from the investment CAPM have important implications for the interpretation of out-of-sample results. For instance, while both the unconditional investment premium and profitability premium are insignificant in the pre-Compustat era, the significant in-sample premiums are not necessarily artifacts of data snooping. The high cross-sectional correlation between investment and profitability in the historical periods, as we uncover, implies weak premiums according to the investment CAPM. Consequently, triple sorts on size, investment, and profitability resurrect the historical premiums.

Appendix A. Sample selection and variable definitions

A1. q-Factors

A1.1. Data and characteristics

We obtain stock information from the Center for Research in Security Prices (CRSP) database. Our sample includes common shares of NYSE, Amex, and NASDAQ stocks from January 1967 to June 2018. We exclude financial firms (SIC codes 6000–6999) and firms with negative book equity.

Following Hou et al. (2015), we use Compustat Annual and Quarterly Fundamental Files to extract accounting information for constructing investment-to-assets (I/A), profitability (Roe), cash-based operating profitability (Cop), and other firm-level measures. We measure investment-to-assets, I/A, as the annual growth rate of total assets: $\text{I/A}_t = (\text{at}_t - \text{at}_{t-1})/\text{at}_{t-1}$. We measure profitability as Roe, which is quarterly income before extraordinary items divided book equity in the previous quarter: $\text{Roe}_q = \text{ibq}_q/\text{be}_{q-1}$. We measure Cop as cash-based operating profits scaled by book assets following Ball et al. (2016) and Hou et al. (2021).[11] We winsorize each variable at the 1%–99% levels in each month to mitigate the impact of outliers.

Following Hou et al. (2015), we measure quarterly book equity as shareholders' equity, plus balance-sheet deferred taxes and investment tax credit (item TXDITC) if available, minus the book value of preferred stock.[12] As pointed out by Hou et al. (2019), Compustat Quarterly Fundamental Files have limited coverage of book equity prior to January 1972. We follow Hou et al. (2019) and impute book equity in the fourth fiscal quarter using year-end book equity if available and the remaining missing quarterly book equity using the clean surplus relation.

We merge I/A, Roe, and Cop with monthly stock returns in CRSP using the Compustat-CRSP link table. In particular, annual I/A in the fiscal year ending in t is matched with stock returns from July of year $t+1$ to June of year $t+2$. For January 1972 onward, we match monthly stock returns with the most recent Roe based on the Compustat quarterly earnings announcement date (item RDQ). As noted by Hou et al. (2019), quarterly earnings announcement dates are missing in Compustat prior to January 1972. We follow Hou et al. (2019) and match monthly stock returns before January 1972 with Roe using Compustat quarter-end date and require at least a 4-month lag between the quarter-end date and stock return month.[13] We match monthly stock returns with Cop requiring at least a 4-month lag between the fiscal year-end and stock return month following the timing alignment in Hou et al. (2021).

[11] We compute cash-based operating profits using Compustat Annual Fundamental Files as total revenue (item REVT) minus cost of goods sold (item COGS), minus selling, general, and administrative expenses (item XSGA), plus research and development expenditures (item XRD, zero if missing), minus change in accounts receivable (item RECT), minus change in inventory (item INVT), minus change in prepaid expenses (item XPP), plus change in deferred revenue (item DRC plus item DRLT), plus change in trade accounts payable (item AP), and plus change in accrued expenses (item XACC).

[12] Shareholder's equity is measured from Compustat Quarterly Fundamental File as stockholders' equity (item SEQQ) if available and otherwise as common equity (item CEQQ) plus the carrying value of preferred stock (item PSTKQ) if available and otherwise as total assets (item ATQ) minus total liabilities (item LTQ). The book value of preferred stock is measured as the redemption value (item PSTKRQ) if available and otherwise as the carrying value for the book value of preferred stock (item PSTKQ).

[13] We also require that the Compustat quarter-end date is no more than 6 months before the stock return month to remove stale earnings information.

