▪ Advances in Scientific and Applied Accounting, ▪ ISSN 1983-8611 ▪ São Paulo ▪ v.16, n.1 ▪ p. 251-266 ▪ Jan. / Apr. de 2023
▪ DOI: 10.14392/asaa.2022160108

Operational investments in R&D as a strategy for differentiated performance

Henrique Suathê Esteves[1], José Francisco Moreira Pessanha[2], Ricardo Lopes Cardoso[3], Renata Kaori Tani Viana[4]

[1]Secretaria de Estado da Fazenda do Rio de Janeiro, Rio de Janeiro, Rio de Janeiro, Brazil
[2]Universidade do Estado do Rio de Janeiro, Rio de Janeiro, Rio de Janeiro, Brazil
[3]Fundação Getúlio Vargas | Universidade do Estado do Rio de Janeiro, Rio de Janeiro, Rio de Janeiro, Brazil
[4]Universidade de São Paulo, São Paulo, São Paulo, Brazil

[1]henrique.suathe@gmail.com
[2]professorjfmp@hotmail.com
[3]ricardo.cardoso@fgv.br
[4]rkaoritv@gmail.com

Edited by:
Moacir Manoel Rodrigues Junior

Abstract

Objective: To analyze the contribution of operational investment strategies focused on R&D to the generation of distinguished returns compared to strategies focused on Capex.
Method: Based on the Fama and French's 3, 5 and 6-factor models, the generation of distinguished returns was measured through the abnormal returns of portfolios sorted to segregate stocks by size and R&D or Capex levels.
Results: There was no significant relationship between Capex levels and an increase in abnormal returns. In portfolios sorted by R&D, a significant relationship was observed between R&D levels and an increase in abnormal returns for microcaps and smallcaps, regardless of the model used. It was also found that the generation of abnormal returns by microcaps with high R&D investments does not depend on the level of investments in Capex.
Contribution: The literature has rejected the existence of abnormal returns of aggressive R&D firms in value-weighted portfolios. This study innovates in the way portfolios are sorted, showing that the relationship between abnormal returns and R&D comes mainly from low market value stocks, even with the use of weighted returns, and that such relationship is considered robust by the main pricing models currently in use. With its findings, this research provides theoretical and empirical support to academia and accounting standard-setting bodies, demonstrating the value relevance of R&D investments. In addition, this study contributes to society and the market by potentially helping companies and shareholders to allocate their resources efficiently.

Keywords: R&D; Capex; Abnormal return; Asset pricing; Fama and French.

How to cite:

Esteves, H. S., Pessanha, J. F. M., Cardoso, R. L., & Viana, R. K. T. (2023). Operational investments in R&D as a strategy for differentiated performance. Advances in Scientific and Applied Accounting, 16(1), 234–250/251. https://doi.org/10.14392/asaa.2022160108

Received: August 01, 2022
Required revisions: September 26, 2022
Accepted: June 07, 2023

© Copyright 2023

Introduction

Due to concerns regarding the reliability, objectivity, and relevance of internally generated intangible capital (IC) for the value of companies, particularly expenditures related to research and development (R&D), the main accounting standards have historically adopted strict rules for its recognition that still have an impact on current standards (Aboody & Lev, 1998).

Currently, in the US, Accounting Standards Codification (ASC) 350: Intangibles - Goodwill and other establishes that, predominantly, only expenditures related to the development of software for external use whose technological feasibility can be demonstrated should be capitalized. The amounts invested in other forms of R&D should be expensed directly in the income statement of the period in question.

In the international context, International Accounting Standards (IAS) 38: Intangible assets allows for the capitalization of internally generated expenditures on IC for commercial purposes when these expenditures reach the development stage, provided that technological, market, and financial viability of the project is demonstrated. However, IAS 38 expressly forbids the capitalization of expenditures related to internally generated brands, publishing titles, customer lists, and other similar items. Therefore, both in the US and under international accounting standards, most of the investment in internally generated IC cannot be capitalized. These expenditures can only be incorporated into the balance sheet when they originate from purchase or, as a last resort, through business combination.

According to Lev and Gu (2016), despite its restricted recognition in accounting standards, IC has proven to be the true differential when it comes to generating growth and value in companies. Fixed assets, inventory, and even financial assets have become mere commodities, available to all competitors. Only operational investments in IC have the ability to generate distinguished returns.

Corroborating this idea, Lev and Sougiannis (1999), Chan et al. (2001), Li (2011), Gu (2016), among others, have observed that companies that aggressively invest in R&D are rewarded in the market with apparent abnormal returns. However, this relationship appears to be highly sensitive to methodology. Hou et al. (2015, 2017, 2021) and Taques et al. (2022) have shown that abnormal returns from R&D, as well as other anomalies, depend on the pricing model used, the measurement of accounting proxies, and how the studied portfolios are formed. Thus, in light of the new asset pricing models that have emerged since the 2010s, the anomaly of R&D in previous studies has apparently ceased to exist for value-weighted portfolios, thus, conflicting with studies that adopted different approaches to calculate abnormal returns (Dargenidou et al., 2021; Mazzi et al., 2019).

Based on the above, this study seeks to answer the following question: “Do operational investments in R&D contribute to a distinguished performance of companies?”.

Studies on the impacts of operational investments in R&D have become increasingly important due to the growing trend of such investments by companies. In 1977, investments in tangible assets such as buildings, machinery, and inventory accounted for 16% of the gross value added of the US economy, while investments in IC, such as R&D, patents, information systems, brands, and media content, accounted for only 8% (Gu & Lev, 2017; Lev, 2019).

Over the years, the level of investments in tangible assets has been declining, while the level of investments in IC has been on the rise. In 1991, for the first time in US history, the volume of investments in IC surpassed that in tangible assets. By the end of 1999, the value of technology and pharmaceutical companies accounted for approximately 40% of the Standard & Poor's 500 index. In aggressive companies, investments in R&D even surpassed the reported profits (Chan et al., 2001). In 2016, the same investments in tangible assets represented only 10% of the gross value added of the economy, while investments in IC nearly doubled, reaching 15% (Gu & Lev, 2017; Lev, 2019).

Therefore, studying the performance of companies that invest aggressively in R&D helps to explain the wave of investments in IC. It is valuable not only from the perspective of companies, but also from that of external investors who equally benefit from such strategies when constructing their stock portfolios. Through its findings, in addition to contributing to society and the market by assisting companies and shareholders in the efficient allocation of their resources, this research provides theoretical and empirical support to academia and accounting regulatory bodies, highlighting the value relevance of investments in R&D.

The general objective of this research is to analyze the contribution of operational investment strategies focusing on R&D to the generation of distinguished returns compared to strategies focusing on Capex. The choice for a comparative analysis is based on the long-term investment choices that a company can make, that is, prioritizing the allocation of resources in IC or physical assets. To achieve the research objectives, the Fama and French (1993, 2015, 2016) 3, 5, and 6-factors pricing models were used aiming to analyze the validity of the research hypotheses.

As Fama (1998) emphasized, anomaly studies are highly sensitive to changes made to the techniques used, and numerous anomalies identified in the past 'ceased to exist' simply because a pricing model would be replaced by another. Many of these anomalies were not even able to withstand simple changes in portfolio organization or return measurement (Hou et al., 2020), which makes it important to test the robustness of research results on abnormal returns with different methodologies. In this regard, this research seeks to contribute to the literature by using portfolios organized differently from those adopted in previous studies on abnormal returns of R&D, especially regarding portfolio breakpoints and segregation of stocks by size ranges. Additionally, it aims to add to the literature tests with the Fama and French (2015) 5-factor model, also comprising the Carhart (1997) momentum factor, as introduced in Fama and French (2016). With these methodological modifications, it was possible to obtain results that complement the current literature, as will be seen throughout this article.

