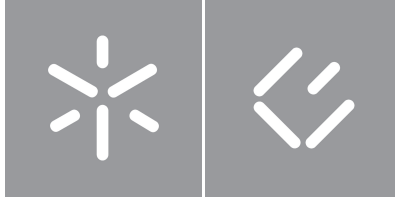


University of Minho
School of Economics and Management

David Silves Ferreira

**Evaluating climate risk and return premiums
in resource-intensive sectors: Evidence from
critical minerals and fossil fuels**



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Master's Dissertation in Finance

Dissertation supervised by

Professor Maria do Céu Cortez, PhD

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I am overjoyed to have completed my master’s degree in finance and deeply grateful for all the help and guidance I received while working on this dissertation and throughout my academic career.

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Abstract

The transition to low-carbon energy systems has heightened the strategic importance of critical minerals while exposing the fossil fuel sector to significant climate-related transition risks. This dissertation evaluates the financial performance and risk-return dynamics of investment portfolios comprised of critical mineral and fossil fuel equities within developed markets. Using monthly data from 1996 to 2026, portfolios were constructed for both resource-intensive sectors.

To assess whether climate and systematic risks translate into distinct return premiums, portfolio performance is evaluated using established multi-factor asset pricing models, including the Fama and French (1993, 2015, 2018) three, five, and six-factor models, as well as the Hou et al. (2021) q-factor model.

The initial baseline results indicate that the excess returns for both sectors are primarily driven by systematic market risk, size, and value exposures, with no evidence of statistically significant abnormal performance. However, we observe that fossil fuel portfolios show negative and statistically significant alphas following the international financial crisis. Furthermore, when portfolios are evaluated under different global oil market conditions, fossil fuel portfolios consistently underperform during periods of market contraction.

Keywords Energy transition, transition risk, asset pricing, systematic risk, equity markets, fossil fuel divestment, sustainable finance

Resumo

A transição para sistemas energéticos de baixo carbono acentuou a importância estratégica dos minerais críticos, ao mesmo tempo que expôs o setor dos combustíveis fósseis a riscos de transição significativos relacionados com o clima. Esta dissertação avalia o desempenho financeiro e a dinâmica de risco-retorno de carteiras de investimento compostas por ações de minerais críticos e de combustíveis fósseis nos mercados desenvolvidos. Utilizando dados mensais de 1996 a 2026, foram construídas carteiras para ambos os setores intensivos em recursos.

Para avaliar se os riscos climáticos e sistemáticos se traduzem em prêmios de retorno distintos, o desempenho das carteiras é avaliado utilizando modelos de avaliação de ativos multifatoriais estabelecidos, incluindo os modelos de três, cinco e seis fatores de Fama e French (1993, 2015, 2018), bem como o modelo de fator q de Hou et al. (2021).

Os resultados de base iniciais indicam que os retornos das carteiras de ambos os setores são impulsionados principalmente pela exposição ao risco de mercado sistemático, dimensão e valor, sem evidência de desempenho anormal estatisticamente significativo. No entanto, observamos que as carteiras de combustíveis fósseis apresentam alfas negativos e estatisticamente significativos após a crise financeira internacional. Além disso, quando as carteiras são avaliadas sob diferentes condições do mercado global de petróleo, as carteiras de combustíveis fósseis apresentam um desempenho consistentemente inferior durante períodos de contração do mercado.

Palavras-chave Transição energética, risco de transição, avaliação de ativos, risco sistemático, mercados acionistas, desinvestimento em combustíveis fósseis, finanças sustentáveis

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1 Introduction

Over past years a considerable movement away from fossil fuels to renewable energy sources has occurred. This movement has increased the demand for transitional minerals and metals which are needed to develop renewable energy systems and increase technological innovation ([Sachs et al., 2019](#); [Plantinga & Scholtens, 2021](#))

“Critical minerals” resources have a major economic importance, yet they are associated to supply risks due to supply interruptions, geopolitical unrest, or restricted availability ([Tan & Keiding, 2023](#)). Climate transition underscores the importance of critical minerals in driving industrial development and achieving climate targets set forth by international organizations like the [United Nations Environment Programme \(2024\)](#). The European Raw Materials Act highlights the strategic relevance of critical minerals for the transition to renewable technologies ([European Commission, 2023](#)).

Critical minerals are essential to produce electronic equipment, manufacturing, energy, and defence. Each of these minerals has a particular importance to the technological industry. It is the case for electronics devices, batteries, aerospace and defence applications, production of steel and various industrial processes, semiconductors, fibre optics, light-emitting diodes (LEDs) and so on. They are especially important for the development of renewable technologies, including electric vehicles (EVs), wind turbines infrastructures, and solar photovoltaic cells ([Calderon et al., 2024](#)).

As the transition to low-carbon energy systems is spreading worldwide, investment choices, particularly in resource extraction and infrastructure, are based not just on market demand but also on perceptions of climate-related hazards.

The relation between finance and sustainability is particularly visible in companies that rely on both fossil fuels and critical minerals. Divestment pressures and regulatory costs are bigger for fossil fuels intensive companies, while critical minerals intensive companies are emerging as strategic assets, facing

their own set of environmental and geopolitical difficulties. The financial performance and investment attractiveness of critical minerals and fossil fuels differ, while both face climate-related risks. Since the Paris Agreement, banks have introduced a "carbon premium" on syndicated loans for carbon-intensive industries; however, the premium remains small compared to the risks. Only direct emissions are consistently charged, and so "green" banks have no pricing differences ([Ehlers et al., 2022](#)).

In this context, the objective of this research is to evaluate the performance of two investment portfolios composed of stocks from developed markets, focusing on the fossil fuel and the critical mineral sectors. We thus assume the perspective of an investor who forms portfolios of stocks in these sectors and assess how these portfolios perform. The dissertation contributes by articulating a sector-based extension that incorporates commodity risks and comparing the performance of portfolios investing in critical sectors of the economy.

2 Literature review

2.1 Climate risk and asset pricing models

Climate-related risks have become a relevant factor in modern asset-pricing research. Through both physical risk¹ and transition risk² channels, climate change affects companies' cash flows and expected returns (Bua et al., 2024). As a result, a growing body of research examines whether, and to what extent, climate-related risk is incorporated into asset prices and reflected in financial markets.

A prominent line of work investigates whether assets with higher carbon risk earn higher expected returns. Bolton and Kacperczyk (2021, 2023) provide evidence that portfolios assuming higher carbon intensity or emission risk tend to provide higher average returns. Similar results are reported by Hsu et al. (2023) for portfolios composed of highly polluting firms. These findings are consistent with the model of Pástor et al. (2021), which predicts higher returns for “brown” assets compared to “green” assets, driven not only by investors' preferences but also by risk-based arguments.

Beyond carbon premia, climate risk (through the physical and transition risk channel), can have substantial impact on the portfolio performance via sectoral and geographic exposures. Bua et al. (2024) show that physical and transition climate risk have heterogeneous effects across markets and countries, and that their influence on stock returns differs before and after 2015. This evidence shows that climate risk is neither static nor uniform but rather change across time and between jurisdictions (Bua et al., 2024).

Despite this growing evidence, financial markets may not fully price climate-related risks. Campiglio et al. (2023) argue that incomplete pricing of climate risk leads to systematic mispricing of climate-exposed

¹ Physical risk refers to damage caused by climate-related events, such as heatwaves, floods, and droughts, as well as chronic changes such as sea-level rise (Bua et al., 2024).

² Transition risk involves financial and operational risks arising from policy changes, technological shifts, and market responses during the transition to a low-carbon economy, such as carbon pricing and stranded assets (Bua et al., 2024).

assets. Assets whose cash-flows benefit from transition-related variables experience price increases, while assets with negative exposure face negative downward valuation pressure. Moreover, because climate-exposed assets are frequently included in leveraged financial statements, climate shocks may be amplified, increasing systematic risk. Therefore, investors require a higher expected return (risk premium) as both physical and transition risks may act as sources of systematic risk.

Another body of research proxies for climate risk using climate news-based indices rather than emissions-based metrics. [Engle et al. \(2020\)](#) , [Ardia et al. \(2023\)](#), and [Zhang \(2022\)](#) construct climate news-based indices capturing transition and physical climate risk in developed equity markets and document the higher performance of portfolios of environmentally friendly stock in periods of higher climate risks. [Zhang \(2022\)](#) further finds that the reaction to physical risk is substantially weaker than that to transition risk, suggesting that investors may underweight physical climate risk relative to regulatory and policy-related risks. Although carbon risk³ has been shown to negatively affect firm value ([Wang et al., 2022](#)), its impact on financial performance is non-linear ([Misani & Pogutz, 2015](#); [Trumpp & Guenther, 2017](#)).

The asset pricing models provide the theoretical basis for securities valuation and for understanding the systematic differences in expected return across different assets ([Fama, 1996](#)). Compared to single-factor models, multifactor asset pricing models offer a stronger prediction by incorporating multiple sources of systematic risk, particularly in sector-specific settings ([Fama & French, 2018](#); [Hou et al., 2019, 2021](#)). In these models, each factor is associated with its own risk premium, and an asset's excess return equals the weighted sum of these factors risk premia, where the weights correspond to the asset's sensitivities (betas) to each factor.

In the context of climate-exposed assets, asset pricing models are therefore essential for identifying, measuring, and pricing climate risk as a distinct source of systematic risk and incorporated into expected return premia ([Bolton & Kacperczyk, 2021, 2023](#)). As climate risk is entailed in a long-term macro-level shocks that impact consumption and productivity, rather than firm-specific risk that can be mitigated.

³ Carbon risk is a transition risk. Carbon risk is used describe the impact of transition to a low-carbon economy on firm value because of policy, legal, technological, market, and reputational changes ([Wang et al., 2022](#)).

2.2 Risk and return dynamics in resource-intensive sectors

According to portfolio theory, portfolio returns are a linear mix of sector weights, expected returns, and covariances. Asset selection therefore influences not only expected return, but also volatility, tail risk, and sensitivity to macroeconomic and policy shocks. As a result, understanding the characteristics of resources-intensive sectors (e.g., exposed to minerals or fossil fuels) is very important to evaluating portfolio performance under a variety of market situations. The sector participation increases exposure to systematic risk variables, including commodity price shocks, changes of regulation, and supply chain concentration. Consequently, portfolios with more exposure to critical minerals sectors and fossil fuel are more exposed to environmental risk, which in turn can shape risk premiums, affecting portfolio return and premiums.

“Minerals” are a wide range of inorganic solid substances that are usually found in or on the ground, distinguished between fuel and nonfuel minerals. Nonfuel minerals can be divided into metals (e.g., copper, gold, nickel) and industrial minerals (e.g. phosphate, sand and gravel). According to [Dou et al. \(2023\)](#), the criticality of a mineral is influenced by its geographically restricted occurrence, presence within national territories, potential for substitution, and feasibility of recycling. Minerals including lithium, cobalt, nickel, graphite, rare earth elements (neodymium, dysprosium and yttrium), manganese, gallium, germanium, gallium, tantalum and, indium are considered “critical minerals”.

These nonfuel minerals (formed through geological processes) are indispensable to produce a wide range of industries such as electronics, semiconductors, fibre optics, energy systems, and to the green transition technologies, as they support the development of renewable technologies, solar and wind farms, and electric vehicles ([Attilio, 2025](#); [Dou et al., 2023](#); [Müller et al., 2025](#)).

In contrast, there are fossil fuel formed from ancient organic matter through geological processes acting on the remains of plants, algae and bacteria. These resources include oil, coal, and natural gas. These sectors are highly concentrated due to high entry barriers, critical minerals processing and refining, together with fossil fuel midstream infrastructure like pipelines and liquefied natural gas (LNG) terminals, show the highest competitive advantages.

