FINANCIAL PERFORMANCE OF MID- AND HIGH-TECH INDUSTRIES IN CRISIS AND NON-CRISIS PERIODS

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Abstract

Investments in research and development (R&D) are crucial for innovation and economic growth, yet distinctions between high-tech and mid-tech industries may lead to varying financial outcomes. Building on Fuest et al. (2024), this study examines the financial performance of publicly listed high- and mid-tech companies from a shareholder's perspective. Using data from the EU Industrial R&D Investment Scoreboard and LSEG Workspace for 2,349 listed companies, market-capitalization-weighted portfolios were constructed and benchmarked against global and local market indices. Performance was evaluated using the Sharpe ratio and multi-factor asset pricing models (Carhart four-factor and Fama-French five-factor), distinguishing between crisis and non-crisis periods, as well as regional and sectoral variations. Results show that, at the aggregate level, high-tech portfolios consistently and significantly outperform mid-tech and "other" categories on absolute and risk-adjusted bases. Mid-tech indus-tries exhibit resilience during crisis but lower alphas than high-tech industries, and sectoral heterogeneity high-lights diversification benefits. Furthermore, the analysis reveals investment opportunities in R&D-intensive sec-tors, emphasizing crisis resilience and regional competitiveness.

Keywords: Financial performance, mid-tech and high-tech industries

INTRODUCTION

Research topicality and problem. Investments in research and development (R&D) are essential for fostering innovation, productivity, and economic growth at both firm and national levels. However, distinctions between high-tech industries, which typically drive radical innovations, and mid-tech industries, typically focused on incremental advancements, highlight potentially varying impacts on financial performance. Building on the idea of Fuest et al. (2024), who analyze mid- and high-tech companies, this study seeks to extend this approach by examining the financial performance of these sectors from a shareholder's perspective. This gap is particularly relevant amid global competition and debates on regional competitiveness, underscoring the need to evaluate how these sectors generate value for investors.

The aim of the research. The aim of this study is to analyze the financial performance of publicly listed high-tech and mid-tech companies from an investor's viewpoint, benchmarked against global market indices. The analysis focuses on risk-adjusted returns during crisis and non-crisis periods, as well as regional and sectoral differences.

Research methodology. Companies from the EU Industrial R&D Investment Scoreboard, covering 2,349 listed firms, were classified into high-tech, mid-tech, and others. Industry portfolios were weighted by market capitalization from 2000 to 2024 using total return data. Performance was assessed via the Sharpe ratio and multi-factor asset pricing models, including Carhart's four-factor and the Fama-French five-factor model. Furthermore, performance analyses considered different market conditions and allowed for insights at industry and regional level.

The research results. High-tech portfolios consistently outperformed the market on both absolute and risk-adjusted bases, with alphas exceeding 1% per month during crises. Mid-tech showed positive but lower alphas, particularly resilient during crises, while other portfolios lagged behind. Regional variations revealed strong financial performance in China, crisis resilience in the United States, and sectoral heterogeneity within the high-tech and mid-tech portfolios.

Originality/Value of the article. This study adopts a shareholder-oriented perspective on high-tech versus mid-tech performance, incorporating crisis and non-crisis dynamics, which, to the best of our knowledge, have so far remained largely unexplored in prior research. By integrating these dimensions, it extends existing research on technology-related firm performance toward a more investor-centered view and adds a focus on the resilience of different industries across varying market conditions, filling a notable gap in current research. This is the first large-scale analysis of 2,349 listed companies that applies multi-factor asset pricing models, including the Fama–French five-factor model, to compare the financial performance of industries with different levels of technological intensity. The results highlight investment opportunities in R&D-intensive sectors and provide insights for investors.

THEORY ANALYSIS

Investments in research and development (R&D) are widely recognized as a cornerstone for driving technological progress, innovation, and sustained economic growth, both at the firm level and across national economies (Kantor & Whalley, 2025; Nelson, 1959; Romer, 1990). By channeling resources into R&D, companies can enhance productivity, reduce operational risks such as business closures, and cultivate competitive advantages through novel products and processes. The relationship between R&D spending, innovation, and productivity improvements has been broadly examined in academic literature. For instance, both Crepon et al. (1998) and Janz et al. (2004) identify a positive correlation between innovation output and firm productivity. At the macroeconomic level, R&D investments stimulate job creation, boost gross domestic product (GDP), and address broader societal challenges by seeding the development of transformative technologies and industries. Empirical evidence underscores this linkage, with R&D expenditures correlating strongly with enhanced economic vitality and long-term prosperity (Aghion & Howitt, 1992; Chmielewski et al., 2025; Ziesemer, 2024). However, a critical nuance lies in the heterogeneity of R&D outcomes: there exists a profound distinction between radical innovations - exemplified by groundbreaking inventions like the automobile, the personal computer, or artificial intelligence, which disrupt established markets and spawn entirely new technological paradigms - and incremental innovations, which entail modest, iterative refinements to existing products or services. Radical innovations typically involve high degrees of novelty and risk, often reshaping industry structures, whereas incremental efforts focus on efficiency gains and sustainability within current frameworks. Despite this split, both forms are encompassed within the broad spectrum of R&D, highlighting the need for nuanced policy and strategic approaches to maximize their respective contributions.