2 Background and Development of the Hypotheses

Since the 2000s, studies on the relationship between R&D expenditures and market value have become more sophisticated, employing asset pricing models to validate their findings. One of the most significant studies during this period is that by Chan et al. (2001).

Chan et al. (2001) identified that portfolios of companies with high R&D/MCap levels (R&D expenses relative to market capitalization) showed superior returns compared to portfolios with low R&D/MCap levels and portfolios of companies with no R&D expenditures. Portfolios created based on the metric R&D/Sales were unable to demonstrate the same pattern. By employing a modified Fama and French (1993) 3-factor model that captured past stock performance through two additional factors, it was shown that the superior returns attributed to portfolios with high R&D/MCap levels were also abnormal returns. Chambers et al. (2002) and Eberhart et al. (2004) conducted studies similar to that of Chan et al. (2001), drawing the same conclusions regarding abnormal returns of portfolios sorted by R&D metrics.

Different explanations have emerged to justify the abnormal returns of these companies. According to Chan et al. (2001), investors used to be highly pessimistic about the future prospects of firms that heavily invested in R&D due to a historical tendency of these firms' stocks to provide low returns. Chambers et al. (2002), on the other hand, dismiss mispricing as a factor and believe that abnormal returns stemmed from inadequate risk control through the incorporation of pricing model factors. The findings of Li (2011) indicate that abnormal returns may be related to the financial constraints faced by these firms. Meanwhile, Gu (2016) identified that the relationship between R&D investments and abnormal returns exists only for companies subject to intense competition.

Until the early 2010s, anomalies associated with R&D investments were primarily tested using the Fama and French (1993) 3-factor pricing model. Then, Hou et al. (2015, 2017, 2021) conducted a comprehensive battery of tests using pricing models. Hou et al. (2015) tested a series of anomalies based on IC, such as the R&D/Sales and R&D/MCap ratios, using the capital asset pricing model (CAPM) developed by Sharpe (1964), Lintner (1965), and Mossin (1966), the Fama and French 3-factor (1993) model, Carhart's (1997) momentum factor model, and the q-factor model by Hou et al. (2015).

Hou et al. (2017) added to the same battery of tests the liquidity factor model by Pástor and Stambaugh (2003) and the Fama and French (2015) 5-factor model. It was found that among the significant anomalies based on R&D pointed out in the literature, only the anomaly of the R&D/MCap ratio proved to be robust, regardless of the pricing model used. This occurred when R&D portfolios excluded microcaps and considered equal-weighted returns. These results suggest that this anomaly particularly affects growth stocks, as the exclusion of microcaps from the tested portfolios not only retains a portion of smallcaps (small, but not micro stocks), but also increases the impact of the return of these stocks on the portfolios by using equally-weighted returns instead of value-weighted returns.

Based on the above, the following research hypotheses were formulated:

Hypothesis 1: Stocks of companies that invest aggressively in Capex generate superior abnormal returns compared to stocks of companies that invest conservatively in Capex.

Hypothesis 2: Stocks of companies that invest aggressively in R&D generate superior abnormal returns compared to stocks of companies that invest conservatively in R&D.

Hypothesis 3: Regardless of the level of R&D investments, stocks of companies benefit from an increase in Capex investments, resulting in abnormal returns.

Hypothesis 4: Regardless of the level of Capex investments, stocks of companies benefit from an increase in R&D investments, resulting in abnormal returns.

The fact that operational investments in IC are currently overlapping physical asset investments may indicate distinguished returns. Therefore, it is expected that operational investments in R&D will contribute to companies' distinguished performances, through the generation of abnormal returns in their stocks, whereas the same is not expected when it comes to Capex investments.

3 Methodological Procedures

3.1 Sample

The initial sample consisted of the common stocks of US companies listed on NYSE, Amex, and Nasdaq by March 30, 2020, with available information related to the period between July 1991 and June 2018, which covers 27 years (324 months). The research window spans the period in which IC investments exceeded physical asset investments in the US. Summary information on the number of companies in the final sample is presented in Table 5, in the Appendices section.

Conducting the study on US companies allowed for a substantial increase in the number of firms included in the research. Due to the limited number of publicly traded companies in Brazil, in a highly concentrated and reduced liquidity market (Assaf Neto et al., 2008), a sample composed of Brazilian firms would result in not truly diversified portfolios. Another important point is that the major existing pricing models have been adjusted based on the US stock market. According to Assaf Neto et al. (2008), the inherent characteristics of the Brazilian emerging market render the application of pricing models in such market unreliable, which is why these models need to be fitted.

3.2 Model

Regression intercepts can be used as a formal test to identify which models best fit market returns (Fama & French, 1993). The best pricing model, therefore, is the one that reduces to zero (or minimizes) the intercept for most of the studied portfolios. A poorly fitted pricing model can be misleading, as it may lead one to assume that the returns will be abnormal or, as commonly referred to in the asset pricing literature, market anomalies.

In order to obtain a model that can explain the variation of returns for as many portfolios as possible, the Fama and French (2015) 5-factor model, supplemented with Carhart's (1997) momentum factor (up minus down, UMD), as used in Fama and French (2016), presented in Eq. (4), was embraced. However, since there is evidence that models with more factors do not always outperform for all types of portfolios (Ball et al., 2016; Hou et al., 2015, 2017, 2021), the Fama and French (1993, 2015) 3-factor and 5-factor models, respectively presented in Eq. (2) and (3), were used complementarily. Additionally, a model consisting only of the market factor, equivalent to CAPM, was employed for comparison purposes, presented in Eq. (1).

$$R_{it} - R_{Ft} = a_i + b_i \cdot (R_{Mt} - R_{Ft}) + e_{it} \quad (1)$$

$$R_{it} - R_{Ft} = a_i + b_i \cdot (R_{Mt} - R_{Ft}) + s_i \cdot SMB_t + h_i \cdot HML_t + e_{it} \quad (2)$$

$$R_{it} - R_{Ft} = a_i + b_i \cdot (R_{Mt} - R_{Ft}) + s_i \cdot SMB_t + h_i \cdot HML_t + r_i \cdot RMW_t + c_i \cdot CMA_t + e_{it} \quad (3)$$

$$R_{it} - R_{Ft} = a_i + b_i \cdot (R_{Mt} - R_{Ft}) + s_i \cdot SMB_t + h_i \cdot HML_t + r_i \cdot RMW_t + c_i \cdot CMA_t + m_i \cdot UMD_t + e_{it} \quad (4)$$

In Eq. (1), (2), (3), and (4), R_{it} represents the return in month *t* of the portfolio *i* studied. R_{Ft} is the risk-free asset return at the beginning of month *t*, represented by the US one-month treasury bill rate. R_{Mt} is the weighted average return of the market representative portfolio. R_{Mt}-R_{Ft} is the market factor. SMB_t is the size factor, represented by the difference in returns between a portfolio of smallcaps and another one of bigcaps. HML_t is the value factor, represented by the difference in returns between a portfolio of high *B/M* stocks and one of low *B/M* stocks. RMW_t is the profitability factor, represented by the difference in returns between a portfolio of robust profitability stocks and another one of weak profitability stocks. CMA_t is the investment factor, represented by the difference in returns between a portfolio of conservative stocks (low investment) and a portfolio of aggressive stocks (high investment). UMD_t is the *momentum* factor, represented by the difference in returns between an ascending portfolio of stocks (up), with positive cumulative returns and a descending portfolio of stocks (down), with negative cumulative returns. The regression coefficients b_i, s_i, h_i, r_i, c_i and m_i correspond to the degrees of exposure to the factors. The random variable e_{it} represents the regression error, normally distributed, with zero mean. The intercept a_i is the abnormal return of the portfolio *i* in question.