A1.2. Portfolio construction

We conduct double (2-by-3), triple (2-by-3-by-3), and quadruple (2-by-3-by-3-by-3) portfolio sorts in this paper. At the end of each June, we independently sort stocks on size and I/A. We also independently sort stocks on Roe and Cop in each month. We define large and small firms based on the median NYSE size, and we define high and low I/A, Roe, and Cop based on 30% and 70% of their respective distributions among NYSE stocks. We then aggregate monthly returns and firm characteristics to the portfolio level weighted by stocks' market capitalization.

A1.3. Replication of q*-factors*

Hou et al. (2015) and Hou et al. (2019) construct *q*-factors based on 2-by-3-by-3 sorts on size, I/A, and Roe. Our triple-sorted investment and profitability factors replicate the *q*-factors well. The correlation of our investment factor with the original $R_{I/A}$ is 98.9% from January 1967 to June 2018 and 99.1% from January 1972 to June 2018.[14] The correlation of our profitability factor with the original R_{Roe} is 99.3% from January 1967 to June 2018 and 99.3% from January 1972 to June 2018. The correlation of our size factor and the original R_{ME} is 99.8% from January 1967 to June 2018 and 99.8% from January 1972 to June 2018.

A1.4. Constructing the high-Corr and low-Corr samples

In our analysis in Section 2, we use samples of 2-digit SIC industries with high and low correlation between I/A and Roe. Similarly, we use samples of 2-digit SIC industries with high and low correlation between I/A and Cop in Section 3. Tiny firms have volatile I/A, Roe, and Cop, which can affect our estimation of within-industry correlations. We thus exclude firms with a market capitalization below the 5th NYSE size percentile. Note that this corresponds to only the smallest firms in the microcap category, which is typically defined as a firm with a market capitalization below the 20th NYSE size percentile (Fama and French, 1993; Hou et al., 2022). We refer to this sample as the "full sample" in Sections 2 and 3.

We compute the within-industry correlations between I/A and Roe in each month by equally weighting firms. We then place the top tercile of firms with the highest within-industry correlation in the High-*Corr* sample and the bottom tercile of firms in the Low-*Corr* sample. The High-*Corr* sample includes an average of 494 firms from 14 industries with an average monthly I/A-Roe correlation of 0.23. The Low-*Corr* sample includes an average of 599 firms from 12 industries with an average monthly I/A-Roe correlation of -0.12. Similarly, we compute within-industry correlations between I/A and Cop and assign the top tercile of firms with the highest correlation in the High-$Corr_{Cop}$ sample and the bottom tercile of firms in the Low-$Corr_{Cop}$ sample.

A2. Fama-French factors

A2.1. Data and characteristics

We obtain stock information from the CRSP database. Our sample includes common shares of NYSE, Amex, and NASDAQ stocks from July 1942 to June 2018.

For the period from July 1963 to June 2018, we construct our sample and factors using the Compustat Annual database following Fama and French (2015). For the period from July 1942 to June 1963, we construct our sample and factors based on historical firm investment and profitability measures from Wahal (2019), which are hand-collected from the Moody's Industrial, Bank and Finance, or Utility Manual. Linnainmaa and Roberts (2018) independently hand-collect similar information from Moody's Manuals. We also obtain historical investment and profitability factors from Linnainmaa and Roberts (2018) to check the robustness of our results.

We measure investment (INV) and profitability (OP) following Fama and French (2015). Investment is defined as the annual growth rate of total assets: $\text{INV}_t = (\text{at}_t - \text{at}_{t-1})/\text{at}_{t-1}$. Operating profitability is defined as revenue minus the cost of goods sold, SG&A, and interest expenses all normalized by the book value of equity: $\text{OP}_t = (\text{revt}_t - \text{cogs}_t - \text{xsga}_t - \text{xint}_t)/\text{be}_t$.[15]

We also measure research and development (R&D) investments and the intangible investment rate. R&D investment is defined as R&D expenses divided by lagged total assets: $\text{R\&D}_t = \text{xrd}_t/\text{at}_{t-1}$, where missing values for *xrd* are filled in with a zero. The intangible investment rate is defined as the sum of R&D expenses and 30% of SG&A expenses following Peters and Taylor (2017) and normalized by lagged total assets: $\text{INTINV}_t = (\text{xrd}_t + 30\%\ \text{sga}_t)/\text{at}_{t-1}$, where *sga* is constructed following Appendix B.1 of Peters and Taylor (2017). We winsorize each variable at the 1%–99% levels in each month to mitigate the impact of outliers.