Correlated with the burning of fossil fuels, the emissions of carbon dioxide contribute to the climate change and increase global warming. Therefore, for an energy transition aligned with climate goals, shifting from fossil fuels to energy systems that rely on critical minerals is considered a preferable alternative.

There are arguments that can be put forward regarding the performance of portfolios formed on fossil fuels and critical minerals. A major argument relates to diversification. Although portfolio theory prescribes holding diversified portfolios, there is evidence that portfolios that are concentrated on specific industries obtain higher returns ([Kacperczyk et al., 2005](#)). On the other hand, the equilibrium model developed by [Pástor et al. \(2021\)](#) predicts that due to investors' tastes and risk properties of green assets, they are expected to produce lower expected returns than brown assets.

As the demand for critical minerals rises, especially during the decarbonization era, control over these resources significantly influences market dynamics ([Zhu et al., 2023](#)), which makes portfolio exposures to these sectors both strategically important and vulnerable to geopolitical shocks. While they offer growth opportunities, the market concentration and the mineral complexity pose increased risks for long term portfolio resilience ([Baz et al., 2022](#)).

In contrast, fossil fuel firms have a greater exposure to transition risk. These companies have a high climate risk premium ([Antoniuk & Leirvik, 2024](#)). Empirical evidence from [Gong et al. \(2023\)](#) suggests that “firms with higher climate risk have higher stock returns”—a 1% increase in climate risk results in a 3.02%–4.27% increase in stock returns. This effect is more evident in high-income nations, where a 1% increase in climate risk results in an annual stock return increment of 3.12% ([Gong et al., 2023](#)). These premiums reflect compensation to investors for regulatory uncertainty and transition shocks. According to [Bouri et al. \(2023\)](#), “brown” energy stocks tend to be more sensitive to transition risk than physical risk. However, extreme weather events and physical climate dangers can also reduce profits, particularly in vulnerable locations.

Although critical minerals support advanced technologies and economic growth, increased mineral complexity can impede growth in the long run. This highlights the need for risk management and targeted investment ([Baz et al., 2022](#)). In the United States of America, green bonds experienced positive effects from the 2015 Paris Agreement and negative effects from the 2016 U.S. Presidential Election, and climate related events generally have a positive impact on stock market returns in the clean energy sector ([Antoniuk & Leirvik, 2024](#)). However, weaker policies can result in abnormal positive returns in the fossil energy sector.

Environmental risks have varied impacts on both fossil fuel and non-fossil sectors, shaped by investor preferences and cash-flow consequences ([Zhu et al., 2023](#)). Although the literature highlights the strategic importance of critical minerals and the climate vulnerability of fossil fuels, less is known about how these

risks are priced at the portfolio level, particularly in resource-intensive sectors. This is an important gap, as sectoral portfolios may reveal patterns in risk-return dynamics that are not fully captured at the firm-level. By focusing on portfolios composed of firms from two resource-intensive sectors, this dissertation contributes to the literature on climate risk pricing.

The main goal of this research is to evaluate the performance of investment portfolios comprised of stocks of two resource-intensive sectors. By applying multifactor asset-pricing models, it enhances understanding of climate risk by directly comparing the risk-return dynamics at the portfolio level, therefore leading to a better understanding of how climate risks are priced at the portfolio level.

3 Methodology

3.1 Portfolio construction

The primary objective of this research is to analyse the performance of investment portfolios holding publicly listed developed market equities in the critical mineral and fossil fuel sectors. We start by constructing two portfolios of stocks of critical minerals and fossil fuels companies. Portfolio total returns include price fluctuations and reinvested cash dividends.

To construct the portfolios, we gathered the end-of-month total return index series for the period from January 1996 to January 2026. Then, we calculated stock returns in a discrete way:

$$R_{i,t} = \frac{TR_{i,t} - TR_{i,t-1}}{TR_{i,t-1}} \quad (3.1)$$

Where $R_{i,t}$ reflects the discrete rate of return of stock i in month t , $TR_{i,t}$ represents the total return index of stock i in month t , and $TR_{i,t-1}$ denotes the total return index of stock i in month $t - 1$.

We form both equal-weighted and value-weighted portfolios, rebalanced monthly on lagged market market capitalisation. In the equal-weighted scheme, each company contributes the same weight to portfolio returns and the results are not mechanically dominated by a small number of large firms. The equally weighted portfolio of equities is constructed as follows:

$$R_{p,t}^E = \frac{1}{N} \sum_{i=1}^N R_{i,t} \quad (3.2)$$

Where $R_{p,t}^E$ is the rate of return of the equally weighted portfolio p in month t , $R_{i,t}$ is the discrete return of stock i in month t , and N corresponds to the number of stocks in portfolio p .

This method represents the performance of a broad range of companies, including smaller companies that are more vulnerable to transition risk. We also form value-weighted portfolios based on market capitalisation to ensure that findings are not solely influenced by the weighting method and to compare whether results are sensitive to firm size and concentration effects. Value-weighted portfolio is formed as follows:

$$R_{p,t}^V = \sum_{i=1}^N \frac{MV_{i,t}}{\sum_{j=1}^N MV_{j,t}} R_{i,t} \quad (3.3)$$

Where $R_{p,t}^V$ corresponds to the rate of return of the value weighted portfolio p in month t , $R_{i,t}$ is the discrete return of stock i in month t , and $MV_{i,t}$ represents the market value of firm i in month t .

Besides the critical minerals and fossil fuel portfolios, we also form a difference portfolio, representing the return spread between the two sectors, calculated as the excess return on the critical mineral portfolio minus the excess return on the fossil fuel portfolio. The difference portfolio thus simulates a strategy of going long in the critical minerals portfolio and short in the fossil fuel portfolio.

3.2 Performance evaluation over the full sample period

Portfolio performance is evaluated through multi-factor models that are recognized in the literature as capturing relevant sources of systematic risk. The [Fama and French \(1993\)](#) three-factor model (Equation 3.4) accounts for the market, size and book-to-market risk factors, as follows:

$$r_{p,t} = \alpha_p + \beta_{p1} r_{m,t} + \beta_{p2} SMB_t + \beta_{p3} HML_t + \varepsilon_{p,t} \quad (3.4)$$

Where $r_{p,t}$ is the excess return of portfolio p in month t over the risk-free rate; α_p represents the abnormal return of portfolio p ; β_p is the systematic risk of portfolio p ; $R_{m,t}$ is the market's excess return during the month; SMB_t is the size factor (Small minus Big), defined as the returns of small-cap companies less returns of large-cap companies in month t ; HML_t is the value factor (High minus Low), defined as the returns of high book-to-market companies less low book-to-market companies in month t ; and $\varepsilon_{p,t}$ is the residual term.

The evaluation then considers the [Fama and French \(2015\)](#) five-factor model (Equation 3.5). This

model includes two additional variables: profitability (RMW) and investment (CMA).

$$r_{p,t} = \alpha_p + \beta_{p1} r_{m,t} + \beta_{p2} SMB_t + \beta_{p3} HML_t + \beta_{p4} RMW_t + \beta_{p5} CMA_t + \varepsilon_{p,t} \quad (3.5)$$

Where RMW_t is the profitability factor (Robust minus Weak), defined as the difference in returns between firms with robust profitability and firms with weak profitability; and CMA_t is the investment factor (Conservative minus Aggressive), defined as the difference in returns between firms that follow a conservative investment policy and firms that follow an aggressive investment policy.

Thereafter, the evaluation includes a momentum factor (UMD) with the [Fama and French \(2018\)](#) six-factor model (Equation 3.6).

$$r_{p,t} = \alpha_p + \beta_{p1} r_{m,t} + \beta_{p2} SMB_t + \beta_{p3} HML_t + \beta_{p4} RMW_t + \beta_{p5} CMA_t + \beta_{p6} UMD_t + \varepsilon_{p,t} \quad (3.6)$$

Where UMD_t is the momentum factor, defined as the difference in returns between stocks with high prior returns and stocks with low prior returns.¹

Finally, to conduct a more thorough analysis, the [Hou et al. \(2021\)](#) q-Factor Model (Equation 3.7), which incorporates the growth factor, is implemented. This model used forecasts based on Tobin's q , operating cash flows, and changes in return on equity ([Hou et al., 2021](#)). This new factor captures the premium associated with firms expected to experience higher future investment growth, *ceteris paribus*.

$$r_{p,t} = \alpha_p + \beta_{p1} r_{m,t} + \beta_{p2} Me_t + \beta_{p3} I/A_t + \beta_{p4} ROE_t + \beta_{p5} EG_t + \varepsilon_{p,t} \quad (3.7)$$

Where $R_{Me,t}$ is the size factor, defined as the returns of small-cap companies less returns of large-cap companies in month t ; $R_{I/A,t}$ is the investment factor, defined as the difference in returns between firms with conservative versus aggressive investment strategies; $R_{ROE,t}$ is the return-on-equity factor, representing the difference in returns between firms with high profitability and firms with low profitability

¹ This factor was introduced by [Carhart \(1997\)](#).

(as measured by return on equity); and $R_{EG,t}$ is the expected growth factor, defined as the difference in returns between firms with high expected growth and firms with low expected growth.

In this model, market risk reflects systematic risk, while the size factor indicates that smaller firms often yield higher returns. The investment factor measures a firm's investment in relation to its total assets, and profitability is assessed through return on equity (ROE). Expected growth captures a firm's growth prospects and is often indicated by equity issuance or valuation metrics.

3.3 Performance evaluation in different market periods

Besides evaluating portfolio performance over the full sample period, we also evaluate the performance of the critical minerals and fossil fuel portfolios across different market periods. For this purpose, we follow two approaches: (1) evaluating portfolio performance according to different states of the oil market, and (2) evaluating portfolio performance in different subperiods.

The first approach is motivated by [Plantinga and Scholtens \(2021\)](#) and [Cortez et al. \(2022\)](#), who use the fossil fuel sector's exposure to oil market conditions as a time-varying performance proxy. The underlying argument is that evaluating fossil fuel portfolios in different market conditions should consider states of contraction and expansion of the fossil fuel industry. The second approach used to evaluate portfolio over time involves evaluating performance over different subsequent subperiods.

4 Data description

4.1 Selection of stocks

For this study, the investment universe consists of publicly listed stocks in developed market equities classified under two resource-based sectors according to the Industry Classification Benchmark (ICB)¹.

The baseline study follows the MSCI Developed Markets (DM) classification. High income levels, established regulations, liquid capital markets, and high accessibility for international investors. This includes North America (the United States and Canada), Europe (Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom), Asia-Pacific (Australia, Japan, New Zealand, Hong Kong, and Singapore), and Israel.

4.1.1 Critical mineral and fossil fuel sector classification

To identify the stocks to be included in the critical minerals portfolio (CM), we resort to the Industrial Metals and Mining classification (ICB 551020). However, to isolate companies with genuine exposure to critical minerals, we apply an additional business-specific filter. We followed the International Energy Agency's definition of the critical minerals for the clean energy transition ([International Energy Agency, 2021, 2025](#)). Motivated by [Müller et al. \(2025\)](#), we selected only the minerals with direct relevance for electrification, energy storage technologies, clean-technology supply chains and renewable energy systems.

To do so we started by retrieving each firm's extended business description variable (WC06092) from LSEG (formerly Refinitiv/Datastream). As the first phase, we standardized these descriptions using a fixed, ex-ante keyword dictionary. The baseline classification, therefore, includes firms if their primary

¹ The ICB is a comprehensive, rules-based, transparent classification approach based on research and industry trends, representing an established approach for categorising businesses firms into four levels: industry, supersector, sector, and subsector.

activities mention at least one core critical mineral: lithium, cobalt, nickel, graphite, rare earth elements, manganese, gallium, and germanium. These minerals are found in battery chemistries, electric motors, photovoltaic systems, and semiconductor components that are essential to the energy transition [Müller et al. \(2025\)](#); [International Energy Agency \(2025\)](#).