3.3 Variables

The independent variables used, represented on the right-hand side of Eq. (1), (2), (3), and (4) by factors R_M-R_F, *SMB*, *HML*, *RMW*, *CMA*, and *UMD*, represent the returns, for each month *t*, of diversified portfolios created to capture the variation of returns from as many portfolios as possible. The monthly factors were obtained from Kenneth French's website[1], where they were calculated following the procedures established by Fama and French (1993, 2015, 2016).

The dependent variables used, represented on the left-hand side of Eq. (1), (2), (3), and (4) by R_i-R_F, refer to the excess return of diverse portfolios R_i, where each group of portfolios R_i is organized based on R&D or Capex characteristics, related to the risk-free rate, R_F, for each month *t*. The information for measuring R&D and Capex characteristics, as well as the prices used for portfolio construction, was obtained from the Capital IQ database of Standard & Poor's[2].

The portfolio groups for each characteristic were created in accordance with a set of procedures similar to those of Fama and French (1993, 2015, 2016), extensively replicated in the literature on market anomalies.

According to Fama and French (2015), returns of value-weighted portfolios can be dominated by a small number of stocks with high market value, which is a concerning limitation in portfolios organized around a single accounting characteristic other than size (univariate portfolios). Thus, separating the portfolios into at least two size levels would be justifiable.

Despite the problem of contamination by high market value stocks, Hou et al. (2017) emphasize that the true challenge faced by pricing models is actually explaining the return patterns of microcaps, which tend to be undervalued when using value-weighted returns. Based on this, a separation into three size levels was adopted in this research.

On the last day of June of each year *t*, US common stocks from Nyse, Amex, and Nasdaq were divided into three groups based on the 20th and 50th percentiles of Nyse stock market value, representing microcaps (up to the 20th percentile), smallcaps (between the 20th and 50th percentiles), and bigcaps (above the 50th percentile). Next, the stocks from each of the three size-based groups were independently divided into three new groups based on the 30th and 70th percentiles of the desired characteristics (R&D or Capex) observed in Nyse companies in the fiscal year prior to portfolio formation (*t-1*). These three groups represent low (conservative), neutral, and high (aggressive) companies regarding those characteristics. The 3×3 process of organizing portfolios by size (microcaps, smallcaps, and bigcaps) and one desired characteristic at a time (low, neutral, and high companies for the desired characteristic) created nine R_i size-characteristic portfolios.

Stocks were allocated to portfolios whenever they had all the information necessary for measuring the specific size-characteristic portfolio. Thus, a particular stock may have been allocated, for example, to the size-R&D portfolios, but not to the size-Capex ones. Another important point is that, due to annual rebalancing, new stocks were included in the portfolios in the year they started to be listed.

After the organization procedure, the average monthly return of each of the nine R_i size-characteristic portfolios was calculated, weighted by the market value of the stocks on the portfolio formation date, from July *t* to June *t+1*.

From the excess return, R_i-R_F, of these nine individual size-characteristic portfolios, portfolios were derived by the time series of differences between the average returns of portfolios with significant investments (high/aggressive) considering the characteristic in question and the average returns of portfolios with modest investments (low/conservative) also considering a given characteristic, which was symbolized by *Hi-Lo*, for each size segregation, as presented in Figure 1 of the Appendices.

The formation of *Hi-Lo* portfolios as a means to test the significance of the return difference between high and low portfolios considering a particular characteristic is widely used in literature on anomalies, as seen in Fama

1 https://mba.tuck.dartmouth.edu/pages/faculty/ken.french.

2 https://www.capitaliq.com.

and French (1993, 2015), Titman et al. (2004), Ball et al. (2016), Gu (2016), Hou et al. (2015, 2017, 2021), Taques et al. (2022), among others.

With the addition of the *Hi-Lo* portfolios, 12 portfolios were created for each characteristic. Analyzing the nine original individual portfolios would allow us to investigate how return patterns evolved with the impact of the characteristics that were put to test. However, only the analysis of the three *Hi-Lo* portfolios confirms that the cause of this impact was indeed an increase in the level of these characteristics, which are the focus of this research. The regression intercept of the returns of each of the three *Hi-Lo* portfolios against the factors in Eq. (1), (2), (3), and (4) represents the average difference between the aggressive and modest portfolios in a given characteristic, for various size segregations, in terms of abnormal return. The application of a two-tailed t-test to the intercept indicates the significance of this difference. When the intercept presented by the *Hi-Lo* portfolios was positive and significant at a 5% level (p-value ≤ 5%), it could be confirmed that the characteristic in question had a positive impact on the generation of abnormal returns.

In order to better isolate the effect of investments in R&D and Capex on returns, trivariate portfolios that explicitly control for size, R&D, and Capex simultaneously were also created, as shown in Figure 2, in the Appendices section.

The trivariate portfolios used a 3x2x3 division. On the last day of June in each year *t*, the US common stocks from Nyse, Amex, and Nasdaq were divided into three size groups, as usual, based on the 20th and 50th percentiles of Nyse stock market value, representing microcaps (up to the 20th percentile), smallcaps (between the 20th and 50th percentile), and bigcaps (above the 50th percentile). Then, the stocks from each of the three size-based groups were independently divided into two new groups based on the median R&D (or Capex) levels observed in Nyse companies in the fiscal year prior to the portfolio formation (*t-1*), representing low/conservative companies (up to the 50th percentile) and high/aggressive companies (above the 50th percentile) considering a given characteristic. This division resulted in six groups, and the stocks from each of them were further divided into three new groups based on the 30th and 70th percentiles of Capex (or R&D) levels observed in Nyse companies in the fiscal year prior to the portfolio formation (*t-1*), representing low, neutral, and high companies in that characteristic.

The 3x2x3 process of portfolio organization resulted in 18 R_i portfolios for each characteristic. The Capex *Hi-Lo* (or R&D *Hi-Lo*) portfolios derived from these 18 portfolios for each low and high R&D (or Capex) portfolio in each size segregation, thus, resulting in 24 portfolios for each characteristic. However, the focus of the research was on the six *Hi-Lo* portfolios.

3.4 Studied characteristics

To measure the operational investments in R&D of the R_i portfolios, the metric proposed by Chan et al. (2001), as presented in Eq. (5), was adopted.

$$IR\&D_t = \frac{R\&D_{t-1}}{MCap_{t-1}} \tag{5}$$

In Eq. (5), $IR\&D_t$ represents the level of operational investment in R&D used as a breakpoint on the date the portfolio was formed. $R\&D_{t-1}$ refers to R&D expenditures in the fiscal year that preceded portfolio formation. $MCap_{t-1}$ is the market value of stocks (market capitalization) on the last day of December of the calendar year before portfolio formation.

To measure operational investments in long-term physical assets, the metric Capex level, similar to that of Gompers et al. (2003) and Jiang and Zhang (2013), was adopted, as shown in Eq. (6).

$$ICap_t = \frac{Capex_{t-1}}{MCap_{t-1}} \tag{6}$$

In Eq. (6), $ICap_t$ represents the level of operational investment in long-term physical assets used as a breakpoint on the date the portfolio was formed. $Capex_{t-1}$ refers to the expenditures on the acquisition of long-term physical assets in the fiscal year prior to portfolio formation. $MCap_{t-1}$ is the market value of stocks (market capitalization) on the last day of December of the calendar year preceding portfolio formation.

4 Analysis and Discussion

4.1 Hypothesis 1: Size-Capex portfolios

Table 1 presents the calculation of the monthly abnormal return of the size-Capex *Hi-Lo* portfolios using the 1, 3, 5, and 6-factor pricing models. In the 3x3 portfolios, there are three *Hi-Lo* portfolios for each pricing model used, one for each size segregation, resulting in 3x4 *Hi-Lo* portfolios.