Based on the approach of Fuest et al. (2024), our paper distinguishes between radical innovation, typically originating from high-tech industries, and incremental innovation, typically stemming from mid-tech industries. Accordingly, the assignment of specific industries to the categories “high-tech,” “mid-tech,” or the residual “other” category is not static but changes over time. For example, the chemical industry, which Verspagen (1995) classified as high-tech approximately 30 years ago, is now considered mid-tech.

The sector-specific impact of R&D expenditures has also been the subject of numerous empirical studies. Braja and Gemzik-Salwach (2019) for example, find that R&D spending enhances the financial performance of high-tech firms. Ortega-Argilés et al. (2011) identify the strongest positive effect of R&D on productivity within high-tech manufacturing, followed by the service sector and, finally, low-tech manufacturing. Similarly, Verspagen (1995) reports a smaller R&D productivity effect in medium-tech sectors relative to high-tech industries, noting, however, the moderating influence of regional and national contexts. Ortega-Argilés et al. (2009) focus even more explicitly on the geographical dimension, analyzing the productivity gap between the United States and the European Union. They likewise find the strongest link between R&D and productivity in high-tech sectors, weaker effects in medium-tech sectors, and no significant R&D impact in low-tech industries. With regard to the transatlantic productivity gap, Ortega-Argilés et al. (2009) draw policy implications for the EU, recommending targeted research policies rather than broad, across-the-board measures. Similar conclusions are drawn by Moncada-Paternò-Castello and Grassano (2022), who also address the R&D intensity gap and advocate customized policies, as they consider sectoral composition an important factor contributing to the gap. They identify four high-tech industries as the main contributors to the transatlantic gap, though the automotive sector - as part of the mid-tech category - at least partly offsets this difference. Their work employs a sectoral classification based on the EU Industrial R&D Investment Scoreboard, which is also adopted in the present study.

The ongoing relevance of the high-tech versus mid-tech industries, as well as the regional perspective, is underscored by Fuest et al. (2024): According to the authors, European industry remains focused on mid-tech sectors with moderate R&D intensity, a situation they describe as the EU's "middle technology trap", since even flagship sectors, such as the automotive field, are increasingly exposed to intensified global competition. To overcome this impasse, they call for a budget-neutral yet radical reform of the EU innovation ecosystem to foster high-tech innovation and stimulate private investment across dynamic growth sectors.

Our research builds on this ongoing discussion but adopts a shareholder-oriented perspective by analyzing the financial performance of high-tech and mid-tech industries.

Previous studies have examined financial performance in terms of returns in R&D-intensive sectors. Chambers et al. (2002), for instance, conclude that R&D-intensive firms systematically earn excess returns following their R&D investment, which the authors interpret as compensation for risk. In contrast, Chan et al. (2001) find that R&D stocks do not yield significantly higher returns than non-R&D stocks overall, though excess returns appear for firms with particularly high R&D-to-equity ratios, especially following periods of poor performance. According to Chan et al. (2001), higher R&D intensity is also associated with increased return volatility.

To the best of our knowledge, no prior study has examined the financial performance of publicly listed companies classified as high-tech, mid-tech or "other" in the context of the broader debate on regional sectoral structures and competitiveness from an investor's viewpoint. Novel in this respect is also our differentiated analysis of industry performance under crisis and non-crisis conditions, following the approach of Nofsinger and Varma (2014), as well as the size of our global dataset covering 2,500 companies (of which 2,349 are listed).

RESEARCH METHODOLOGY

In order to evaluate the financial outcomes of high-tech and mid-tech sectors globally, our study draws on information from the EU Industrial R&D Investment Scoreboard, mirroring the approach of Fuest et al. (2024). The EU Industrial R&D Investment Scoreboard (for further details, please refer to Grassano et al. (2023)), issued yearly by the European Commission, monitors and compares R&D expenditures among leading international corporations, encompassing more than 85% of worldwide corporate R&D investments. It includes categorizations by region, sector, and indicators such as expansion trends, revenue figures, and efficiency measures. These entities collectively allocated about USD 1.3 trillion globally toward R&D activities.