A2.2. Portfolio construction

Similar to our *q*-factor analysis, we conduct double (2-by-3) and triple (2-by-3-by-3) portfolio sorts on INV and OP. At the end of each June, we independently sort stocks by size, INV, and OP. For the double and triple sorts, we define large and small firms based on the median of NYSE size, and we define high and low INV and OP based on 30% and 70% of their respective distributions among NYSE stocks. We then aggregate monthly returns and firm characteristics to the portfolio level weighted by stocks' market capitalization.

A2.3. Replication of the Fama-French five factors

Fama and French (2015) construct the investment (CMA) and profitability (RMW) factors based on 2-by-3 sorts on size-INV and size-OP, respectively. Our double-sorted investment and profitability factors replicate CMA and RMW well. The correlation of our CMA (RMW) factor with the original CMA (RMW) factor is 99.5% (98.3%) from July 1963 to June 2018.[16] Given the high correlation, we refer to our replicated CMA and RMW as the FF five factors in our analyses unless otherwise stated.

[14] We obtain the original *q*-factors from http://global-q.org/.

[15] Linnainmaa and Roberts (2018) construct the operating profitability measure without subtracting the SG&A expenses.

[16] We obtain the original CMA and RMW from Kenneth French's website.

A2.4. Constructing high-Corr and low-Corr samples

In Section 2.6, we use samples of 2-digit SIC industries with high and low correlation between INV and OP. Following our procedure in Section A.1.4, we exclude firms with market capitalization below the 5th NYSE size percentile. We refer to this sample as the “full sample” in Section 2.6. Next, we compute the within-industry correlations between INV and OP by equally weighting firms. We then place the top tercile of firms with the highest correlation in the High-*Corr* sample and the bottom tercile of firms in the Low-*Corr* sample in Section 2.6. The High-*Corr* sample includes an average of 715 firms from 17 industries with an average INV-OP correlation of 0.23. The Low-*Corr* sample includes an average of 876 firms from 15 industries with an average INV-OP correlation of -0.11.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfineco.2022.06.003.

References

Ball, R., Gerakos, J., Linnainmaa, J.T., Nikolaev, V., 2016. Accruals, cash flows, and operating profitability in the cross section of stock returns . J. Financ. Econ. 121 (1), 28–45. doi:10.1016/j.jfineco.2016.03.002.

Ball, R., Gerakos, J., Linnainmaa, J.T., Nikolaev, V.V., 2015. Deflating profitability . J. Financ. Econ. 117 (2), 225–248. doi:10.1016/j.jfineco.2015.02.004.

Cooper, M.J., Gulen, H., Ion, M., 2020. The Use of Asset Growth in Empirical Asset Pricing Models. Working paper.

Cooper, M.J., Gulen, H., Schill, M.J., 2008. Asset growth and the cross-section of stock returns. J. Finance 63 (4), 1609–1651. doi:10.1111/j.1540-6261.2008.01370.x.

Crouzet, N., Eberly, J., 2020. Rents and Intangible Capital: A Q+ Framework. Working Paper. Northwestern University.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33 (1), 3–56. doi:10.1016/0304-405X(93)90023-5.

Fama, E.F., French, K.R., 2006. Profitability, investment and average returns. J. Financ. Econ. 82 (3), 491–518. doi:10.1016/j.jfineco.2005.09.009.

Fama, E.F., French, K.R., 2008. Dissecting anomalies. J. Finance 63 (4), 1653–1678. doi:10.1111/j.1540-6261.2008.01371.x.

Fama, E.F., French, K.R., 2015. A five-factor asset pricing model . J. Financ. Econ. 116 (1), 1–22. doi:10.1016/j.jfineco.2014.10.010.