Table 1: Monthly abnormal return of size-Capex Hi-Lo portfolios

	6 factor	5 factor	3 factor	1 factor
Panel A: Micro				
α	0,32	0,24	0,41	0,60
Pr(>|t|)	5,82	16,43	1,32*	0,44**
Pr(>F)	0***	0***	0***	27,19
Panel B: Small				
α	-0,01	-0,03	0,18	0,34
Pr(>|t|)	97,08	84,18	21,24	5,18
Pr(>F)	0***	0***	0***	14,25
Panel C: Big				
α	-0,22	-0,20	-0,05	0,15
Pr(>|t|)	18,51	25,30	76,85	51,74
Pr(>F)	0***	0***	0***	0,24**

Caption: *Hi-Lo* is the portfolio created by the difference between the monthly excess returns of high and low companies in the *ICap* characteristic. *α* represents the monthly abnormal return of the portfolios. *Pr(>|t|)* is the p-value of the two-tailed t-test that tested the null hypothesis that α = 0. *Pr(>F)* is the p-value of the heteroscedasticity and autocorrelation robust Wald test analogous to the F-test, which tests the null hypothesis that a regression model with only the intercept has greater explanatory power than models with a combination of factors.
Note: All values are presented as percentage points. Significant values at the 5%, 1%, and 0.1% levels are represented by "*", "**", and "***", respectively. Robust covariance matrix estimators accounting for heteroscedasticity and autocorrelation, following Newey and West (1987), were used.
Source: The authors.

Only two out of the 12 tested Hi-Lo portfolios did not pass the Wald test analogous to the F-test. As for the remaining Hi-Lo portfolios, the Wald test rejected, at least at the 1% level, the null hypothesis that a model with only the intercept has greater explanatory power than models with 1, 3, 5, or 6 factors. The test failed to reject the null hypothesis when the 1-factor model was used for microcaps (p-value = 27.19%) and smallcaps (p-value = 14.25%). In practice, this result indicates that the 1-factor model is not suitable for measuring abnormal returns in these two Hi-Lo portfolios.

The 1-factor and 3-factor models were the only ones to identify statistically significant abnormal returns among all the models tested against the Hi-Lo portfolios, rejecting the null hypothesis of the t-test. Significant positive abnormal returns were observed in the Hi-Lo portfolios of microcaps, measuring 0.60% (p-value = 0.44%) and 0.41% (p-value = 1.32%) for the 1-factor and 3-factor models, respectively. In comparison, when it comes to the 5-factor and 6-factor models, the abnormal returns in the microcaps Hi-Lo portfolios were not significant, corresponding to 0.24% (p-value = 16.43%) and 0.32% (p-value = 5.82%), respectively.

As observed, the addition of the CMA and RMW factors to the 3-factor model is enough to eliminate any perception of anomaly in the size-Capex Hi-Lo portfolios. Although the 5-factor and 6-factor models dismiss the presence of abnormal returns in the Hi-Lo portfolios, the addition of the sixth factor, that is, UMD, actually compromised the overall ability of the model to explain the return patterns of the individual low, neutral, and high portfolios. In this regard, while the 6-factor model rejected the existence of abnormal returns in only three out of the nine individual portfolios (rejected in the small-neutral and big-neutral portfolios, as well as in the big-high portfolio), the 5-factor model rejected the existence of abnormal returns in six out of the nine individual portfolios (rejected in all three smallcaps portfolios and in all three bigcaps portfolios). Therefore, the results refute the first hypothesis of this research.

4.2 Hypothesis 2: Size-R&D portfolios

Table 2 presents the calculation of the monthly abnormal return of the size-R&D *Hi-Lo* portfolios using the 1, 3, 5, and 6-factor pricing models.

Table 2: Monthly abnormal return of size-R&D Hi-Lo portfolios

	6 factor	5 factor	3 factor	1 factor
Panel A: Micro				
A	1,34	1,43	0,95	0,84
Pr(>|t|)	0,01***	0,01***	0,68**	1,88*
Pr(>F)	0***	0***	0***	0***
Panel B: Small				
A	0,54	0,57	0,47	0,46
Pr(>|t|)	0,35**	0,18**	0,92**	1,51*
Pr(>F)	0***	0***	0***	0***
Panel C: Big				
A	0,23	0,20	0,15	0,26
Pr(>|t|)	23,79	31,01	44,13	28,37
Pr(>F)	0***	0***	0***	0,09***

Caption: *Hi-Lo* is the portfolio created by the difference between the monthly excess returns of high and low companies for the *IR&D* characteristic.
Source: The authors.

All nine *Hi-Lo* portfolios passed the Wald test analogous to the F-test with p-values lower than 0.1%. Thus, the models with 1, 3, 5, or 6 factors have greater explanatory power than a model with only the intercept, which confirms the consistency of using these models to measure abnormal returns in any of the tested size-R&D *Hi-Lo* portfolios.
Significant positive abnormal returns were observed in the microcaps and smallcaps *Hi-Lo* portfolios, regardless of the model used. The abnormal returns in the microcaps *Hi-Lo* portfolios were 0.95% (p-value = 0.68%), 1.43% (p-value = 0.01%), and 1.34% (p-value = 0.01%) for the 3-factor, 5-factor, and 6-factor models, respectively. For the smallcaps *Hi-Lo* portfolios, the abnormal returns were 0.47% (p-value = 0.92%), 0.57% (p-value = 0.18%), and 0.54% (p-value = 0.35%) for the 3-factor, 5-factor, and 6-factor models, respectively. In comparison, the abnormal returns obtained with the 1-factor model were 0.84% (p-value = 1.88%) and 0.46% (p-value = 1.51%)

for the microcaps and smallcaps portfolios, respectively. No abnormal returns were detected in the bigcaps *Hi-Lo* portfolios.

Contrarily to what was observed in the size-Capex *Hi-Lo* portfolios, the addition of the other factors to the market factor did not contribute to the models' ability to explain the return patterns of the size-R&D portfolios. Instead, it led to an increase in the magnitude of the detected abnormal returns. Thus, the model containing only the market factor showed lower intercepts for the microcaps and smallcaps *Hi-Lo* portfolios, despite being a much simpler model. Therefore, the obtained results support Hypothesis 2 of this research.

4.3 Hypothesis 3: Size-R&D-Capex portfolios

Table 3 presents the calculation of the monthly abnormal return of the size-R&D-Capex *Hi-Lo* portfolios using the 1, 3, 5, and 6-factor pricing models. In the 3x2x3 size-R&D-Capex portfolios, there were six *ICap Hi-Lo* portfolios, three for low R&D companies and three for high R&D companies, for each pricing model used, which means 6x4 *ICap Hi-Lo* portfolios.

Tabela 3: Monthly abnormal return of size-R&D-Capex Hi-Lo portfolios

	Micro	Small	Big		Micro	Small	Big
Panel A: 6-factor				Panel B: 5-factor			
Low IR&D:				Low IR&D:			
α	0,10	-0,46	-0,43	α	0,05	-0,41	-0,40
Pr(>|t|)	79,17	15,62	4,59*	Pr(>|t|)	87,76	17,35	6,21
Pr(>F)	0***	0***	0***	Pr(>F)	0***	0***	0***
High IR&D:				High IR&D:			
α	0,30	0,09	-0,03	α	0,22	-0,14	-0,11
Pr(>|t|)	48,77	77,72	92,44	Pr(>|t|)	62,53	67,07	70,28
Pr(>F)	0***	0***	0***	Pr(>F)	0***	0***	0***
Panel C: 3-factor				Panel D: 1-factor			
Low IR&D:				Low IR&D:			
α	0,35	-0,02	-0,22	α	0,58	0,21	0,12
Pr(>|t|)	25,41	95,50	27,11	Pr(>|t|)	10,03	54,52	71,28
Pr(>F)	0***	0***	0***	Pr(>F)	91,36	31,80	0,95**
High IR&D:				High IR&D:			
α	0,61	0,06	-0,15	α	0,90	0,42	0,06
Pr(>|t|)	16,86	85,58	57,18	Pr(>|t|)	7,02	34,25	83,22
Pr(>F)	0***	0***	0***	Pr(>F)	90,68	75,73	0,12**

Caption: Hi-Lo is the portfolio created by the difference between the monthly excess returns of high and low companies for the ICap characteristic with low or high IR&D.
Source: The authors.