In this study, we follow the approach of Fuest et al. (2024) when classifying the sample into three broad categories: high-tech, mid-tech, and a residual category called "other", which primarily encompasses services and utility companies. This classification scheme not only aligns with Fuest et al. (2024), but also closely corresponds to those employed by Eurostat and the Organization for Economic Co-operation and Development (OECD). The high-tech category includes the following sectors: aerospace and defense, alternative energy, electronic and electrical equipment, health care equipment and services, pharmaceuticals and biotechnology, software and computer services, and technology hardware and equipment. The mid-tech category comprises automobiles and parts, chemicals, financial services, fixed-line telecommunications, industrial engineering, industrial metals and mining, industrial transportation, leisure goods, mobile telecommunications, and personal goods. The "other" category encompasses banks, beverages, construction and materials, electricity, food and drug retailers, food producers, forestry and paper, gas, water and multi-utilities, general industrials, general retailers, household goods and home construction, life insurance, media, mining, non-life insurance, oil and gas producers, oil equipment, services and distribution, real estate investment and services, support services, tobacco, and travel and leisure. The sector definitions were taken from the EU Industrial R&D Investment Scoreboard, which uses the Industry Classification Benchmark (ICB) as a basis for its categorization.

To assess whether investments in the mid- or high-tech sector yield benefits for shareholders, we benchmark the financial results of companies from the EU Industrial R&D Investment Scoreboard against international market benchmarks provided by Kenneth R. French[1]. For this purpose, we construct portfolios weighted by market capitalization monthly. This weighting economically mirrors efficient market hypothesis assumptions, where larger firms exert greater influence due to liquidity and information efficiency, allowing the portfolio to capture aggregate market sentiments and diversification effects inherent in R&D-driven growth and is a standard approach in financial studies and well-known indices (e.g., Standard & Poor´s 500). Outliers with incorrect values were corrected manually. To include stock splits and dividends, among others, we take total return data. All data are in USD and sourced from LSEG Workspace.

1 table. Summary Statistics

Category	Unit	Firms	Listed firms
Firms	#	2,500	2,349
High-tech	#	1,412	1,340
Mid-tech	#	611	579
Other	#	477	430
Ø R&D Investment	$mn	517.4	521.2

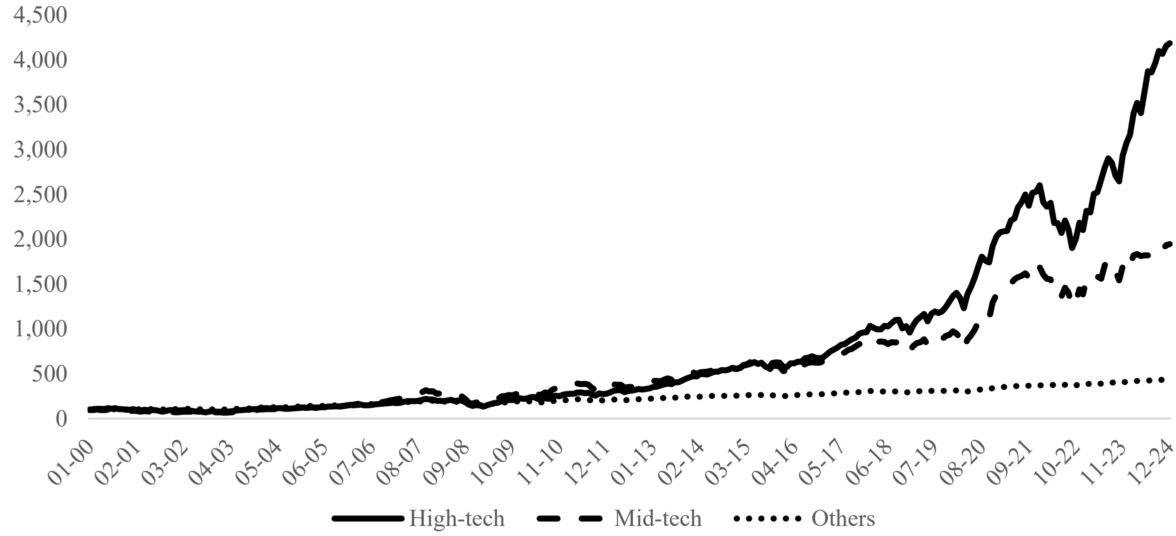
Source: compiled by the authors based on data from the EU Industrial R&D Investment Scoreboard (Grassano et al., 2023) and from LSEG Workspace, 2025

Table 1 provides an overview of the firm distribution and R&D investment patterns across different portfolios. The dataset drawn from the EU Industrial R&D Investment Scoreboard (Grassano et al., 2023) comprises a total of 2,500 firms. For the purpose of this study, which follows a shareholder-based perspective, only listed companies are included in the analysis. Of the total population, 2,349 firms could be matched with an International Securities Identification Number (ISIN) in LSEG Workspace, resulting in an inclusion ratio of about 94%. The data may reflect a certain degree of survivorship bias, as the Scoreboard focuses on persistent R&D investors that remain listed over time. High-tech firms represent the largest group, accounting for more than half of all companies, followed by mid-tech firms and, lastly, the "other" category. Across all firms, the average R&D investment amounted to USD 517.4 million, underlining the substantial financial resources dedicated to innovation within this portfolio.