Finally, to reduce false positives (i.e., unrelated uses of mineral terms), we additionally require the presence of mining-context language. Minerals primarily driven by agricultural or traditional industrial demand are not included, to improve alignment with energy-transition exposure. The basis for the classification of stocks for the fossil fuel portfolio (FF) was Oil, Gas, and Coal (ICB 601010), without further filtering.

We then gathered end-of-month total return indices (in USD) for all constituents and the market value time series. All the historical financial data used is obtained through the financial analysis platform LSEG. Table 1 presents the number of stocks that comprise each portfolio.

Table 1: Portfolio composition

This table provides the number of constituents of the fossil fuel and critical mineral portfolios.

Portfolio	Const.
Fossil Fuel	2,547
Critical Mineral	832
Total	3,379

4.1.2 Data cleaning

Although the initial universe comprises a high number of firms, not all stocks are eligible for portfolio construction. Firms must have valid return and market capitalisation data on their establishment date, otherwise they were excluded from the database. Additionally, we treated returns equal or lower than -100% or equal or higher than $+500\%$ as data errors and excluded them, prior to winsorisation at 1%/99%.

Micro-cap companies were omitted to reduce the impact of extremely small companies which can contribute to microstructure noise and non-investable return patterns, in order to have liquid and economically significant exposures before portfolio construction.

Then, at each monthly rebalancing date, the constituents in each portfolio are ranked by market

capitalisation (in USD), ensuring cross-country comparability and consistency in value-weighted portfolio construction to focus on the most economically important portion of each industry. Only enterprises accounting for the top 99% of cumulative market capitalisation are maintained. Between rebalancing dates, portfolio weights are allowed to drift with relative price movements, reflecting a buy-and-hold strategy within each period.

The combination of micro-cap exclusion and cumulative market capitalisation selection allows that portfolio returns are influenced by systematic sector exposure rather than microstructure effects. And restricting the sample to developed equity markets improves comparability and the detection of fossil fuel and critical minerals risk premia by reducing currency, liquidity, and structural effects present in emerging economies.

4.2 Multi-factor models and risk factors

In order to perform the regression analysis in the [Fama and French \(1993\)](#) three-factor, the [Fama and French \(2015\)](#) five-factor, and the [Fama and French \(2018\)](#) six-factor models, we retrieve from Professor Kenneth R. French's website², the Developed Markets (DM) market risk, size, value/growth, momentum, investment, and profitability factors.

We also retrieve the factors for the q-factor model: investment factor, the return-on-equity factor, the expected growth factor, from the Global-q website³. Unlike the Fama-French model, which relies on empirical data, the q-factors model incorporates economic theory, particularly the q-theory of investment. The yield on the 1-month U.S. Treasury Bill is used as a proxy for the risk-free rate since the analysis is focused on the Developed Markets and all returns are denominated in USD.

4.3 Periods of contraction and expansion in the oil industry

To implement the analysis of portfolio performance in different states of the market, we use two approaches to identify the market subperiods, as mentioned in section 3.3. The first approach involves evaluating portfolio performance across periods of contraction and expansion in the oil industry. The

² https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

³ <https://global-q.org/factors.html>

second approach involves evaluating portfolio performance across subsequent subperiods.

As to the first approach, we follow [Plantinga and Scholtens \(2021\)](#) and define market states based on the growth and decline in the number of oil rigs in operation using the Baker Hughes Worldwide Rig Count database⁴. Periods of expansion (contraction) are identified by a positive (negative) 12-month rolling growth rate in the number of the active and operating international oil rigs. This classification allows us to understand whether there are systematic differences in the performance of critical mineral and fossil fuel portfolios under expansionary and contractionary oil market regimes.

The estimated contraction periods in the periods under analysis are April 1998 to September 1999, November 2001 to November 2002, July 2007 to August 2007, October 2007, January 2009 to January 2010, August 2012 to November 2013, January 2015 to December 2016, July 2019 to April 2021, August 2023 to December 2023 and January 2025 to February 2026.

Regarding the second approach, we test whether abnormal performance is stable or whether it varies over time by estimating alphas for different subperiods. For this purpose, we decompose the overall sample period (January 1996 to January 2026) into five non-overlapping subperiods. The subperiods are defined along two dimensions: two equal-length windows (1996 to 2010 and 2011 to 2026), and three equal-length windows (1996 to 2005, 2006 to 2015, and 2016 to 2026). This allows comparing portfolio alphas across different historical phases.

4.4 Descriptive statistics

Observing Table 2, there is substantial heterogeneity across the portfolios. The critical mineral value-weighted portfolio exhibits the highest monthly average excess return and cumulative excess return. However, both critical mineral portfolios are more volatile than the fossil fuel portfolios. The Jarque–Bera tests strongly reject normality for the long-only portfolios, whose returns are negatively skewed and leptokurtic, indicating fat-tailed distributions. By contrast, the long–short portfolios appear closer to normality. Importantly, the equal-weighted difference portfolio has a negative monthly average excess return, whereas the value-weighted difference portfolio has a positive one. This suggests that the relative outperformance of critical mineral stocks is concentrated among larger firms rather than being broadly distributed across the entire cross-section.

⁴ <https://rigcount.bakerhughes.com/intl-rig-count>

Table 2: Descriptive statistics of monthly portfolio excess returns

This table provides the descriptive statistics of the monthly excess returns of the critical mineral (CM) and fossil fuel (FF) equally weighted, value weighted portfolios and the portfolio difference. This includes the number of observations, the mean, standard deviation, minimum, maximum, skewness, kurtosis, Jarque-Bera test's p-value, and cumulative return from January 1996 to January 2026.

Variable	No. of Obs.	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis	JB Test P-value	Cumulative Return
Critical Mineral (EW)	360	0.0042	0.0861	-0.4697	0.2514	-0.4736	5.6139	0.0000	0.1330
Critical Mineral (VW)	360	0.0105	0.0825	-0.3483	0.2579	-0.1876	4.1512	0.0000	11.4250
Fossil Fuel (EW)	360	0.0073	0.0624	-0.2884	0.2100	-0.4643	5.4866	0.0000	5.8242
Fossil Fuel (VW)	360	0.0079	0.0544	-0.2188	0.1678	-0.2532	4.3873	0.0000	8.9242
CM — FF (EW)	360	-0.0031	0.0571	-0.1813	0.1821	0.0931	3.2030	0.5662	-0.8197
CM — FF (VW)	360	0.0026	0.0593	-0.1831	0.1989	0.2150	3.3887	0.0805	0.3537

The risk factors reported in Table 3 reveal substantial heterogeneity in both average monthly returns and higher moments. Across the different model specifications, the market factor exhibits the highest average monthly return and remains one of the most economically important sources of systematic risk. The Jarque–Bera test strongly rejects normality for all factors. Moreover, the factor return distributions are asymmetric and display excess kurtosis, indicating pronounced skewness and fat tails.

Table 3: Descriptive statistics of the public information variables and risk factors

This table provides the descriptive statistics of the monthly returns of the factors used in the Fama and French (1993) three-factor model, the Fama and French (2015) five-factor model, the Fama and French (2018) six-factor model, and the Hou et al. (2021) q-factor model. This includes the number of observations, mean, standard deviation, minimum, maximum, skewness, kurtosis, and Jarque-Bera test p-value from January 1996 to January 2026.

Factor	Model	No. Obs	Mean	Std. Dev.	Minimum	Maximum	Skewness	Kurtosis	JB Test P-value
Fama-French multi-factor models									
Mkt	FF3	360	0.0060	0.0441	-0.1951	0.1334	-0.6669	4.4822	0.0000
SMB	FF3	360	-0.0010	0.0202	-0.1008	0.1086	0.0354	6.5785	0.0000
HML	FF3	360	0.0025	0.0273	-0.1014	0.1224	0.4258	6.3936	0.0000
Mkt	FF5	360	0.0060	0.0441	-0.1951	0.1334	-0.6669	4.4822	0.0000
SMB	FF5	360	-0.0002	0.0195	-0.0865	0.0837	-0.0926	4.7354	0.0000
HML	FF5	360	0.0025	0.0273	-0.1014	0.1224	0.4258	6.3936	0.0000
RMW	FF5	360	0.0034	0.0153	-0.0575	0.0620	0.0300	4.6664	0.0000
CMA	FF5	360	0.0017	0.0201	-0.0644	0.0957	0.7666	6.3377	0.0000
UMD	FF6	360	0.0053	0.0392	-0.2426	0.1773	-0.9192	9.1355	0.0000
q-factor model									
Mkt		353	0.0074	0.0456	-0.1718	0.1359	-0.5909	3.9321	0.0000
Me		353	0.0017	0.0327	-0.1441	0.2214	0.7144	9.0110	0.0000
I/A		353	0.0018	0.0237	-0.0713	0.1044	0.5005	4.7766	0.0000
ROE		353	0.0041	0.0297	-0.1436	0.1036	-0.8003	7.5036	0.0000
EG		353	0.0057	0.0245	-0.0976	0.1188	0.2554	5.8457	0.0000
U.S. 1-Month T-Bill									
RF		360	0.0019	0.0018	0.0000	0.0056	0.3534	1.5346	0.0000

5 Empirical results

The performance of the critical mineral and fossil fuel portfolios in the developed markets is evaluated using the [Fama and French \(1993\)](#) three-factor model, the [Fama and French \(2015\)](#) five-factor model, the [Fama and French \(2018\)](#) six-factor model, and the [Hou et al. \(2021\)](#) q-Factor model. All estimations are adjusted for autocorrelation and heteroscedasticity through the [Newey and West \(1987\)](#) methodology. Given the monthly frequency of the data, we employed a lag length of 12 to account for potential serial dependence over a one-year horizon. The reported results should be interpreted as upper bounds on implementable performance since they are gross of transaction costs. Moreover, between rebalancing dates, weights are allowed to evolve endogenously in response to relative price movements. While the following models do not explicitly account for climate change risk, differential factors in investment and profitability may serve as a proxy for capital reallocation driven by energy transition dynamics.

5.1 Overall performance

5.1.1 The Fama and French (1993) three-factor model

In Table 4, the estimated alphas are not statistically significant across any portfolio. This indicates that there is no strong evidence of abnormal returns, once exposures to the risk factors are included, suggesting that the excess returns are largely explained by systematic risk factors. Although not statistically significant, the value-weighted difference portfolio is the only portfolio with a positive alpha. As such, both the critical minerals and fossil fuel portfolios show a neutral performance relative to the benchmark. The alpha of the difference portfolios is also insignificant, indicating no statistically significant difference between the performance of both portfolio.

The coefficients on the market excess return factor (Mkt) are positive and statistically significant at

a 1% level across all portfolios. Furthermore, the results of the difference portfolio suggest that critical mineral stocks exhibit a greater systematic risk than fossil fuel stocks. Both portfolios show a significant exposure to the size factor. However, the positive and significant size factor coefficient of the difference portfolio indicates that the critical minerals portfolio is more exposed toward smaller capitalization firms than the fossil fuel portfolio. Regarding the coefficient on HML, the portfolios' coefficients are positive and statistically significant, indicating that both are exposed to growth stocks, although the results of the difference portfolio show that the critical mineral portfolio is less exposed to value stocks than its fossil fuel counterpart.

In sum, while the performance of both portfolios is not statistically different, differences in the estimated factor loadings indicate that critical mineral firms appear to be more sensitive to market fluctuations, to small-capitalization stocks, and to growth stocks than the fossil fuel portfolio.