Fama, E.F., French, K.R., 2017. International tests of a five-factor asset pricing model. J. Financ. Econ. 123 (3), 441–463. doi:10.1016/j.jfineco.2016.11.004.

Fazzari, S.M., Hubbard, R.G., Petersen, B.C., Blinder, A.S., Poterba, J.M., 1988. Financing constraints and corporate investment. Brookings Pap. Econ. Act. (Washington) (1) 141.

Gonçalves, A.S., Xue, C., Zhang, L., 2020. Aggregation, capital heterogeneity, and the investment CAPM. Rev. Financ. Stud. 33 (6), 2728–2771. doi:10.1093/rfs/hhz091.

Gourio, F., Rudanko, L., 2014. Can intangible capital explain cyclical movements in the labor wedge? Am. Econ. Rev. 104 (5), 183–188.

Graham, B., Dodd, D., 1934. Security Analysis. McGraw-Hill: New York.

Gutiérrez, G., Philippon, T., 2017. Declining Competition and Investment in the U.S. Working Paper 23583. National Bureau of Economic Research doi:10.3386/w23583.

Harvey, C.R., Liu, Y., Zhu, H., 2016. … And the cross-section of expected returns. Rev. Financ. Stud. 29 (1), 5–68.

Hou, K., Mo, H., Xue, C., Zhang, L., 2019. Which factors? . Rev. Financ. 23 (1), 1–35. doi:10.1093/rof/rfy032.

Hou, K., Mo, H., Xue, C., Zhang, L., 2021. An augmented q-factor model with expected growth. Rev. Financ. 25 (1), 1–41. doi:10.1093/rof/rfaa004.

Hou, K., Mo, H., Xue, C., Zhang, L., 2022. The Economics of Security Analysis. Working paper.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: an investment approach. Rev. Financ. Stud. 28 (3), 650–705.

Jensen, T.I., Kelly, B.T., Pedersen, L.H., 2021. Is There A Replication Crisis In Finance? Technical Report w28432. National Bureau of Economic Research doi:10.3386/w28432.

Kaplan, S.N., Zingales, L., 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? Q. J. Econ. 112 (1), 169–215. doi:10.1162/003355397555163.

Kumar, P., Li, D., 2016. Capital investment, innovative capacity, and stock returns. J. Finance 71 (5), 2059–2094.

Linnainmaa, J.T., Roberts, M.R., 2018. The history of the cross-section of stock returns. Rev. Financ. Stud. 31 (7), 2606–2649. doi:10.1093/rfs/hhy030.

Liu, L.X., Whited, T.M., Zhang, L., 2009. Investment-based expected stock returns. J. Polit. Economy 117 (6), 1105–1139. doi:10.1086/649760.

McGrattan, E.R., Prescott, E.C., 2010. Unmeasured investment and the puzzling us boom in the 1990s. Am. Econ. J. 2 (4), 88–123.

Mclean, R.D., Pontiff, J., 2016. Does academic research destroy stock return predictability? J. Finance 71 (1), 5–32. doi:10.1111/jofi.12365.

Novy-Marx, R., 2013. The other side of value: the gross profitability premium. J. Financ. Econ. 108 (1), 1–28. doi:10.1016/j.jfineco.2013.01.003.

Peters, R.H., Taylor, L.A., 2017. Intangible capital and the investment-q relation. J. Financ. Econ. 123 (2), 251–272.

Titman, S., Wei, K.-C., Xie, F., 2004. Capital investments and stock returns. J. Financ. Quant. Anal. 39 (04), 677–700.

Wahal, S., 2019. The profitability and investment premium: pre-1963 evidence. J. Financ. Econ. 131 (2), 362–377. doi:10.1016/j.jfineco.2018.09.007.

Xing, Y., 2008. Interpreting the value effect through the q-theory: an empirical investigation. Rev. Financ. Stud. 21 (4), 1767–1795. doi:10.1093/rfs/hhm051.

Zhang, L., 2017. The investment CAPM. Eur. Financ. Manage. 23 (4), 545–603.