The Wald test analogous to the F-test did not reject, at the 5% significance level, the null hypothesis according to which a model with only the intercept has greater explanatory power than the 1-factor model in explaining the return patterns of microcaps and smallcaps, either for low or high R&D companies. For most *ICap Hi-Lo* portfolios, the Wald test rejected, at the usual levels of significance, the null hypothesis that the model with only the intercept has greater explanatory power than the models with 1, 3, 5, or 6 factors. Therefore, similarly to what was observed in the size-Capex portfolios, the 1-factor model was not suitable for assessing abnormal returns in the *ICap Hi-Lo* portfolios of microcaps and smallcaps, regardless of the level of the R&D characteristic in these portfolios.

Just like in the size-Capex portfolios, the addition of the *UMD* factor worsened the overall ability of the model to explain return patterns in the size-R&D-Capex portfolios. The 6-factor model identified significant negative abnormal returns in the *ICap Hi-Lo* portfolios of bigcaps with low R&D (α = -0.43%, p-value = 4.59%). The 1, 3, and 5-factor models did not identify abnormal returns in any of the portfolios, with intercepts having p-values higher than 5%. However, it should be noted that since the 1-factor model failed the Wald test, it was not suitable to be used in the microcaps and smallcaps *ICap Hi-Lo* portfolios. Thus, only the 3 and 5-factor models were able to satisfactorily explain the return patterns in the *ICap Hi-Lo* portfolios. Therefore, the results obtained refute Hypothesis 3 of this research.

4.4 Hypothesis 4: Size-Capex-R&D portfolios

Table 4 presents the calculation of the monthly abnormal return of the size-Capex-R&D portfolios using the 1, 3, 5, and 6-factor pricing models. In the 3x2x3 size-Capex-R&D portfolios, there are six *IR&D Hi-Lo* portfolios, three for low Capex and three for high Capex companies, for each pricing model used, thus, resulting in 6x4 *IR&D Hi-Lo* portfolios.

The Wald test analogous to the F-test failed to reject the null hypothesis at the 5% level when using the 1-factor model for bigcaps with low Capex portfolios. However, for the remaining *IR&D Hi-Lo* portfolios, the null hypothesis according to which a model with only the intercept has greater explanatory power than the models with 1, 3, 5, or 6 factors was rejected at the 0.1% level. Therefore, in contrast to the findings in the size-R&D-Capex portfolios, where the 1-factor model was not suitable for assessing abnormal returns in the microcaps and smallcaps *ICap Hi-Lo* portfolios, regardless of the level of the R&D characteristic, it was observed in the size-Capex-R&D portfolios that the 1-factor model was not adequate specifically for bigcaps with a low Capex portfolio.

All the models used identified positive abnormal returns in the microcaps *IR&D Hi-Lo* portfolios. The 6-factor model identified abnormal returns of 1.23% (p-value = 0.07%) in the low Capex portfolio and 1.36% (p-value = 0.07%) in the high Capex portfolio.

Table 4: Monthly abnormal return of size-Capex-R&D Hi-Lo portfolios

	Micro	Small	Big		Micro	Small	Big
Panel A: 6-factor				Panel B: 5-factor			
Low ICap:			Low ICap:				
α	1.23	0.55	0.12	α	1.34	0.64	0.16
Pr(>|t|)	0.07***	3.67*	59.65	Pr(>|t|)	0.09***	1.81*	47.37
Pr(>F)	0***	0***	0***	Pr(>F)	0.01***	0***	0***
High ICap:			High ICap:				
α	1.36	0.83	0.15	α	1.36	0.66	0.01
Pr(>|t|)	0.07***	0.76**	52.83	Pr(>|t|)	0.08***	2.25*	97.19
Pr(>F)	0***	0***	0***	Pr(>F)	0***	0***	0***
Panel C: 3-factor				Panel D: 1-factor			
Low ICap:			Low ICap:				
α	0.87	0.52	0.15	α	0.77	0.41	0.25
Pr(>|t|)	2.2*	5.16	46.96	Pr(>|t|)	4.36*	13.85	32.64
Pr(>F)	0.05***	0***	0.02***	Pr(>F)	0***	0***	18.81
High ICap:			High ICap:				
α	1.02	0.50	-0.19	α	0.98	0.59	-0.15
Pr(>|t|)	0.74**	7.67	40.71	Pr(>|t|)	1.26*	4.98*	50.49
Pr(>F)	0.03***	0***	0***	Pr(>F)	0.03***	0***	0***

Caption: Hi-Lo is the portfolio created by the difference between the monthly excess returns of high and low companies for the IR&D characteristic with low or high ICap.
Source: The authors.

Comparatively, the 1-factor model identified abnormal returns of 0.77% (p-value = 4.36%) and 0.98% (p-value = 1.26%) for the same portfolios, respectively. In the IR&D Hi-Lo portfolios of smallcaps, only the 3-factor model rejected the presence of abnormal returns for both low Capex (α = 0.52%, p-value = 5.16%) and high Capex stocks (α = 0.50%, p-value = 7.67%). The 1-factor model rejected abnormal returns in the IR&D Hi-Lo portfolio of smallcaps with low Capex (α = 0.41%, p-value = 13.85%), but not in the portfolio of smallcaps with high Capex (α = 0.59%, p-value = 4.98%). Therefore, the results obtained refute Hypothesis 4 of this research.

4.5 Discussion

While tests with size-Capex portfolios found a positive, but insignificant relationship between Capex levels and abnormal returns for microcaps, previous studies have identified a negative relationship between Capex and returns [3] (Anderson & Garcia-Feijoo, 2006; Titman et al., 2004; Xing, 2008). The results differ because the aforementioned studies adopted metrics based on the variation (growth) of Capex, thus, capturing distinct effects. According to Titman et al. (2004), an increase in Capex can be seen either positively or negatively by the market. From a positive point of view, this increase may be associated with better investment opportunities, in addition to indicating the confidence of the capital market in the management of the company as financiers. The Capex-level based metric adopted to organize size-Capex portfolios captures exactly this positive effect. Through a negative point of view, companies that invest more are more likely to be run by people with a tendency to overinvest. Metrics based on Capex variation (growth), by measuring abnormal investment, capture this negative effect.

In another study, which is more similar to the one on size-Capex portfolios, Jiang and Zhang (2013) identified a positive relationship between *Capex/Asset* levels and abnormal returns. The study used univariate portfolios with equally-weighted returns, tested with the Fama and French (1993) 3-factor model, Carhart (1997) 4-factor model, and Pástor and Stambaugh (2003) 5-factor model. For comparison purposes, if a univariate *Hi-Lo* portfolio (which includes all stocks) had been constructed in the present research, using equally-weighted returns, this portfolio would have presented an abnormal return of 0.29% (p-value = 2.02%), using Fama and French (1993) 3-factor model. However, with the use of the Fama and French (2015, 2016) 5-factor and 6-factor models, the abnormal return would fall, respectively, to 0.14% (p-value = 32.20%) and 0.17% (p-value = 23.24%), thus, ceasing to be significant. Apparently, the results of Jiang and Zhang (2013) were contaminated by the problem of the bad model, discussed in Fama and French (1998).