Table 4: Performance of fossil fuel and critical mineral portfolios – Fama-French (1993) model

This table provides the estimation results of the Fama-French (1993) three-factor model for the critical mineral (CM), the fossil fuel (FF) portfolio and the difference portfolio, defined as the critical mineral portfolio minus fossil fuel portfolio. Mkt is the market's excess return; SMB is the size factor, defined as the returns of small-cap companies less returns of large-cap companies; HML is the value factor, defined as the returns of high book-to-market companies less low book-to-market companies; and alpha denotes the abnormal return of each portfolio.

	<i>Dependent Variable: Excess Return</i>					
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Mkt	1.4081 ^{***} (0.0985)	1.3347 ^{***} (0.0795)	1.0471 ^{***} (0.0579)	0.9178 ^{***} (0.0466)	0.3610 ^{***} (0.0722)	0.4169 ^{***} (0.0763)
SMB	1.3077 ^{***} (0.1544)	0.4652 ^{**} (0.1836)	0.7440 ^{***} (0.1134)	0.1598 [*] (0.0855)	0.5636 ^{***} (0.1217)	0.3054 ^{**} (0.1533)
HML	0.4593 ^{***} (0.1211)	0.5424 ^{***} (0.1299)	0.6952 ^{***} (0.0940)	0.6593 ^{***} (0.1014)	-0.2359 ^{**} (0.0923)	-0.1168 (0.1332)
α	-0.0062 (0.0041)	-0.0006 (0.0034)	-0.0019 (0.0023)	-0.0011 (0.0018)	-0.0043 (0.0038)	0.0005 (0.0031)
Observations	359	359	359	359	359	359

Table 4: Performance of fossil fuel and critical mineral portfolios – Fama-French (1993) model (continued)

<i>Dependent variable: Excess Return</i>						
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
R^2	0.6251	0.5261	0.6371	0.5979	0.1545	0.1217
Adjusted R^2	0.6220	0.5221	0.6341	0.5945	0.1473	0.1143

Note: Heteroscedasticity and autocorrelation were corrected by following the Newey-West (1987) method. Standard errors are reported in parentheses. Adj. R^2 is the adjusted coefficient of determination. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.1.2 The Fama and French (2015) five-factor model

Table 5 presents the estimates obtained with the Fama-French five-factor model. Again, there is no evidence of abnormal performance, as the alpha coefficients are insignificant. In Table 5, the estimates for the market excess return factor (Mkt), size factor (SMB), and the value factor (HML) remain comparable to those found using the three-factor model. The market excess return is positive and statistically significant at the 1% level for all portfolios, with the difference portfolio indicating that the critical minerals portfolio is more sensitive to market movements. As to size, both portfolios continue to exhibit positive and statistically significant coefficients, supporting exposure to small cap stocks. Again, the results of the difference portfolio show that critical minerals lean more towards small caps than fossil fuels. The value factor is positive and statistically significant for the long portfolios, suggesting a value orientation. In this model, however, there is no difference in exposure to this factor. Overall, these results suggest that both critical mineral and fossil fuel portfolios are highly exposed to market risk, small caps and value firms. The additional profitability (RMW) and investment factors (CMA) are not statistically significant, implying that there is no strong evidence that the portfolios' excess returns are explained by differences in profitability or investment decision.

Table 5: Performance of fossil fuel and critical mineral portfolios – Fama-French (2015) model

This table provides the estimation results of the Fama-French (2015) five-factor model for the critical mineral (CM), the fossil fuel (FF) portfolio and the difference portfolio, defined as the critical mineral portfolio minus fossil fuel portfolio. Mkt is the market's excess return; SMB is the size factor, defined as the returns of small-cap companies less returns of large-cap companies; HML is the value factor, defined as the returns of high book-to-market companies less low book-to-market companies; RMW is the profitability factor, defined as the difference in returns between firms with robust profitability and firms with weak profitability; CMA is the investment factor, defined as the difference in returns between firms that follow a conservative investment policy and firms that follow an aggressive investment policy; and alpha denotes the abnormal return of each portfolio.

	<i>Dependent Variable: Excess Return</i>					
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Mkt	1.3478*** (0.0972)	1.2914*** (0.0892)	1.0016*** (0.0617)	0.9266*** (0.0555)	0.3462*** (0.0820)	0.3648*** (0.0767)
SMB	1.3534*** (0.1568)	0.5037*** (0.1747)	0.7742*** (0.1161)	0.2088** (0.0971)	0.5791*** (0.1291)	0.2949* (0.1638)
HML	0.6073** (0.2428)	0.7383*** (0.2462)	0.8558*** (0.1430)	0.7182*** (0.1429)	-0.2485 (0.1894)	0.0200 (0.2564)
RMW	0.2012 (0.2695)	0.2265 (0.2642)	0.2090 (0.2183)	0.2569 (0.2350)	-0.0077 (0.2379)	-0.0304 (0.2754)
CMA	-0.6756 (0.4604)	-0.5115 (0.4584)	-0.5315* (0.2907)	-0.1547 (0.2136)	-0.1441 (0.3095)	-0.3568 (0.3913)
α	-0.0068 (0.0043)	-0.0011 (0.0035)	-0.0024 (0.0024)	-0.0021 (0.0020)	-0.0044 (0.0040)	0.0009 (0.0034)
Observations	359	359	359	359	359	359
R^2	0.6350	0.5326	0.6473	0.6027	0.1567	0.1272
Adjusted R^2	0.6298	0.5260	0.6423	0.5971	0.1447	0.1148

Note: Heteroscedasticity and autocorrelation were corrected by following the Newey-West (1987) method. Standard errors are reported in parentheses. Adj. R^2 is the adjusted coefficient of determination. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.1.3 The Fama and French (2018) six-factor model

The results of the six-factor model, including the momentum factor (UMD), are reported in Table 6. These results reinforce the evidence that portfolio excess returns are primarily driven by market fluctuations, size, and value exposures, while no statistically significant abnormal performance is detected. All portfolios report positive and statistically significant coefficients on the market and size factors, suggesting exposure to systematic market risk and a tilt toward smaller-capitalization firms, particularly in the critical mineral portfolios. The value factor is significant only for the long portfolios. By contrast, the profitability and investment factors remain insignificant, suggesting that these factors do not explain the portfolios' excess returns, *ceteris paribus*.

Table 6: Performance of fossil fuel and critical mineral portfolios – Fama-French (2018) model

This table provides the estimation results of the Fama-French (2018) factor model for the critical mineral (CM), the fossil fuel (FF) portfolio and the difference portfolio, defined as the critical mineral portfolio minus fossil fuel portfolio. Mkt is the market's excess return; SMB is the size factor, defined as the returns of small-cap companies less returns of large-cap companies; HML is the value factor, defined as the returns of high book-to-market companies less low book-to-market companies; RMW is the profitability factor; CMA is the investment factor; UMD is the momentum factor; and alpha denotes the abnormal return of each portfolio.

	<i>Dependent variable: Excess Return</i>					
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Mkt	1.3401*** (0.1048)	1.2899*** (0.0930)	1.0050*** (0.0631)	0.9433*** (0.0545)	0.3351*** (0.0861)	0.3466*** (0.0815)
SMB	1.3641*** (0.1580)	0.5057*** (0.1840)	0.7695*** (0.1180)	0.1854* (0.0996)	0.5946*** (0.1299)	0.3203* (0.1681)
HML	0.5822** (0.2592)	0.7336*** (0.2735)	0.8669*** (0.1599)	0.7730*** (0.1634)	-0.2847 (0.2014)	-0.0394 (0.2691)
RMW	0.2109 (0.2651)	0.2283 (0.2617)	0.2047 (0.2147)	0.2358 (0.2228)	0.0062 (0.2260)	-0.0074 (0.2630)
CMA	-0.6629 (0.4628)	-0.5091 (0.4707)	-0.5371* (0.3001)	-0.1824 (0.2260)	-0.1258 (0.3152)	-0.3267 (0.3908)

Table 6: Performance of fossil fuel and critical mineral portfolios – Fama-French (2018) model (continued)

	<i>Dependent variable: Excess Return</i>					
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
UMD	-0.0386 (0.1038)	-0.0072 (0.1012)	0.0170 (0.0802)	0.0842 (0.0754)	-0.0557 (0.0776)	-0.0914 (0.0893)
α	-0.0066 (0.0041)	-0.0011 (0.0033)	-0.0025 (0.0023)	-0.0026 (0.0019)	-0.0040 (0.0039)	0.0016 (0.0032)
Observations	359	359	359	359	359	359
R^2	0.6352	0.5327	0.6474	0.6057	0.1579	0.1301
Adjusted R^2	0.6290	0.5247	0.6413	0.5990	0.1435	0.1153

Note: Heteroscedasticity and autocorrelation were corrected by following the Newey-West (1987) method. Standard errors are reported in parentheses. Adj. R^2 is the adjusted coefficient of determination. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.1.4 The Hou et al. (2021) q-factor model

The results of the Hou et al. (2021) model, reported in Table 7, show that alpha remains insignificant across all portfolios. This indicates that there is no evidence of abnormal excess returns for the critical mineral portfolios, fossil fuel portfolios, or the long-short portfolios. Moreover, the Hou et al. (2021) q-factor model exhibits lower adjusted R^2 values, suggesting that it explains these portfolios less effectively than the Fama-French models. The lower R^2 can be attributed to the fact that the q-factors are constructed using U.S. data, whereas the Fama-French factors used are based on developed markets. The market excess return factor (Mkt) is positive and statistically significant for all portfolios, indicating that aggregate market exposure remains the principal determinant of the portfolios' excess returns.

Consistent with the Fama-French models results, critical mineral firms appear more sensitive to market fluctuations than fossil fuel firms. The size factor loadings (Me) are positive and statistically significant only for the equal-weighted long portfolios, suggesting that the small-capitalization tilt is limited. Relative to the Fama-French models, the size effect is weaker and less pervasive in the q-factor model. The investment factor (I/A) is positive and statistically significant for the critical mineral long portfolios and only weakly significant for the equal-weighted fossil fuel portfolio. This suggests that critical mineral firms may display

stronger investment-related characteristics in this model. However, since the loading for the long-short portfolios is not statistically significant, there is no sufficient evidence to conclude that investment related characteristics differ from critical mineral firms and fossil fuel firms.

The profitability factor (ROE) provides one of most distinctive results relative to the Fama-French models. The coefficients are negative and statistically significant for the equal-weighted fossil fuel portfolio, and for the equal-weighted difference portfolio. This suggests that fossil fuel firms are associated with lower return-on-equity when compared to the critical mineral firms. The expected growth factor (EG) is negative and statistically significant for the critical mineral portfolios, suggesting that critical mineral excess returns are negatively related to the expected growth factor in this model. However, as the long-short portfolio coefficients are not statistically significant, there is no sufficient evidence to conclude that expected growth prospects are different between critical mineral firms and fossil fuel firms, *ceteris paribus*.

Table 7: Performance of fossil fuel and critical mineral portfolios – Hou et al. (2021) model

This table provides the estimation results of the Hou et al. (2021) q-factor model for the critical mineral (CM), the fossil fuel (FF) portfolio and the difference portfolio, defined as the critical mineral portfolio minus fossil fuel portfolio. Mkt is the market's excess return; Me is the size factor, defined as the returns of small-cap companies less returns of large-cap companies; I/A is the investment factor; ROE is the profitability factor measured by return on equity; EG is the expected growth factor; and alpha denotes the abnormal return of each portfolio.