For an initial overview of the fiscal results among the mid-tech and high-tech companies, 1 fig. depicts the growth of a USD 100 investment over the period from January 2000 through December 2024. Over this twenty-five-year period, the high-tech portfolio substantially outperforms both mid-tech firms and the category labeled "other." In the initial years, the trajectories of the three portfolios exhibit only limited divergence. From 2017 onward, however, the high-tech segment experiences rapid growth, reaching USD 4,186 by the end of 2024. Mid-tech firms also demonstrate notable growth, albeit at a more moderate pace, attaining a peak value of USD 1,945. In contrast, the "other" portfolio remains relatively stagnant throughout the period, reaching USD 431.

[1] The data is taken from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

These findings indicate heterogeneity in portfolio performance, highlighting the potential value of further investigation. Notably, this analysis does not explicitly account for investment risk, and the observed portfolios may plausibly include high-risk assets. Therefore, the results should be interpreted solely as a preliminary assessment.



1 fig. USD 100 Investment from Jan 2000 to Dec 2024
Source: compiled by the authors based on data from LSEG Workspace, 2025

To incorporate investment risk, this article uses the Sharpe (1964) ratio (SR), which measures the index return above the risk-free rate, divided by the total risk of the portfolio. It is calculated by the following formula:

$$SR = \frac{R_i - R_f}{\sigma}. \quad (1)$$

In formula (1), R_i denotes the mean return of the portfolio, R_f represents the risk-free rate, and σ is the standard deviation of returns, which captures the volatility of the investment and thus serves as a measure of total risk.

To obtain a more profound understanding of the determinants of returns, multi-factor models are employed: Multi-factor models are essential as they adjust for systematic risk factors, allowing us to determine if the observed returns are due to genuine outperformance or merely exposure to market risks. By incorporating factors like size, value, momentum, profitability, and investment, they provide a robust framework for isolating alpha (see e.g., Jensen (1968)) and ensuring a comprehensive evaluation of portfolio efficiency. Abnormal returns may be model-specific. Thus, we apply various multi-factor regression approaches over time to scrutinize the fiscal results of the industries. The initial approach follows the four-factor framework from Carhart (1997), a staple in finance studies. To incorporate newer advancements in assessment techniques, we expand this with the five-factor framework by Fama and French (2015), which builds on their earlier three-factor model by integrating elements tied to firms´ profitability and investment behavior.

This analytical structure leads to the subsequent equations for monthly time-series factor regressions:

$$R_i - R_f = a + b_i MKT + s_i SMB + h_i HML + w_i WML + e_i, \quad (2)$$

$$R_i - R_f = a + b_i MKT + s_i SMB + h_i HML + c_i CMA + r_i RMW + e_i. \quad (3)$$

Within these regressions (regression 2 relates to the Carhart (1997) model and regression 3 to the Fama and French (2015) model), $R_i - R_f$ denotes the monthly excess return for portfolio i, while MKT signifies the monthly surplus of the reference index. R_f represents the monthly risk-free rate and e_i is the regression residual. The factors SMB, HML, WML, RMW and CMA are, respectively, the returns on the explanatory factors related to size, value, momentum, profitability and investment: SMB (small minus big) captures the gap in returns between small and large firms by market value; HML (high minus low) shows the disparity between high and low book-to-market ratios; WML (winners minus losers) reflects the spread between high versus low recent 12-month performance stocks. RMW (robust minus weak) measures the variance in returns from portfolios with solid versus weak operational earnings, and CMA (conservative minus aggressive) indicates the difference between conservative versus aggressive capital deployment companies. All factors are provided by the Kenneth French's data library. The statistical significance of all estimates is calculated using robust standard errors, as proposed by Newey and West (1987).