With regard to size-R&D portfolios, although it seems counterintuitive, previous research has also found that the addition of more factors does not always increase the efficiency of the pricing model in discarding or decreasing the magnitude of abnormal returns, with the performance of the models varying in relation to the criteria used for the formation of the portfolios with the characteristics to be tested and of those that give rise to the factors.

This has been verified by Ball et al. (2016), who tested portfolios sorted by profitability, accruals, and cash-based profitability. In these 3 sets of portfolios, sometimes the model with only the market factor performed better than Fama and French (1993) 3-factor model, ruling out the existence of abnormal returns detected in some portfolios by the latter.

Hou et al. (2017) also found that models with a greater number of factors, such as Fama and French (2015) 5-factor model and the 4-factor *q*-model by Hou et al. (2015) exhibited higher intercepts compared to Fama and French (1993) 3-factor model, with the *q*-model even failing to eliminate the R&D anomaly for the portfolio with no size control. The literature confirms our findings,

3 These same studies also found a negative relationship between Capex and abnormal returns. However, this relationship did not prove to be robust when tested with different pricing models later (Hou et al., 2015, 2017).

indicating that although the 5-factor model performs well with most portfolios investigated in other studies, its specific contribution to portfolios sorted by R&D levels is limited and worsens with the addition of the *UMD* factor.

In the studies by Lev and Sougiannis (1999), Chan et al. (2001), Chambers et al. (2002), and Eberhart et al. (2004), abnormal returns were identified in portfolios sorted by R&D metrics, but there was no concern for isolating the size effect in these studies, as they mixed the effect caused by smallcaps (with returns typically undervalued due to value weighting) with the effect of bigcaps. Subsequently, Hou et al. (2015, 2017) conducted tests with univariate portfolios (without size control) using more robust pricing models. As a result, the R&D anomaly identified in previous studies seemingly ceased to exist for value-weighted portfolios.

Hou et al. (2021) proposed adding to the Hou et al. (2015) *q*-factor model a factor capable of capturing the expected growth of company investments. The new model, namely called q^5 model, was created to outperform competitors in explaining patterns of returns in portfolios sorted by a series of accounting characteristics, with a focus on portfolios involving R&D, as R&D investments reduce current earnings but lead to increased growth. However, despite having been considered a promising model in explaining various anomalies, it is only able to eliminate the R&D anomaly in univariate portfolios, similarly to its competitors.

For comparison purposes, applying the q^5 model to the size-R&D portfolios in this study resulted in an abnormal return of 0.94% (p-value = 0.26%) for microcaps *IR&D Hi-Lo* portfolio. When excluding microcaps, the abnormal return in the *Hi-Lo* portfolio becomes -0.21% (p-value = 30.83%), which is statistically insignificant. In the size-Capex-R&D portfolios, applying the model resulted in an abnormal return of 0.65% (p-value = 4.59%) for *IR&D Hi-Lo* portfolio of microcaps with low Capex, and 1.10% (p-value = 0.83%) for *IR&D Hi-Lo* portfolio of microcaps with high Capex. When excluding microcaps, the abnormal returns for the same *IR&D Hi-Lo* portfolios become -0.12% (p-value = 62.62%) and -0.18% (p-value = 52.98%), respectively, which makes them statistically insignificant. This comparison demonstrates the importance of firm size in the results.

In another study, Taques et al. (2022) used portfolios constructed from equally-weighted returns and the Fama and French (1993, 2015) and Carhart (1997) pricing models. They identified that companies with high innovation capacity and aggressive investments in R&D had higher abnormal returns compared to those with low innovation capacity and conservative investments in R&D. However, when reconstructing the portfolios with value-weighted returns, no statistically significant differences in abnormal returns between the two groups were observed with any of the models tested at a 5% significance level.

As argued, recent research on abnormal returns of portfolios sorted by R&D metrics, from the perspective of pricing models, insist on rejecting the anomaly due to inadequate control for the size effect. They have disregarded the fact that R&D projects of younger companies (smaller in terms of market value, and consequently more aggressive and less risk-averse) tend to yield different results compared to projects of more mature companies (bigger in terms of market value, less aggressive, with limited room for expansion and growth). This rejection contradicts studies that employed alternative approaches to measure abnormal returns.

Mazzi et al. (2019), using the buy-and-hold approach, identified medium-term (5 years) global abnormal returns in a sample comprising companies from 20 countries, excluding the United States, that adopt the International Financial Reporting Standards (IFRS). By applying the same approach to measure abnormal returns, Dargenidou et al. (2021) identified positive short-term (1 year) and medium-term (5 years) abnormal returns associated with R&D investments in UK companies before and after the adoption of IAS 38.

The findings of this study shed light on this apparent contradiction among studies, contributing to the literature by confirming that the relationship between abnormal returns and operational investments in R&D mainly stems from low-market-value stocks, even when using value-weighted returns. This relationship remains robust across the major contemporary pricing models.

Unlike Capex investments, R&D investments generally involve the creation of new technologies, products, or processes that can generate significant long-term competitive advantages. When successful, these innovations can lead to cost reduction and an increased demand for the company's products and services, thus, resulting in revenue and profit growth. Companies with low-value stocks can particularly benefit from these R&D investments, as the potential success of these projects can change investors' perception of the company's growth prospects, leading to an increase in stock prices and abnormal returns.

The observed abnormal returns can have significant implications for the economy, including benefits for innovation and economic growth. Abnormal returns with R&D investments can incentivize these companies to further invest in R&D, triggering an acceleration of innovation and technological progress. Successful innovations can allow low-value stock companies to become more competitive, challenging market leaders, which leads to a fierce competition and benefits for consumers, such as lower prices and better products. There is also a stimulus to economic growth by generating jobs and, consequently, increasing productivity. Additionally, the generated abnormal returns can attract additional investments and boost the stock market as a whole.

However, the success of R&D investments also poses challenges on the economy. The innovations resulting from these investments can be responsible for generating a wave of creative destruction, as described by Schumpeter (1942) in his theory of innovation cycles. According to the theory, creative destruction is a constant process in the capitalist economy, where technological innovations gradually replace existing technologies and business models. Although this is a natural process that leads to continuous economic progress by generating economic growth and creating new opportunities for companies and consumers, it can trigger the bankruptcy of established companies and market concentration.

5 Conclusions

This research aimed to analyze the contribution of operational investment strategies focusing on R&D to generate distinguished returns compared to strategies focusing on Capex. The results indicated a positive relationship between investments in R&D and distinguished performance. The relationship was found to be limited to low market value stocks (microcaps and smallcaps) when using bivariate portfolios, and to microcaps when using trivariate portfolios. No relationship was observed between investments in long-term physical assets and abnormal returns, which justifies this type of investment being neglected in the US since the early 1990s.

By proposing a new method for segregating portfolios, the results presented here show to be differential, thus, complementing the recent literature. They highlight that operational investments in R&D play a crucial role, particularly for growing companies, which benefited from results higher than expected. In order to maximize the relevance of disclosed accounting information, the correct accounting treatment of R&D expenditures in financial statements as assets generating economic benefits becomes evident as well.

Regarding the models used, it was observed that adding the momentum factor to the Fama and French (2015) 5-factor model did not improve its overall ability to explain return patterns in any of the tested portfolio sets. The 5-factor model itself contributed little to the bivariate portfolios sorted by R&D levels, showing better results with the bivariate portfolios sorted by Capex levels. In the trivariate portfolios, the Fama and French (1993) 3-factor model stood out as the only one capable of explaining abnormal returns in the smallcaps size-Capex-R&D portfolios.

Over the past 40 years, numerous studies on market anomalies have succumbed to the emergence of new pricing models. To overcome this limitation, the current leading pricing models were employed. The abnormal returns identified in this research remained robust across all selected models.