	<i>Dependent variable: Excess Return</i>					
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Mkt	1.0328*** (0.1205)	1.0451*** (0.1139)	0.8085*** (0.0765)	0.7852*** (0.0503)	0.2242*** (0.0814)	0.2600*** (0.0958)
Me	0.2854** (0.1353)	-0.0313 (0.1435)	0.2395* (0.1325)	-0.0099 (0.1122)	0.0459 (0.1105)	-0.0214 (0.1014)
I/A	0.3203* (0.1924)	0.3628 (0.2228)	0.4102** (0.1684)	0.4904*** (0.1426)	-0.0899 (0.1162)	-0.1276 (0.1474)
ROE	-0.3286** (0.1649)	-0.0340 (0.2014)	-0.0207 (0.1610)	0.1813 (0.1349)	-0.3080*** (0.1169)	-0.2153 (0.1418)
EG	-0.1762 (0.2147)	-0.3725 (0.2336)	-0.3651** (0.1467)	-0.4567*** (0.1337)	0.1889 (0.1404)	0.0842 (0.2004)

Table 7: Performance of fossil fuel and critical mineral portfolios – Hou et al. (2021) model (continued)

	<i>Dependent variable: Excess Return</i>					
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
α	-0.0052 (0.0054)	0.0017 (0.0043)	0.0005 (0.0031)	0.0012 (0.0025)	-0.0057 (0.0041)	0.0006 (0.0034)
Observations	347	347	347	347	347	347
R^2	0.4295	0.3797	0.4827	0.4866	0.0727	0.0704
Adjusted R^2	0.4212	0.3706	0.4751	0.4791	0.0591	0.0568

Note: Heteroscedasticity and autocorrelation were corrected by following the Newey-West (1987) method. Standard errors are reported in parentheses. Adj. R^2 is the adjusted coefficient of determination. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Across all model specifications, we do not have a robust evidence of critical mineral portfolios outperformance relative to fossil fuel portfolios.

5.2 Time-varying performance

In the previous sections, the models assumed constant risk exposures over the full sample period (1996 to 2026). This assumption is restrictive, particularly for sectors that are highly sensitive to commodity market fluctuations, such as the fossil fuel and critical mineral sectors. In practice, both systematic risk and the sensitivity of portfolio excess returns may vary across different phases of the economic cycles. In this section, we evaluate critical mineral and fossil fuel portfolio performance according to different states of the oil market and to different subperiods.

5.2.1 Portfolio performance under different states of the oil market

This section presents the results of portfolio performance across different states of the oil market, as in [Plantinga and Scholtens \(2021\)](#). The analysis will be implemented using the multi-factor models presented before.

5.2.1.1 The Fama and French (1993) three-factor model: analysis for oil market states

In Table 8, the results show that in contraction periods, the performance of the critical minerals portfolio is neutral while that of the fossil fuel portfolio is negative. However, there is only weak evidence that critical minerals outperform fossil fuels in this market state, since only the value-weighted difference portfolio is statistically significant, and even so, only at the 10% significance level. In the expansion periods, alpha estimates also remain mostly statistically insignificant, although the equal-weighted critical mineral portfolio and the equal-weighted difference portfolio exhibit negative and significant alphas. In this market scenario, there is some evidence, although weak, of fossil fuel outperformance.

In both periods, the market factor is positive and highly significant across all portfolios, indicating that market exposure remains a key driver of excess returns. The estimates further suggest that critical mineral portfolios exhibit greater sensitivity to market fluctuations than fossil fuel portfolios. The size factor is also more pronounced for critical mineral portfolios in both regimes, pointing to stronger exposure to smaller-capitalization firms. By contrast, fossil fuel portfolios display stronger exposure to the value factor, as reflected in the larger HML coefficients, particularly during contraction periods. The negative and statistically significant HML coefficients for the difference portfolios in the contraction regime indicate that critical mineral stocks behave less like value stocks than fossil fuel stocks during downturns. However, this coefficient becomes statistically insignificant in the expansion regime, suggesting that the relative value distinction between critical mineral and fossil fuel stocks weakens when oil market conditions improve.

Table 8: Performance in periods of expansion and contraction in the oil market – Fama-French (1993) model

This table provides the estimation results of the Fama and French (1993) three-factor model across oil market states, for the critical mineral (CM), fossil fuel (FF), and difference portfolios, defined as the critical mineral portfolio minus the fossil fuel portfolio. Panel A presents the results for contraction periods, while Panel B reports the results for expansion periods. Mkt is the market's excess return; SMB is the size factor, defined as the returns of small-cap companies less returns of large-cap companies; HML is the value factor, defined as the returns of high book-to-market companies less low book-to-market companies; and alpha denotes the abnormal return of each portfolio.

<i>Dependent variable: Excess Return</i>						
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Panel A: Regression coefficients in a contraction scenario						
Mkt	1.2424***	1.2047***	0.9909***	0.8197***	0.2515***	0.3850***

Table 8: Performance in periods of expansion and contraction in the oil market – Fama-French (1993) model (*continued*)

	<i>Dependent variable: Excess Return</i>					
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
	(0.0967)	(0.0846)	(0.0797)	(0.0741)	(0.0929)	(0.1007)
SMB	1.5006*** (0.2300)	0.6721*** (0.2405)	0.9364*** (0.2100)	0.3093* (0.1591)	0.5642** (0.2570)	0.3628 (0.2644)
HML	0.2774* (0.1653)	0.3740* (0.2074)	0.6547*** (0.1591)	0.6886*** (0.1628)	−0.3773*** (0.1212)	−0.3146* (0.1704)
α	−0.0021 (0.0076)	0.0037 (0.0067)	−0.0069* (0.0036)	−0.0061*** (0.0023)	0.0047 (0.0060)	0.0099* (0.0058)
Observations	126	126	126	126	126	126
R^2	0.6222	0.5390	0.6675	0.6291	0.0948	0.1170
Adjusted R^2	0.6129	0.5276	0.6593	0.6200	0.0726	0.0953

Panel B: Regression coefficients in an expansion scenario

Mkt	1.5414*** (0.1356)	1.4403*** (0.1058)	1.0954*** (0.0796)	0.9886*** (0.0470)	0.4460*** (0.0876)	0.4517*** (0.0982)
SMB	1.2679*** (0.1653)	0.4151** (0.2008)	0.7030*** (0.1114)	0.1276 (0.0943)	0.5648*** (0.1537)	0.2875* (0.1718)
HML	0.6097*** (0.1190)	0.6700*** (0.1148)	0.7142*** (0.1038)	0.6639*** (0.1191)	−0.1046 (0.1198)	0.0061 (0.1549)
α	−0.0088* (0.0047)	−0.0034 (0.0042)	0.0006 (0.0029)	0.0016 (0.0023)	−0.0094** (0.0044)	−0.0050 (0.0037)
Observations	233	233	233	233	233	233
R^2	0.6351	0.5258	0.6271	0.5960	0.1874	0.1233
Adjusted R^2	0.6303	0.5196	0.6222	0.5907	0.1767	0.1118

Note: Heteroscedasticity and autocorrelation were corrected by following the Newey-West (1987) method. Standard errors are reported in parentheses. Adj. R^2 is the adjusted coefficient of determination. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.2.1.2 The Fama and French (2015) three-factor model: analysis for oil market states

In Table 9, the alpha estimates during contraction periods are similar, as we can observe that the fossil fuel portfolios display negative and statistically significant alphas in periods of turmoil in the oil market. The results of the value-weighted difference portfolio show a positive and statistically significant alpha, supporting the outperformance of the critical minerals portfolio in this market state. As in the previous model, the equal-weighted critical mineral portfolio exhibits a negative alpha in expansion periods, suggesting some underperformance. The negative and statistically significant alphas of the equal-weighted difference portfolio further supports the underperformance of the critical minerals portfolio relative to its fossil fuel counterpart in times of expansion of the oil market.

In both periods, the market factor is positive and highly significant across all portfolios, indicating that market exposure remains a key driver of excess returns of both portfolios regardless of the oil market state. The estimates further suggest that the critical mineral portfolio exhibits greater sensitivity to market fluctuations. Critical mineral portfolios exhibit stronger exposure to smaller-capitalization firms than fossil fuel portfolios, as the size factor is more pronounced for these portfolios.

Both the critical mineral and the fossil fuel portfolios exhibit positive and statistically significant value coefficients in expansion periods. During contraction periods, only the fossil fuel portfolios exhibit a positive and statistically significant HML coefficients. Yet, there are no statistically significant differences in exposure to this value factor. The profitability factor is generally not statistically significant in either periods, suggesting that profitability does not materially explain portfolio excess returns. The investment factor is also generally not statistically significant, although it is negative and statistically significant for the fossil fuel portfolios in expansion periods, suggesting a stronger association with firms exhibiting more aggressive investment behaviour, *ceteris paribus*.

Table 9: Performance in periods of expansion and contraction in the oil market – Fama-French (2015) model

This table provides the estimation results of the Fama and French (2015) five-factor model across oil market states, for the critical mineral (CM), fossil fuel (FF), and difference portfolios, defined as the critical mineral portfolio minus the fossil fuel portfolio. Panel A presents the results for contraction periods, while Panel B reports the results for expansion periods. Mkt is the market's excess return; SMB is the size factor, defined as the returns of small-cap companies less returns of large-cap companies; HML is the value factor, defined as the returns of high book-to-market companies less low book-to-market companies; RMW is the profitability factor; CMA is the investment factor; and alpha denotes the abnormal return of each portfolio.

	<i>Dependent variable: Excess Return</i>					
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Panel A: Regression coefficients in a contraction scenario						
Mkt	1.1352*** (0.1091)	1.1031*** (0.1137)	0.9642*** (0.0887)	0.8808*** (0.0921)	0.1711 (0.1130)	0.2224** (0.0914)
SMB	1.4630*** (0.2245)	0.6466** (0.2501)	0.9008*** (0.2096)	0.3219* (0.1657)	0.5622** (0.2460)	0.3247 (0.2491)
HML	0.2610 (0.2525)	0.3806 (0.2704)	0.6126*** (0.2247)	0.4993** (0.2371)	−0.3515 (0.2682)	−0.1187 (0.3002)
RMW	−0.3316 (0.3378)	−0.4544 (0.4332)	−0.0354 (0.3531)	0.0386 (0.2684)	−0.2962 (0.3379)	−0.4930 (0.3133)
CMA	−0.5607 (0.5294)	−0.3518 (0.5896)	−0.2272 (0.4644)	0.3453 (0.3778)	−0.3335 (0.3745)	−0.6971* (0.3808)
α	−0.0014 (0.0073)	0.0051 (0.0063)	−0.0070** (0.0033)	−0.0066** (0.0027)	0.0056 (0.0060)	0.0117** (0.0052)
Observations	126	126	126	126	126	126
R^2	0.6310	0.5473	0.6665	0.6347	0.1075	0.1562
Adjusted R^2	0.6156	0.5284	0.6526	0.6194	0.0703	0.1210
Panel B: Regression coefficients in an expansion scenario						
Mkt	1.4926***	1.4166***	1.0277***	0.9520***	0.4649***	0.4646***

Table 9: Performance in periods of expansion and contraction in the oil market – Fama-French (2015) model (*continued*)

	<i>Dependent variable: Excess Return</i>					
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
	(0.1299)	(0.1121)	(0.0812)	(0.0644)	(0.0991)	(0.0985)
SMB	1.4241*** (0.1889)	0.5777*** (0.2145)	0.7807*** (0.1531)	0.1980 (0.1478)	0.6434*** (0.1748)	0.3797* (0.2030)
HML	0.8619*** (0.2875)	0.9502*** (0.2694)	1.0438*** (0.1708)	0.9307*** (0.1697)	−0.1819 (0.2448)	0.0195 (0.2986)
RMW	0.3937 (0.3046)	0.4932 (0.3057)	0.2453 (0.2865)	0.2687 (0.3312)	0.1484 (0.2677)	0.2245 (0.3214)
CMA	−0.8027 (0.4990)	−0.6140 (0.4842)	−0.7788** (0.3029)	−0.5075** (0.2211)	−0.0239 (0.3856)	−0.1065 (0.4525)
α	−0.0098* (0.0050)	−0.0046 (0.0045)	0.0005 (0.0031)	0.0012 (0.0026)	−0.0102** (0.0047)	−0.0059 (0.0042)
Observations	233	233	233	233	233	233
R^2	0.6508	0.5400	0.6502	0.6118	0.1905	0.1275
Adjusted R^2	0.6431	0.5298	0.6425	0.6032	0.1727	0.1083

Note: Heteroscedasticity and autocorrelation were corrected by following the Newey-West (1987) method. Standard errors are reported in parentheses. Adj. R^2 is the adjusted coefficient of determination. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.2.1.3 The Fama and French (2018) three-factor model: analysis for oil market states

The inclusion of the momentum factor (UMD) in Table 10 supports the previous results regarding performance. During contraction periods, fossil fuel portfolios have a negative and statistically significant alphas, indicating underperformance. The value-weighted difference portfolio shows a positive and statistically significant alpha, indicating outperformance of critical minerals in times of oil market turmoil. In the expansion periods, the fossil fuel portfolio shows neutral performance, while the equal-weighted critical mineral portfolio shows negative performance. The equal-weighted difference portfolio exhibits a negative

and statistically significant alpha, highlighting that critical minerals perform worse than fossil fuels in times of expansion.