Incorporating new insights into asset pricing, we further examine varying market conditions (for instance, as in Nofsinger and Varma (2014) or Dorfleitner et al. (2019)). From January 2000 to December 2024, we identify three downturn phases in global stock markets, determined by highs and lows in the MSCI (Morgan Stanley Capital International) World Index. The initial downturn spans from March 2000 to October 2002, linked to the tech sector collapse. A subsequent one occurred between October 2007 and March 2009, associated with the worldwide economic downturn. These first two global intervals match the phases noted by Nofsinger and Varma (2014) in the US context. The third downturn spans the period from February 2020 to May 2023, linked to the COVID-19 pandemic, with the World Health Organization (WHO) officially declaring the end of the global health emergency in May 2023; this period also encompasses the escalation of the Russia-Ukraine war in February 2022 and is characterized by pronounced highs and lows in global stock markets, reflecting heightened volatility.

This extended structure results in the following pair of monthly time-series factor regression equations, augmenting the foundational models with indicator variables to separate outcomes by market phases:

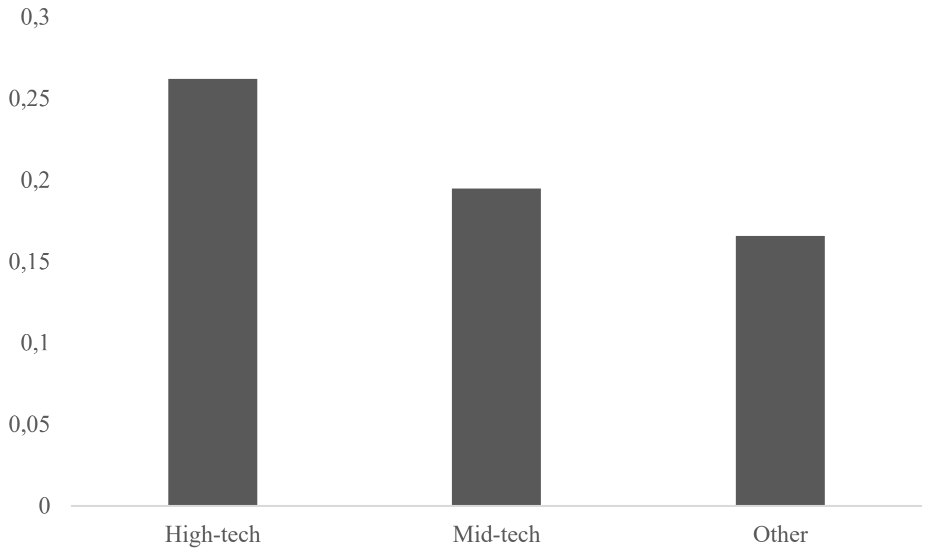
$$R_i - R_f = D_C a_C + D_{NC} a_{NC} + b_i MKT + s_i SMB + h_i HML + w_i WML + e_i, \quad (4)$$

$$R_i - R_f = D_C a_C + D_{NC} a_{NC} + b_i MKT + s_i SMB + h_i HML + c_i CMA + r_i RMW + e_i. \quad (5)$$

Here (formula 4 relates to the Carhart (1997) model and formula 5 to the Fama and French (2015) model), a_C and a_{NC} indicate alpha values for superior or inferior performance during crisis periods (a_C) and non-crisis periods (a_{NC}), respectively, with D_C and D_{NC} as an indicator equaling one in crisis (non-crisis) periods and zero otherwise, and e_i as the error term. Remaining terms and components align with those in the core models previously outlined (see formulas 3 and 4). The statistical significance of all estimates is again derived from robust standard errors following Newey and West (1987).

RESEARCH RESULTS AND DATA ANALYSIS

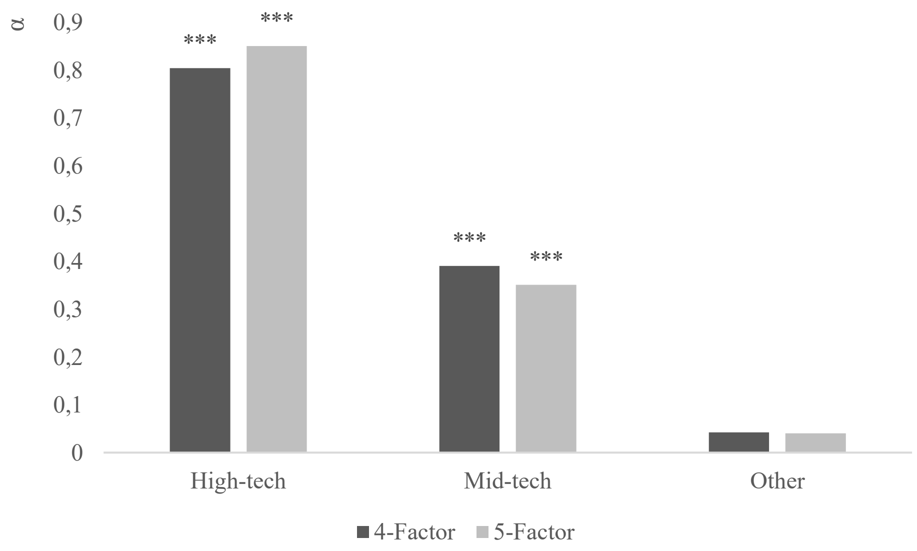
Building upon the methodological framework outlined in the previous section, the following part presents the main research findings and data analysis outcomes.