Although this is a study on US companies, which is due to limitations regarding the Brazilian sample, it is indeed of great importance for the national context as it demonstrates the impact of operational investments in R&D on returns when it comes to companies with low market value, thus, encouraging the emergence of successful startups and fostering the domestic market. Therefore, for future studies, it is recommended to examine the performance of operational investments in R&D in emerging global markets, in light of pricing models well-adjusted to them. An investigation like that would be important to verify the extent to which emerging markets behave similarly to established markets, particularly regarding the literature on market anomalies, asset pricing, and accounting disclosure. Investigating these markets would also help demonstrate whether there are benefits in developing intellectual and high-tech capital in more turbulent markets since these investments, as suggested by the literature applied in established markets, have the potential to generate distinguished (abnormal) returns.

References

Aboody, D., & Lev, B. (1998). The value relevance of intangibles: The case of software capitalization. *Journal of Accounting Research*, *36*, 161-191. https://doi.org/10.2307/2491312

Anderson, C., & Garcia Feijoo, L. (2006). Empirical evidence on capital investment, growth options, and security returns. *Journal of Finance*, *61*(1), 171-194. https://doi.org/10.1111/j.1540-6261.2006.00833.x

Assaf Neto, A., Lima, F., & Araújo, A. (2008). Uma proposta metodológica para o cálculo do custo de capital no Brasil. *Revista de Administração da USP*, *43*(1), 72-83. https://doi.org/10.1590/S0080-21072008000100006

Ball, R., Gerakos, J., Linnainmaa, J., & Nikolaev, V. (2016). Accruals, cash flows, and operating profitability in the cross section of stock returns. *Journal of Financial Economics*, *121*(1), 28-45. https://dx.doi.org/10.1016/j.jfineco.2016.03.002

Carhart, M. (1997). On persistence in mutual fund performance. *Journal of Finance*, *52*(1), 57-82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Chambers, D., Jennings, R., & Thompson, R. (2002). Excess returns to R&D-intensive firms. *Review of Accounting Studies*, *7*(2-3), 133-158. https://doi.org/10.1023/A:1020217817156

Chan, L., Lakonishok, J., & Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *Journal of Finance*, *56*(6), 2431-2456. https://doi.org/10.1111/0022-1082.00411

Dargenidou, C., Jackson, R. H. G., Tsalavoutas, I., & Tsoligkas, F. (2021). Capitalisation of R&D and the informativeness of stock prices: Pre- and post-IFRS evidence. *The British Accounting Review, 53*(4)*, 100998*. https://doi.org/10.1016/j.bar.2021.100998

Eberhart, A., Maxwell, W., & Siddique, A. (2004). An examination of long term abnormal stock returns and operating performance following R&D increases. *Journal of Finance*, *59*(2), 623-650. https://doi.org/10.1111/j.1540-6261.2004.00644.x

Fama, E. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, *49*(3), 283-306. https://doi.org/10.1016/S0304-405X(98)00026-9

Fama, E., & French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3-56. https://doi.org/10.1016/0304-405X(93)90023-5

Fama, E., & French, K. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1-22. https://dx.doi.org/10.1016/j.jfineco.2014.10.010

Fama, E., & French, K. (2016). Dissecting anomalies with a five-factor model. *Review of Financial Studies*, *29*(1), 69-103. https://doi.org/10.1093/rfs/hhv043

Gompers, P., Ishii, J., & Metrick, A. (2003). Corporate governance and equity prices. *Quarterly Journal of Economics*, *118*(1), 107-156. https://doi.org/10.1162/00335530360535162

Gu, F., & Lev, B. (2017). Time to change your investment model. *Financial Analysts Journal*, *73*(4), 23-33. https://doi.org/10.2469/faj.v73.n4.4

Gu, L. (2016). Product market competition, R&D investment, and stock returns. *Journal of Financial Economics*, *119*(2), 441-455. https://doi.org/10.1016/j.jfineco.2015.09.008

Hou, K., Mo, H., Xue, C., & Zhang, L. (2021). An augmented q-factor model with expected growth. *Review of Finance*, *25*(1), 1-41. https://doi.org/10.1093/rof/rfaa004

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *Review of Financial Studies*, *28*(3), 650-705. https://doi.org/10.1093/rfs/hhu068

Hou, K., Xue, C., & Zhang, L. (2017). *A comparison of new factor models* (Working Paper No. 2015-05). Charles A. Dice Center. https://doi.org/10.2139/ssrn.2520929

Hou, K., Xue, C., & Zhang, L. (2020). Replicating anomalies. *Review of Financial Studies*, *33*(5), 2019-2133. https://doi.org/10.1093/rfs/hhy131

Jiang, G., & Zhang, A. (2013). The shrinking space for anomalies. *Journal of Financial Research*, *36*(3), 299-324. https://doi.org/10.1111/j.1475-6803.2013.12012.x

Lev, B. (2019). Ending the accounting-for-intangibles status quo. *European Accounting Review*, *28*(4), 713-736. https://doi.org/10.1080/09638180.2018.1521614

Lev, B., & Gu, F. (2016). *The end of accounting and the path forward for investors and managers* (1st ed.). John Wiley & Sons.

Lev, B., & Sougiannis, T. (1999). Penetrating the book to market black box: The R&D effect. *Journal of Business*

Finance & Accounting, *26*(3-4), 419-449. https://doi.org/10.1111/1468-5957.00262

Li, D. (2011). Financial constraints, R&D investment, and stock returns. *Review of Financial Studies*, *24*(9), 2974-3007. https://doi.org/10.1093/rfs/hhr043

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics, 47*(1), 13-37.

Mazzi, F., Slack, R., Tsalavoutas, I., & Tsoligkas, F. (2019). Country-level corruption and accounting choice: Research & development capitalization under IFRS. *The British Accounting Review*, *51*(5), 100821. https://doi.org/10.1016/j.bar.2019.02.003

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica, 34*(4), 768-783. https://doi.org/10.2307/1910098

Newey, W., & West, K. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica, 55*(3), 703-708. https://doi.org/10.2307/1913610

Pástor, L., & Stambaugh, R. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy*, *111*(3), 642-685. https://doi.org/10.1086/374184

Sharpe, W. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance*, *19*(3), 425-442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Schumpeter, J. A. (1942). Capitalism, socialism and democracy (1st ed.). Harper & Brothers.