In both periods, the market factor is positive and statistically significant across all portfolios, confirming that systematic market risk remains the main source of excess returns. The size factor is also generally positive and statistically significant, especially in the critical mineral portfolios, suggesting stronger exposure to smaller-capitalization firms. With respect to the value factor, the estimates suggest that critical mineral stocks behave less like value stocks than fossil fuel stocks during contraction periods.

The profitability factor remains largely insignificant, suggesting that this factor does not explain portfolio excess returns in either period. In contrast, the investment factor is negative and statistically significant only for the fossil fuel portfolios during the expansion regime, indicating greater exposure to firms with more aggressive investment behaviour. Finally, the momentum factor is negative and statistically significant only for the long portfolios during the contraction period, *ceteris paribus*.

Table 10: Performance in periods of expansion and contraction in the oil market – Fama-French (2018) model

This table provides the estimation results of the Fama and French (2018) six-factor model across oil market states, for the critical mineral (CM), fossil fuel (FF), and difference portfolios, defined as the critical mineral portfolio minus the fossil fuel portfolio. Panel A presents the results for contraction periods, while Panel B reports the results for expansion periods. Mkt is the market's excess return; SMB is the size factor, defined as the returns of small-cap companies less returns of large-cap companies; HML is the value factor, defined as the returns of high book-to-market companies less low book-to-market companies; RMW is the profitability factor; CMA is the investment factor; UMD is the momentum factor; and alpha denotes the abnormal return of each portfolio.

<i>Dependent variable: Excess Return</i>						
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Panel A: Regression coefficients in a contraction scenario						
Mkt	1.0423*** (0.1036)	1.0156*** (0.1177)	0.9019*** (0.0971)	0.8474*** (0.0938)	0.1404 (0.1070)	0.1682* (0.0955)
SMB	1.5123*** (0.2242)	0.6931*** (0.2539)	0.9339*** (0.1991)	0.3396** (0.1608)	0.5785** (0.2492)	0.3535 (0.2566)
HML	−0.0530 (0.1663)	0.0849 (0.2559)	0.4021* (0.2211)	0.3865 (0.2541)	−0.4551* (0.2608)	−0.3016 (0.2821)

Table 10: Performance in periods of expansion and contraction in the oil market – Fama-French (2018) model (*continued*)

	<i>Dependent variable: Excess Return</i>					
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
RMW	−0.0724 (0.3675)	−0.2103 (0.4230)	0.1383 (0.3162)	0.1317 (0.2406)	−0.2107 (0.3858)	−0.3420 (0.3466)
CMA	−0.3440 (0.3602)	−0.1478 (0.4700)	−0.0820 (0.3420)	0.4231 (0.3430)	−0.2620 (0.3752)	−0.5709* (0.3282)
UMD	−0.3984*** (0.1355)	−0.3752*** (0.1219)	−0.2671*** (0.0862)	−0.1431* (0.0732)	−0.1314 (0.1072)	−0.2321** (0.0967)
α	−0.0003 (0.0064)	0.0062 (0.0055)	−0.0062** (0.0028)	−0.0062** (0.0026)	0.0060 (0.0058)	0.0123** (0.0048)
Observations	126	126	126	126	126	126
R^2	0.6549	0.5696	0.6833	0.6415	0.1132	0.1728
Adjusted R^2	0.6375	0.5479	0.6674	0.6234	0.0685	0.1311
Panel B: Regression coefficients in an expansion scenario						
Mkt	1.5078*** (0.1308)	1.4412*** (0.1074)	1.0459*** (0.0808)	0.9760*** (0.0635)	0.4619*** (0.1044)	0.4652*** (0.1018)
SMB	1.3954*** (0.2007)	0.5311** (0.2383)	0.7461*** (0.1575)	0.1524 (0.1499)	0.6492*** (0.1782)	0.3786* (0.2171)
HML	0.8953*** (0.3120)	1.0044*** (0.3045)	1.0840*** (0.1808)	0.9837*** (0.1750)	−0.1887 (0.2541)	0.0207 (0.3185)
RMW	0.3912 (0.3030)	0.4890 (0.3016)	0.2423 (0.2726)	0.2646 (0.3159)	0.1489 (0.2650)	0.2244 (0.3219)
CMA	−0.8021 (0.4991)	−0.6131 (0.4762)	−0.7781*** (0.2909)	−0.5067** (0.2060)	−0.0240 (0.3837)	−0.1064 (0.4522)
UMD	0.0942 (0.1155)	0.1531 (0.1135)	0.1133 (0.1042)	0.1497 (0.1004)	−0.0191 (0.0927)	0.0034 (0.1021)

Table 10: Performance in periods of expansion and contraction in the oil market – Fama-French (2018) model (*continued*)

	<i>Dependent variable: Excess Return</i>					
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
α	−0.0107** (0.0046)	−0.0061 (0.0041)	−0.0007 (0.0030)	−0.0002 (0.0025)	−0.0100** (0.0045)	−0.0059 (0.0040)
Observations	233	233	233	233	233	233
R^2	0.6522	0.5442	0.6545	0.6214	0.1907	0.1275
Adjusted R^2	0.6430	0.5321	0.6454	0.6114	0.1692	0.1043

Note: Heteroscedasticity and autocorrelation were corrected by following the Newey-West (1987) method. Standard errors are reported in parentheses. Adj. R^2 is the adjusted coefficient of determination. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.2.1.4 The Hou et al. (2021) q-factor model: analysis for oil market states

The results of the [Hou et al. \(2021\)](#) q-factor model, presented in Table 11, show that there is limited evidence of abnormal excess returns. Compared with the Fama and French models, fossil fuels now do not show underperformance in contraction periods. Yet, consistent with the Fama and French models, the value-weighted difference portfolio shows a positive and statistically significant alpha during contraction periods, although only at a 10% significance level, suggesting a tendency for fossil fuels to underperform critical minerals. In expansion periods, both the critical minerals and the fossil fuel portfolios show neutral performance relative to the benchmark, although the results of the equal-weighted difference portfolio suggest there is a tendency for critical minerals to underperform their fossil fuels counterparts.

In both the expansion and contraction scenarios, the market factor is positive and statistically significant across all portfolios, confirming that market exposure remains the key determinant of excess returns. The estimates also suggest that critical mineral portfolios are more sensitive to market movements than fossil fuel portfolios. By contrast, the size factor is only weakly statistically significant in contraction periods and becomes statistically insignificant in expansion periods, indicating a weaker size effect than in the Fama and French models. The investment factor is statistically significant only for fossil fuel portfolios, indicating also a greater exposure to firms with more aggressive investment behaviour, particularly in

expansion periods.

Unlike the Fama and French models, the profitability factor is negative and statistically significant for critical mineral and difference portfolios during contraction periods, indicating weaker profitability characteristics for critical mineral firms relative to fossil fuel firms. However, this effect disappears during expansion periods. The expected growth factor is positive and statistically significant for the difference portfolios during contraction periods, but negative and statistically significant for the long portfolios in expansion periods, with a stronger effect in the fossil fuel portfolios.

Table 11: Performance in periods of expansion and contraction in the oil market – Hou et al. (2021) model

This table provides the estimation results of the Hou et al. (2021) q-factor model across oil market states, for the critical mineral (CM), fossil fuel (FF), and difference portfolios, defined as the critical mineral portfolio minus the fossil fuel portfolio. Panel A presents the results for contraction periods, while Panel B reports the results for expansion periods. Mkt is the market's excess return; Me is the size factor, defined as the returns of small-cap companies less returns of large-cap companies; I/A is the investment factor; ROE is the profitability factor measured by return on equity; EG is the expected growth factor; and alpha denotes the abnormal return of each portfolio.

	<i>Dependent variable: Excess Return</i>					
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
Panel A: Regression coefficients in a contraction scenario						
Mkt	0.8443*** (0.1191)	0.8718*** (0.1480)	0.7006*** (0.1165)	0.6776*** (0.0834)	0.1438* (0.0813)	0.1942* (0.1034)
Me	0.5031** (0.2245)	0.1072 (0.1637)	0.4242** (0.1814)	0.0821 (0.1609)	0.0788 (0.2297)	0.0251 (0.1326)
I/A	0.3710 (0.2697)	0.3042 (0.4053)	0.2298 (0.2579)	0.4728* (0.2592)	0.1412 (0.2137)	−0.1686 (0.2149)
ROE	−0.7193*** (0.2119)	−0.6661*** (0.2424)	−0.3505 (0.2322)	−0.0724 (0.1871)	−0.3688** (0.1670)	−0.5936*** (0.1408)
EG	0.2674 (0.3238)	0.0894 (0.3209)	−0.1247 (0.2743)	−0.3641 (0.2660)	0.3920** (0.1969)	0.4535* (0.2704)
α	−0.0013	0.0052	−0.0036	−0.0042	0.0023	0.0093*

Table 11: Performance in periods of expansion and contraction in the oil market – Hou et al. (2021) model (*continued*)

	<i>Dependent variable: Excess Return</i>					
	Critical Mineral		Fossil Fuel		Difference Portfolio	
	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted	Eq. Weighted	Val. Weighted
	(0.0087)	(0.0071)	(0.0050)	(0.0034)	(0.0064)	(0.0050)
Observations	114	114	114	114	114	114
R^2	0.5316	0.5033	0.5617	0.5507	0.0577	0.1359
Adjusted R^2	0.5100	0.4803	0.5415	0.5299	0.0141	0.0958
Panel B: Regression coefficients in an expansion scenario						
Mkt	1.1067*** (0.1912)	1.0739*** (0.1665)	0.8317*** (0.1118)	0.8133*** (0.0685)	0.2750** (0.1095)	0.2606** (0.1299)
Me	0.2212 (0.1690)	−0.0304 (0.1829)	0.1887 (0.1282)	−0.0420 (0.1126)	0.0325 (0.1297)	0.0116 (0.1462)
I/A	0.2163 (0.2514)	0.2082 (0.2629)	0.3862** (0.1806)	0.4346** (0.1732)	−0.1700 (0.1417)	−0.2265 (0.1846)
ROE	−0.0459 (0.2046)	0.4783** (0.2200)	0.1780 (0.1540)	0.3334** (0.1366)	−0.2238 (0.1505)	0.1449 (0.1661)
EG	−0.4578 (0.3095)	−0.6889** (0.2798)	−0.5001*** (0.1730)	−0.5269*** (0.1366)	0.0423 (0.2106)	−0.1620 (0.2226)
α	−0.0075 (0.0069)	−0.0016 (0.0057)	0.0020 (0.0040)	0.0034 (0.0031)	−0.0095* (0.0052)	−0.0050 (0.0047)
Observations	233	233	233	233	233	233
R^2	0.3964	0.3488	0.4535	0.4703	0.0912	0.0605
Adjusted R^2	0.3832	0.3344	0.4414	0.4587	0.0712	0.0398
<i>Note:</i> Heteroscedasticity and autocorrelation were corrected by following the Newey-West (1987) method. Standard errors are reported in parentheses. Adj. R^2 is the adjusted coefficient of determination. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.						