2 fig. Monthly Sharpe Ratio
Source: compiled by the authors based on data from LSEG Workspace, 2025

Fig. 2 illustrates the monthly Sharpe ratio for the three portfolios. All portfolios demonstrate positive ratios, thereby suggesting superior performance even after accounting for risk adjustments. When contrasted with 1 fig., the "other" portfolio exhibits relatively stronger performance, as the elevated risk associated with the high-tech portfolio substantially diminishes its risk-adjusted returns.

While the Sharpe ratio analysis provides a first overview of risk-adjusted performance, further insights can be gained by examining returns derived from multi-factor models, as explained in the previous section.



3 fig. Full period performance of the different industries
Source: compiled by the authors based on data from LSEG Workspace, 2025

Fig. 3 illustrates the full-period financial performance of the high-tech, mid-tech, and "other" industry portfolios, measured through monthly alpha estimates obtained from the four-factor and five-factor models. The statistical significance of the alpha estimates is determined using robust standard errors in accordance with Newey and West (1987) and is indicated in the figure by asterisks: *** for 1%, ** for 5%, and * for 10%. Across both models, the high-tech portfolio consistently exhibits the highest and significant alphas, indicating substantial outperformance, followed by mid-tech, whereas the "other" portfolio records the lowest alphas. The value of the high-tech results across both models suggests that common risk factors such as market, size, value, profitability, and investment cannot fully explain the excess returns, leading to the respective outperformance of the portfolios. The persistent alphas economically suggest market inefficiencies in pricing R&D intangibles. In comparison, mid-tech industries also generate positive and significant alphas, although their magnitude is considerably smaller than that of high-tech firms. This indicates that while mid-tech companies also outperform the market benchmark, their excess returns are less pronounced. The "other" portfolio, on the other hand, does not show significant and meaningful abnormal performance, highlighting the sectoral heterogeneity across industries. The results confirm the first impression from the USD 100 investment.

After establishing the general performance patterns over the full period, further insights can be gained by examining how the portfolios behave under varying market conditions:

2 table. Performance during crisis and non-crisis periods

Category	Model	α during crisis	α during non-crisis
High-tech	4-Factor	1.07***	0.73***
	5-Factor	1.15***	0.77***
Mid-tech	4-Factor	0.75***	0.28**
	5-Factor	0.78***	0.23*
Other	4-Factor	0.17	0.00
	5-Factor	0.14	0.01

Source: compiled by the authors based on data from LSEG Workspace, 2025

2 table reports the monthly alpha estimates for the high-tech, mid-tech, and "other" portfolios, based on both the four- and five-factor model, across crisis and non-crisis markets. The statistical significance of the alpha estimates is calculated using robust standard errors following Newey and West (1987). Significance levels are indicated by asterisks: *** for 1%, ** for 5%, and * for 10%. A clear difference emerges between the periods. In crisis periods, both high-tech and mid-tech portfolios achieve large and statistically significant alphas across both models. High-tech industries generate crisis-period alphas exceeding 1% per month, indicating strong resilience and capacity to create shareholder value, especially under adverse market conditions. Mid-tech portfolios also exhibit substantial crisis alphas though somewhat lower in magnitude compared to high-tech. The "other" portfolio performs better during crisis than non-crisis periods, but at a rather low level and the values are not statistically significant. In non-crisis periods, the magnitude of alphas declines markedly. For the high-tech sector, non-crisis alphas remain positive and at a high level, while mid-tech portfolios see their outperformance shrinking more. This pattern implies that the excess returns of high- and mid-tech industries are not solely a reflection of structural advantages in non-crisis periods but become particularly pronounced in phases of financial stress. A potential explanation is that technological firms possess innovation-driven competitive advantages which might provide them with greater resilience against downturns. In the high-tech category in particular, many firms operate within global megatrends such as digitalization or artificial intelligence, for which demand may remain relatively robust or increase during crises. For example, during the COVID-19 pandemic, digital communication solutions and related services gained increased importance, which may

partly explain the observed strong performance of these firms. Investors may also expect continued success for such companies, potentially contributing to their outperformance during periods of financial stress.