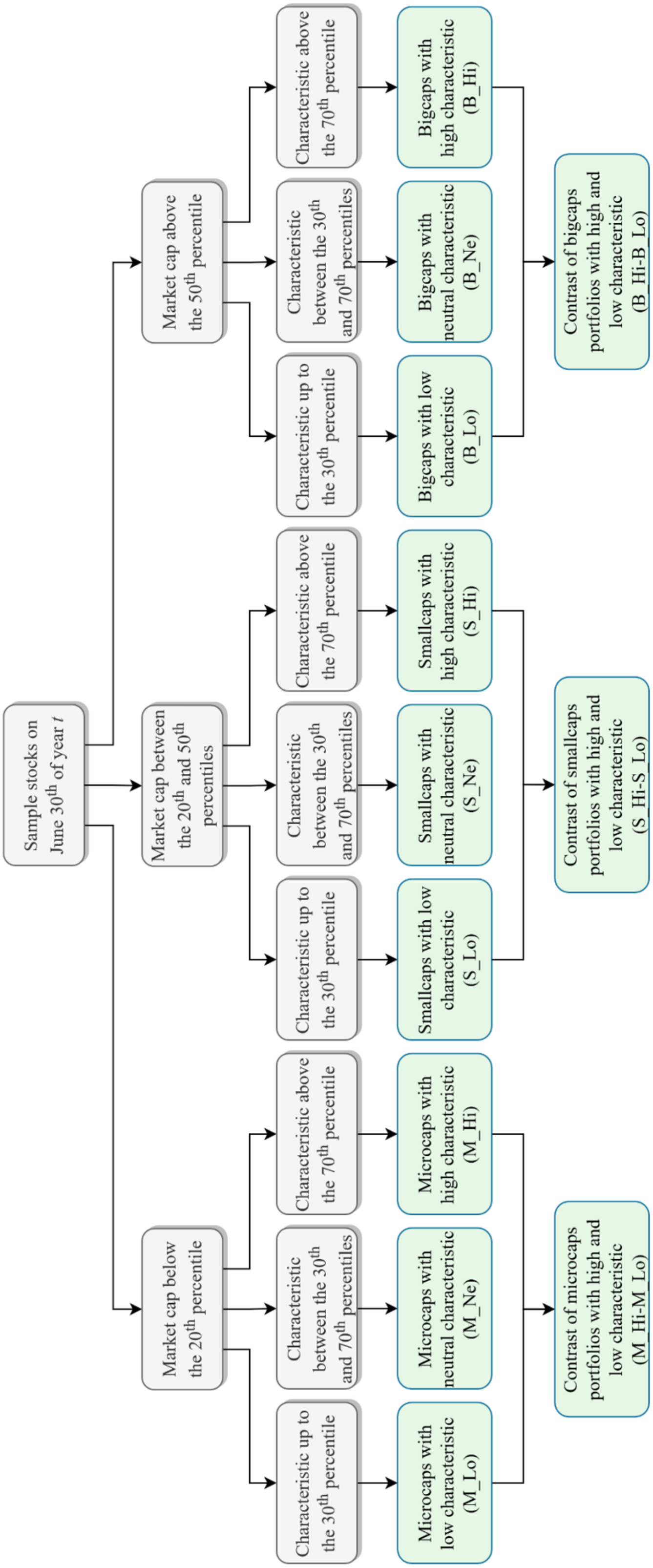
Taques, F. H., Areal, N., & Basso, L. F. C. (2022). Benefits on sales generated by innovation. *International Journal of Innovation and Technology Management*, *19*(1), 2140010. https://doi.org/10.1142/S0219877021400101

Titman, S., Wei, K., & Xie, F. (2004). Capital investments and stock returns. *Journal of Financial and Quantitative Analysis, 39*(4), 677-700. https://doi.org/10.1017/S0022109000003173

Xing, Y. (2008). Interpreting the value effect through the Q-theory: An empirical investigation. *Review of Financial Studies*, *21*(4), 1767-1795. https://doi.org/10.1093/rfs/hhm051

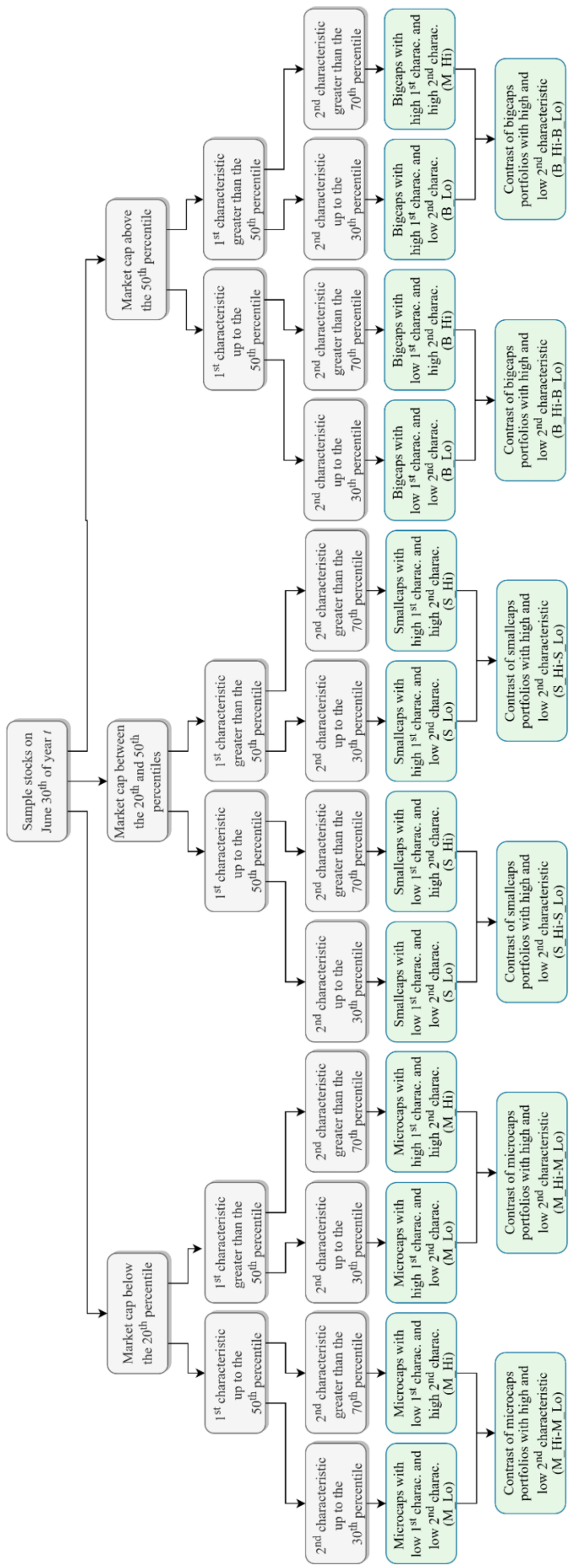
Appendices

Figure 1 - Bivariate portfolio formation process



Source: The authors.

Figure 2 - Trivariate portfolio formation process



Source: The authors.

Table 5: Sample companies

Panel A: Hypothesis 1

Year	Micro		Small		Big		Total
	Low	High	Low	High	Low	High	
2017	747	200	270	141	315	197	1870
2016	691	180	276	147	277	186	1757
1992	47	20	62	40	68	58	295
1991	43	25	45	36	49	43	241
Mean	390	154	162	90	171	120	1087

Panel B: Hypothesis 2

Year	Micro		Small		Big		Total
	Low	High	Low	High	Low	High	
2017	93	356	69	141	84	171	914
2016	113	326	78	134	77	132	860
1992	11	8	11	19	24	28	101
1991	8	11	9	14	13	10	65
Mean	68	172	41	71	52	77	481

Panel C: Hypothesis 3

Year	Micro				Small				Big				Total
	Low IR&D		High IR&D		Low IR&D		High IR&D		Low IR&D		High IR&D		
	ICap		ICap		ICap		ICap		ICap		ICap		
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	
2017	100	44	341	50	42	26	100	30	51	36	112	48	980
2016	113	36	289	50	40	28	106	35	46	31	88	44	906
1992	7	3	10	2	11	3	10	5	17	12	19	13	112
1991	2	3	11	4	7	2	8	3	9	4	5	5	63
Mean	56	24	152	26	27	16	55	18	34	22	49	28	507

Panel D: Hypothesis 4

Year	Micro				Small				Big				Total
	Low ICap		High ICap		Low ICap		High ICap		Low ICap		High ICap		
	IP&D		IP&D		IP&D		IP&D		IP&D		IP&D		
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High	
2017	59	339	30	60	45	101	24	31	58	129	29	43	948
2016	79	242	28	66	49	113	27	32	52	104	26	30	848
1992	7	9	3	2	4	10	3	11	12	16	12	15	104
1991	2	10	4	7	6	6	3	6	9	5	4	5	67
Mean	39	144	25	35	25	56	15	19	33	52	20	26	489

Caption: Low and High represent, respectively, portfolios of low and high ICap or IR&D companies.
Note: The table presents the average monthly number of companies in the first two years of the research period, in the last two years, and the overall average of the 27-year period covered by this study.
Source: The authors.