Across all model specifications, critical mineral portfolios show a slight outperformance relative to

fossil fuel portfolios primarily during periods of contraction in the oil market. This suggests that divestment may provide investors with downside protection during adverse oil market conditions, consistent with the findings of Cortez et al. (2022). In contrast, the fossil fuel portfolio tends to outperform in periods of expansion in the oil market.

5.2.2 Portfolio performance across subperiods

While the previous evaluation examines the performance of critical mineral and fossil fuel portfolios across cyclical oil market conditions, we now adopt a complementary time-varying perspective by estimating portfolio performance over two and three consecutive subperiods.

The early windows (1996-2005 and 1996-2010) capture the pre-crisis years and the oil boom preceding the 2008 financial crisis. The middle window (2006-2015) covers the global financial crisis, the subsequent recovery, and the 2014 to 2016 oil price collapse. The most recent windows (2011-2026 and 2016-2026) reflect the post-crisis period and the growing importance of the energy transition following the Paris Agreement in 2015. Table 12 summarizes estimates of alphas obtained with different specifications of the models across different subperiods considered¹.

Table 12: Performance of critical mineral and fossil fuel portfolios over different subperiods across factor models

This table reports the risk-adjusted abnormal returns (α) of the critical mineral and fossil fuel portfolios estimated using with the Fama and French (1993, 2015, 2018) multifactor models and the Hou et al.(2021) q-factor model across six subperiods. EW and VW denote equal-weighted and value-weighted portfolios, respectively. CM — FF denotes the difference portfolio, defined as the critical mineral portfolio minus the fossil fuel portfolio

Portfolio	1996–2010	2011–2026	1996–2005	2006–2015	2016–2026
Fama–French (1993) three-factor model					
Critical Mineral (EW)	−0.0022	−0.0107*	−0.0102*	−0.0123	0.0018
Critical Mineral (VW)	0.0048	−0.0047	−0.0027	−0.0047	0.0049
Fossil Fuel (EW)	0.0029	−0.0071***	0.0011	−0.0056	−0.0032
Fossil Fuel (VW)	0.0032	−0.0047**	0.0017	−0.0024	−0.0031
CM — FF (EW)	−0.0051	−0.0037	−0.0113*	−0.0067	0.0050

¹ The full regression results for each model specification are presented in Appendixes B.1–B.4.

Table 12: Performance of critical mineral and fossil fuel portfolios over different subperiods across factor models (*continued*)

Portfolio	1996–2010	2011–2026	1996–2005	2006–2015	2016–2026
CM — FF (VW)	0.0016	−0.0000	−0.0044	−0.0022	0.0081**
Fama–French (2015) five-factor model					
Critical Mineral (EW)	−0.0051	−0.0096	−0.0106*	−0.0097	0.0022
Critical Mineral (VW)	0.0023	−0.0038	−0.0033	−0.0004	0.0053
Fossil Fuel (EW)	0.0007	−0.0068**	0.0002	−0.0059	−0.0030
Fossil Fuel (VW)	−0.0006	−0.0047*	−0.0009	−0.0050	−0.0029
CM — FF (EW)	−0.0058	−0.0028	−0.0108	−0.0038	0.0052
CM — FF (VW)	0.0029	0.0008	−0.0024	0.0046	0.0082*
Fama–French (2018) six-factor model					
Critical Mineral (EW)	−0.0047	−0.0086	−0.0092	−0.0097	0.0015
Critical Mineral (VW)	0.0021	−0.0018	−0.0031	−0.0003	0.0060*
Fossil Fuel (EW)	0.0010	−0.0068**	0.0010	−0.0059	−0.0035
Fossil Fuel (VW)	−0.0008	−0.0047*	−0.0003	−0.0049	−0.0033
CM — FF (EW)	−0.0056	−0.0018	−0.0103	−0.0038	0.0050
CM — FF (VW)	0.0029	0.0029	−0.0029	0.0046	0.0093**
Hou et al. (2021) q-factor model					
Critical Mineral (EW)	0.0013	−0.0130*	−0.0043	−0.0060	−0.0014
Critical Mineral (VW)	0.0065	−0.0048	0.0020	0.0012	0.0042
Fossil Fuel (EW)	0.0056	−0.0060*	0.0070	−0.0009	−0.0015
Fossil Fuel (VW)	0.0042	−0.0034	0.0054	−0.0008	−0.0007
CM — FF (EW)	−0.0043	−0.0071	−0.0113	−0.0051	0.0001
CM — FF (VW)	0.0023	−0.0014	−0.0034	0.0020	0.0049

Note: Heteroskedasticity and autocorrelation consistent standard errors following Newey–West (1987) are reported in parentheses. Adj. R^2 is the adjusted coefficient of determination. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 12 shows that most alpha estimates are statistically insignificant, suggesting that the performance of both critical mineral and fossil fuel portfolios is neutral.

However, we observe a pattern in the 2011–2026 subperiod, where fossil fuel performance alphas become negative and statistically significant, particularly in the case of the Fama-French models. The equal-weighted critical mineral portfolio shows weak evidence underperformance under the q-factor model. By contrast, the earlier subperiods provide only limited evidence of abnormal returns, with some weakly negative and statistically significant alphas for the critical mineral equal-weighted portfolio in 1996–2005.

Another interesting result is that in the 2016–2026 period there is some evidence that the critical minerals portfolio outperforms the fossil fuel portfolio, as we observe, mainly in the Fama-French specifications, a positive and statistically significant alpha of the difference portfolio. This result may be driven by rising awareness of climate-related risks after the Paris Agreement and a stronger perceived need to shift toward a low-carbon economy.

6 Conclusions

Climate change has stimulated divestment campaigns aimed at reducing investor exposure to fossil fuel companies and, indirectly, has increased interest in energy-transition sectors such as critical minerals. In this context, this dissertation examines whether this divestment has implications for portfolio performance by comparing the performance of a fossil fuel portfolio and a critical mineral portfolio over a 30-year horizon.

To address this question, four multi-factor asset pricing models were employed to assess whether the critical mineral and fossil fuel portfolios reflect a distinct climate-related premium. Using the [Fama and French \(1993, 2015, 2018\)](#) models and the [Hou et al. \(2021\)](#) q-factor model, the overall result is that neither the critical mineral portfolio nor the fossil fuel portfolio generates statistically significant alpha. This indicates that, once exposure to common risk factors is considered, neither portfolio systematically outperforms nor underperforms the benchmark on a risk-adjusted basis. Instead, the excess returns of both the critical mineral and fossil fuel portfolios are primarily explained by the market excess return, the size, and the value factors. By contrast, the profitability, investment expected growth and momentum factors contribute limited incremental explanatory power.

However, the absence of unconditional statistically significant alpha does not imply that the two portfolios perform similarly in different market states. The analysis of performance in subsequent subperiods shows that following the international financial crisis, fossil fuel portfolios exhibit negative and statistically significant alphas, and in particular, critical minerals show outperformance relative to fossil fuels in the post-Paris Agreement period. This temporal shift suggests that the market has reassessed the risk-premium of fossil fuel assets, as the energy transition has accelerated. More specifically, this finding is consistent with a gradual repricing mechanism through which transition-related pressures have eroded the risk-adjusted performance of fossil fuel investments over time.

When the portfolios are evaluated under different global oil market conditions, the results show that,

during contraction regimes, fossil fuel portfolios exhibit negative and statistically significant alphas, whereas the critical mineral portfolios display modest relative outperformance over the same period. This indicates that fossil fuel firms underperform even after controlling for the systematic risks embedded in the factor models. Accordingly, oil market contractions expose fossil fuel investors to downside risk for which they do not appear to be compensated. Critical mineral portfolios, while not generating persistent abnormal returns in normal periods, may therefore offer relative downside protection under adverse oil market conditions.

A substantial strand of the literature argues that carbon-intensive or climate-exposed assets should command higher expected returns. [Bolton and Kacperczyk \(2021, 2023\)](#), for example, interpret higher returns among more carbon-intensive firms as compensation for climate-related risk. Similarly, [Gong et al. \(2023\)](#) and [Antoniuk and Leirvik \(2024\)](#) suggest that investors require a premium for bearing transition-related uncertainty. At a theoretical level, [Pástor et al. \(2021\)](#) also imply that “brown” assets may deliver higher expected returns than greener alternatives because they are more exposed to climate-transition risk. However, the model [Pástor et al. \(2021\)](#) also explains that green portfolios may underperform their brown counterparts in times when there is unexpected shifts towards greenness. The present findings may be interpreted under this perspective. The absence of statistically significant positive alphas for fossil fuel portfolios suggests that the alleged “carbon premium” is not observed and may be due to the increasing preferences for greenness in times characterized by the energy transition.

At the same time, the results align more closely with the argument of [Cortez et al. \(2022\)](#) and [Plantinga and Scholtens \(2021\)](#) that fossil fuel divestment can provide downside protection during adverse market conditions without necessarily requiring investors to sacrifice long-run return. The time-varying evidence reported supports the view that markets have begun internalising transition risk more systematically following the progressive institutionalisation of carbon pricing mechanisms, the Paris Agreement commitments, and the expansion of renewable energy deployment. Negative and significant fossil fuel alphas are observed during oil market contractions and in the post-2011 period, but not before, while critical mineral portfolios show relative resilience. Fossil fuels divestment appears to reduce exposure to asymmetric downside risk rather than require investors to forgo a stable compensatory premium.

Taken together, the theoretical contribution of this dissertation is twofold. First, it advances a more sceptical interpretation of the carbon premium hypothesis by demonstrating that multifactor asset pricing models effectively absorb the alleged climate risk premium into common factor loadings, at least at the sector-portfolio level. Second, it provides evidence in favour of a time-varying and asymmetric risk-pricing

structure, whereby the principal financial consequence of fossil fuel exposure is not a sustained return premium, but rather an increased downside risk during commodity contractions and a gradual deterioration in risk-adjusted performance in the post-2011 period.

While this study contributes to the existing literature, the limitations should be acknowledged. The principal limitation is that sector classification is applied ex-post using the Industry Classification Benchmark (ICB). Although this methodology ensures consistency in sector definitions throughout the sample period, it also implies that sector assignments might not accurately reflect the information available to investors at each point in time. Additionally, the portfolio construction relied on a fixed keyword filter for the critical mineral portfolio, whereby companies were included if their business descriptions mentioned at least one core mineral. Consequently, a company with only minor exposure to lithium, for example, may be classified in the same way as a pure critical minerals firm. This could mask significant variations in the portfolios' exposure levels.

Future research could address this limitation by employing more detailed firm-level measures, such as the share of firms' revenue derived from critical mineral, in order to better capture differences in climate risk and performance across these two sectors. Finally, to better capture the time-varying effects and isolate the effects of major policy events (e.g. the Paris Agreement), future work could employ event studies methodologies to evaluate how policy shocks affect excess returns over time more precisely.