Following the examination of crisis and non-crisis market phases, the analysis now turns to the geographical dimension (as also highlighted by Fuest et al. (2024)) to assess potential regional differences in portfolio performance: 3 table reports the monthly alpha estimates by region. As the factors in the multifactor models are country-specific, local benchmark data was used (see e.g., Griffin (2002)). Significance levels are indicated by asterisks: *** for 1%, ** for 5%, and * for 10%. The following insights emerge: The pattern identified in the previous results - namely, that the high-tech sector exhibits the highest performance, followed by the mid-tech sector and, lastly, the “other” category - is also evident across all portfolios, with the exception of Japan, where performance in the “other” category exceeds that of the mid-tech portfolio, however, not statistically significant.

3 table. Performance by region

Category	Region	# Firms	Model	α full period	α during crisis	α during non-crisis
High-tech	Europe	122	4-Factor	0.78***	0.97***	0.72***
			5-Factor	0.76***	0.92***	0.71***
	US	613	4-Factor	0.62***	1.05***	0.50***
			5-Factor	0.63***	1.11***	0.50***
	China	318	4-Factor	1.45***	0.94	1.61***
			5-Factor	1.63***	1.19	1.75***
	Japan	80	4-Factor	0.65***	0.77***	0.61***
			5-Factor	0.64***	0.78***	0.60***
	RoW (Rest of World)	207	4-Factor	0.57***	0.82**	0.50***
			5-Factor	0.54***	0.78**	0.47***
Mid-tech	Europe	93	4-Factor	0.37***	0.48**	0.33*
			5-Factor	0.32**	0.35	0.31*
	US	107	4-Factor	0.36***	1.02**	0.16
			5-Factor	0.24	0.78*	0.09
	China	203	4-Factor	0.45	0.82	0.33
			5-Factor	0.71**	1.12	0.59
	Japan	94	4-Factor	-0.01	-0.02	-0.01
			5-Factor	-0.01	-0.02	-0.01
	RoW	82	4-Factor	0.36**	0.85***	0.21
			5-Factor	0.26	0.72***	0.14
Other	Europe	72	4-Factor	0.05	0.05	0.05
			5-Factor	0.05	0.06	0.05
	US	77	4-Factor	-0.06*	-0.03	-0.07*
			5-Factor	-0.07**	-0.06	-0.08*
	China	143	4-Factor	0.13***	0.15**	0.12**
			5-Factor	0.06	0.09	0.06
	Japan	58	4-Factor	0.07	0.11	0.06
			5-Factor	0.06	0.11	0.05
	RoW	80	4-Factor	-0.04	-0.01	-0.05
			5-Factor	-0.04	-0.04	-0.05

Source: compiled by the authors based on data from LSEG Workspace, 2025

All high-tech portfolios display strong positive abnormal returns, which may be interpreted as evidence of systematically higher excess returns, resembling the findings of Chambers et al. (2002). Although positive abnormal returns are also observable in the mid-tech sector, they are generally smaller in magnitude. In the “other” sector, alpha estimates are generally smaller and mostly statistically insignificant. Notably, this category shows pronounced underperformance in the US and comparatively strong performance in China. However, the factors of the Fama and French (2015) model seem to explain the outperformance in China. Nevertheless, economically, China's alphas seem to reflect state capitalism's role in subsidizing R&D to overcome mid-tech traps, fostering rapid catch-up growth. During crisis periods, all portfolios - except for the China high-tech and Japan mid-tech portfolios – show higher alphas than their respective non-crisis period counterparts, thereby reinforcing the results from 2 table and confirming these findings within a regional framework. The US high- and mid-tech portfolios perform comparatively well during crisis periods but lag behind, for example, Europe, during non-crisis periods. In contrast to the positive excess returns in the high- and mid-tech sectors, the US' "other" category even records (statistically insignificant) underperformance. Across the three-time spans - full period, crisis periods, and non-crisis periods - Europe and Japan display comparatively low intra-sectoral variation in alpha values. However, Japan's portfolio performance varies markedly across sectors, driven by slight and statistically insignificant underperformance in the mid-tech sector.

Overall, the regional analysis confirms the results observed previously - with high-tech sectors consistently generating statistically significant superior returns - while highlighting notable cross-regional differences, for example the resilience of Chinese portfolios and the crisis-period strength of the portfolios of the US.

After examining regional variations in portfolio performance, the analysis next divides the portfolios by industries (see e.g., Dorfleitner and Rößle (2018)) to explore whether the previously observed sectoral hierarchy also holds within individual industries.

4 table. Performance by sector

Category	Sector	# Firms	Model	α full period	α during crisis	α during non-crisis
High-tech	Electronic & Electrical Equipment	249	4-Factor	0.59***	1.03***	0.46***
			5-Factor	0.64***	1.13***	0.50***
	Pharmaceuticals & Biotechnology	478	4-Factor	0.44***	0.51	0.42**
			5-Factor	0.47***	0.39	0.49**
	Software & Computer Services	336	4-Factor	0.85***	0.86**	0.84***
			5-Factor	0.97***	1.12***	0.93***
Mid-tech	Automobiles & Parts	149	4-Factor	0.74***	1.42***	0.53
			5-Factor	0.79***	1.75***	0.52
	Chemicals	115	4-Factor	0.25*	0.43	0.19
			5-Factor	0.23	0.39	0.19
	Industrial Engineering	167	4-Factor	0.42**	0.70*	0.33
			5-Factor	0.41**	0.73*	0.32
Other	Construction & Materials	65	4-Factor	0.23	0.07	0.28
			5-Factor	0.15	0.04	0.19
	Food Producers	45	4-Factor	0.20	0.24	0.19
			5-Factor	0.08	-0.09	0.13
	General Industrials	64	4-Factor	0.30*	0.31	0.29
			5-Factor	0.24	0.25	0.24

Source: compiled by the authors based on data from LSEG Workspace, 2025

4 table reports the monthly alpha estimates for the industries most frequently represented in our sample (based on the ICB taxonomy) within the high-tech, mid-tech, and "other" categories. Estimates are presented for both the four- and five-factor models, across crisis and non-crisis market periods. Significance levels are indicated by asterisks: *** for 1%, ** for 5%, and * for 10%. Consistent with previous findings, the high-tech and mid-tech sectors generally exhibit positive abnormal returns, with high-tech industries clearly outperforming those in the "other" category. However, when analyzed at the level of individual representative industries, the hierarchical performance pattern - with high-tech industries performing best, followed by

mid-tech industries, and then by the “other” sector - is no longer uniformly observable. Instead, substantial industry-specific heterogeneity emerges. This indicates that when investing, a broad approach covering a large set of companies is an advantage. For instance, compared with the aggregate high-tech category results presented in 3 fig. and 2 table, the high-tech industry Software & Computer Services shows higher alpha values over the full period and during non-crisis periods, but slightly weaker values during crises. In contrast, the Pharmaceuticals & Biotechnology industry performs markedly worse than the overall high-tech sector and even falls behind the mid-tech industry Automobiles & Parts.

The exceptionally strong performance of Automobiles & Parts within the mid-tech group is particularly notable during crisis periods, where its outperformance even exceeds that of all high-tech industries included in table 4. Testing the hypothesis that the outperformance is driven by Tesla, which recorded strong stock price increases and has a strong influence on the market-capitalization-based portfolio, reveals that after excluding Tesla from the Automobiles & Parts portfolio, the outperformance is no longer measurable (not even at the 10% level). One could argue that Tesla is more a high-tech company than a mid-tech company, which would further strengthen the previous findings.

The Chemicals industry exhibits consistently weaker results compared with the aggregate mid-tech sector performance. Within both the high-tech and mid-tech sectors, performance during crisis periods is generally stronger than during non-crisis periods. Overall, table 4 reveals substantial heterogeneity, particularly within the mid-tech category. Therefore, a generalized statement about performance patterns across all industries subsumed under the high-tech, mid-tech, and “other” categories cannot be made.

Moreover, potential regional heterogeneity within individual industries - such as performance differences between the US and Europe - cannot be ruled out and could be relevant for interpreting performance gaps; however, such regional analysis lies beyond the scope of this study.

The overall findings of this study also suggest that sectoral and regional characteristics may influence the effectiveness of innovation policies. Consequently, uniform R&D subsidies might not be equally appropriate across all contexts. This conclusion supports the recommendations of Ortega-Argilés et al. (2009) and Moncada-Paternò-Castello and Grassano (2022), as presented in the theory analysis. Considering sectoral differences could help policymakers design more targeted and effective support mechanisms.

CONCLUSIONS

1. High-tech industries demonstrate superior financial performance compared to mid-tech and other sectors, as evidenced by higher absolute returns and significant positive alphas in multi-factor models, aligning with theoretical expectations of successful radical innovation driving competitive advantages.
2. Risk-adjusted metrics, including Sharpe ratios and alphas, confirm that high-tech outperformance persists after accounting for market, size, value, momentum, profitability, and investment factors, supporting empirical literature on R&D's positive impact on productivity and returns.
3. Performance is stronger during crisis periods, with high-tech and mid-tech portfolios generating alphas over 1% and 0.5% per month, respectively, suggesting that innovation provides resilience against market downturns.
4. Regional analysis reveals heterogeneity, with China leading in overall alphas, the US excelling during crises, and Europe/Japan showing more stable performance across the full, crisis and non-crisis periods.

5. Sectoral breakdowns indicate substantial intra-category variation, implying that diversified portfolios across R&D-intensive firms yield better risk-adjusted returns than narrow industry focus.

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