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Appendices

A Portfolio performance under different states of the oil market

A.1 Structural break tests across factor models and portfolios

We apply the [Chow \(1960\)](#) structural break test to each portfolio to assess whether factor loadings differ across oil market contraction and expansion periods, using the oil rig count–based regime indicator described in Section 3.3 to define the break point. The null hypothesis is parameter constancy across regimes. As reported in Table A.1, evidence of structural instability is strongest under the [Fama and French \(2018\)](#) model, whereas the [Fama and French \(1993\)](#), [Fama and French \(2015\)](#), and [Hou et al. \(2021\)](#) models show weaker and less consistent evidence of structural breaks. The long–short portfolios exhibit little robust evidence of structural change, suggesting that the relative performance of critical mineral and fossil fuel equities is more stable across oil market cycles than the absolute performance of either sector. Given heteroskedasticity in the return series, the Chow test is treated as an auxiliary diagnostic, while primary inference is based on the [Newey and West \(1987\)](#) corrected regime regressions reported in Tables 8–11.

Portfolio	<i>F</i> -stat	<i>p</i> -value
Fama–French (1993) three-factor model		
Critical Mineral (EW)	2.0070	0.0931 [*]
Critical Mineral (VW)	1.3052	0.2677
Fossil Fuel (EW)	1.5312	0.1926
Fossil Fuel (VW)	2.5185	0.0411 ^{**}
Difference Portfolio (EW)	2.0063	0.0932 [*]
Difference Portfolio (VW)	1.8158	0.1252
Fama–French (2015) five-factor model		
Critical Mineral (EW)	1.9988	0.0652 [*]

Table A.1: Structural Break Tests Across Factor Models and Portfolios (*continued*)

Portfolio	<i>F</i> -stat	<i>p</i> -value
Critical Mineral (VW)	1.5975	0.1469
Fossil Fuel (EW)	1.5866	0.1500
Fossil Fuel (VW)	2.7785	0.0119**
Difference Portfolio (EW)	1.6108	0.1431
Difference Portfolio (VW)	1.9357	0.0744*
Fama–French (2018) six-factor model		
Critical Mineral (EW)	2.9672	0.0049***
Critical Mineral (VW)	2.5365	0.0148**
Fossil Fuel (EW)	2.7486	0.0086***
Fossil Fuel (VW)	3.1692	0.0029***
Difference Portfolio (EW)	1.4274	0.1931
Difference Portfolio (VW)	1.8175	0.0829*
Hou et al. (2021) <i>q</i>-factor model		
Critical Mineral (EW)	1.4162	0.2075
Critical Mineral (VW)	2.2490	0.0384**
Fossil Fuel (EW)	1.5036	0.1761
Fossil Fuel (VW)	1.5757	0.1534
Difference Portfolio (EW)	1.3475	0.2355
Difference Portfolio (VW)	1.9882	0.0668*

Note: The null hypothesis of parameter stability across subperiods is tested using the Chow *F*-test. * $p < 0.1$; ** $p < 0.05$;

*** $p < 0.01$.

B Portfolio performance across subperiods

B.1 Full regression results for the Fama–French (1993) three-factor model

This table reports full estimation results for the Fama–French (1993) three-factor model across five subperiods (1996–2005, 1996–2010, 2006–2015, 2011–2026, and 2016–2026). Results are reported for equal-weighted (EW) and value-weighted (VW) portfolios of critical minerals, fossil fuel, and their difference (CM – FF).

<i>Dependent variable: Excess Return</i>										
1996–2005		1996–2010		2006–2015		2011–2026		2016–2026		
EW	VW	EW	VW	EW	VW	EW	VW	EW	VW	
Critical Mineral Portfolio										
α	−0.0102 [*]	−0.0027	−0.0022	0.0048	−0.0123	−0.0047	−0.0107 [*]	−0.0047	0.0018	0.0049
	(−1.93)	(−0.48)	(−0.40)	(0.88)	(−1.36)	(−0.63)	(−1.81)	(−1.13)	(0.33)	(1.44)
Mkt	1.4356 ^{***}	1.3842 ^{***}	1.6069 ^{***}	1.4111 ^{***}	1.8124 ^{***}	1.6566 ^{***}	1.1877 ^{***}	1.2354 ^{***}	1.0430 ^{***}	1.0469 ^{***}
	(12.53)	(7.37)	(15.70)	(13.51)	(18.10)	(19.53)	(11.36)	(10.20)	(12.06)	(14.24)
SMB	1.3601 ^{***}	0.4504 ^{**}	1.4031 ^{***}	0.3397	1.6729 ^{***}	0.3488	1.1290 ^{***}	0.7065 ^{***}	1.2307 ^{***}	0.8902 ^{***}
	(9.56)	(2.05)	(8.08)	(1.39)	(6.70)	(1.06)	(4.15)	(3.72)	(3.67)	(3.73)
HML	0.8099 ^{***}	0.8303 ^{***}	0.6374 ^{***}	0.5229 ^{**}	−0.3971	−0.5644	0.3035 ^{**}	0.5174 ^{***}	0.2497 ^{***}	0.4724 ^{***}
	(7.44)	(4.85)	(3.43)	(2.33)	(−0.76)	(−0.92)	(2.53)	(3.27)	(3.24)	(4.17)
Adj. R^2	0.590	0.438	0.672	0.519	0.729	0.633	0.565	0.533	0.574	0.506
Fossil Fuel Portfolio										
α	0.0011	0.0017	0.0029	0.0032	−0.0056	−0.0024	−0.0071 ^{***}	−0.0047 ^{**}	−0.0032	−0.0031
	(0.29)	(0.69)	(0.90)	(1.37)	(−1.25)	(−0.72)	(−2.62)	(−2.03)	(−1.09)	(−1.04)
Mkt	1.1317 ^{***}	0.9091 ^{***}	1.1259 ^{***}	0.8980 ^{***}	1.2572 ^{***}	1.0384 ^{***}	0.9613 ^{***}	0.9283 ^{***}	0.8469 ^{***}	0.8589 ^{***}
	(10.64)	(12.46)	(17.97)	(16.46)	(22.02)	(18.42)	(10.47)	(14.25)	(8.99)	(10.70)
SMB	0.7944 ^{***}	0.1462	0.8448 ^{***}	0.1562	1.0432 ^{***}	0.2280	0.4045 ^{**}	−0.0286	0.4252 ^{**}	−0.0093
	(4.85)	(1.08)	(5.15)	(1.12)	(5.54)	(1.19)	(2.53)	(−0.18)	(2.24)	(−0.05)
HML	0.8500 ^{***}	0.5945 ^{***}	0.6606 ^{***}	0.4320 ^{***}	−0.0277	−0.0876	0.7377 ^{***}	0.8771 ^{***}	0.7014 ^{***}	0.8809 ^{***}

Table B.1: Full regression results for the Fama–French (1993) three-factor model (*continued*)

<i>Dependent variable: Excess Return</i>										
	1996–2005		1996–2010		2006–2015		2011–2026		2016–2026	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
	(5.38)	(4.81)	(3.79)	(2.96)	(−0.06)	(−0.21)	(7.06)	(9.12)	(10.52)	(10.93)
Adj. R^2	0.519	0.418	0.614	0.516	0.729	0.678	0.696	0.722	0.714	0.715
Difference Portfolio										
α	−0.0113 [*]	−0.0044	−0.0051	0.0016	−0.0067	−0.0022	−0.0037	−0.0000	0.0050	0.0081 ^{**}
	(−1.84)	(−0.70)	(−0.93)	(0.31)	(−0.94)	(−0.44)	(−0.69)	(−0.01)	(0.90)	(2.19)
Mkt	0.3039 ^{**}	0.4751 ^{***}	0.4810 ^{***}	0.5131 ^{***}	0.5552 ^{***}	0.6182 ^{***}	0.2264 ^{***}	0.3071 ^{***}	0.1960 [*]	0.1880 [*]
	(2.22)	(3.09)	(5.53)	(6.22)	(6.29)	(7.34)	(2.97)	(2.78)	(1.84)	(1.82)
SMB	0.5657 ^{***}	0.3042 [*]	0.5582 ^{***}	0.1835	0.6297 ^{**}	0.1207	0.7245 ^{***}	0.7351 ^{***}	0.8056 ^{***}	0.8995 ^{***}
	(3.28)	(1.81)	(4.19)	(1.08)	(2.26)	(0.37)	(2.84)	(2.93)	(2.63)	(3.04)
HML	−0.0401	0.2358	−0.0232	0.0910	−0.3694 [*]	−0.4768	−0.4342 ^{***}	−0.3597 ^{***}	−0.4516 ^{***}	−0.4085 ^{***}
	(−0.23)	(1.27)	(−0.20)	(0.60)	(−1.69)	(−1.66)	(−5.12)	(−2.65)	(−5.58)	(−3.35)
Adj. R^2	0.069	0.070	0.158	0.132	0.268	0.219	0.155	0.127	0.192	0.132
N	119	119	179	179	120	120	180	180	120	120

Note: Heteroskedasticity and autocorrelation consistent standard errors following Newey–West (1987) are reported in parentheses. Adj. R^2 is the adjusted coefficient of determination ^{*} $p < 0.1$; ^{**} $p < 0.05$; ^{***} $p < 0.01$.

B.2 Full regression results for the Fama–French (2015) five-factor model

This table reports full estimation results for the Fama–French (2015) five-factor model across five subperiods (1996–2005, 1996–2010, 2006–2015, 2011–2026, and 2016–2026). Results are reported for equal-weighted (EW) and value-weighted (VW) portfolios of critical minerals, fossil fuel, and their difference (CM – FF).

<i>Dependent variable: Excess Return</i>										
	1996–2005		1996–2010		2006–2015		2011–2026		2016–2026	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Critical Mineral Portfolio										
α	−0.0106 [*]	−0.0033	−0.0051	0.0023	−0.0097	−0.0004	−0.0096	−0.0038	0.0022	0.0053
	(−1.69)	(−0.55)	(−0.85)	(0.41)	(−1.19)	(−0.05)	(−1.61)	(−0.88)	(0.38)	(1.45)

Table B.2: Full regression results for the Fama–French (2015) five-factor model (*continued*)

<i>Dependent variable: Excess Return</i>										
	1996–2005		1996–2010		2006–2015		2011–2026		2016–2026	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Mkt	1.4122*** (10.00)	1.3873*** (5.86)	1.6205*** (13.44)	1.4100*** (11.46)	1.5199*** (6.32)	1.3123*** (5.13)	1.1668*** (10.94)	1.2527*** (11.15)	1.0990*** (9.15)	1.1508*** (11.38)
SMB	1.3937*** (7.94)	0.4792** (2.02)	1.5811*** (7.80)	0.4862** (1.99)	1.4149*** (5.96)	0.0116 (0.03)	0.9623*** (3.80)	0.6069*** (3.05)	1.1668*** (3.53)	0.8735*** (3.89)
HML	0.7687** (2.24)	0.8619* (1.92)	0.6098** (2.07)	0.6910** (2.15)	0.4196 (0.68)	0.4148 (0.65)	−0.0073 (−0.02)	0.0804 (0.25)	−0.2630 (−1.00)	−0.2199 (−0.83)
RMW	−0.0053 (−0.01)	0.1055 (0.23)	0.7378* (1.85)	0.7309* (1.76)	0.3178 (0.62)	0.0823 (0.18)	−0.6996* (−1.90)	−0.6426* (−1.71)	−0.5702 (−1.26)	−0.6034 (−1.33)
CMA	−0.3688 (−0.75)	−0.2286 (−0.38)	−0.6528 (−1.30)	−0.6431 (−1.21)	−2.0672** (−2.59)	−2.2491*** (−3.02)	0.0185 (0.04)	0.4156 (0.83)	0.4700 (1.13)	0.9083** (2.27)
Adj. R^2	0.584	0.428	0.692	0.539	0.768	0.688	0.569	0.537	0.577	0.520
Fossil Fuel Portfolio										
α	0.0002 (0.06)	−0.0009 (−0.36)	0.0007 (0.21)	−0.0006 (−0.25)	−0.0059 (−1.23)	−0.0050 (−1.49)	−0.0068** (−2.25)	−0.0047* (−1.71)	−0.0030 (−0.95)	−0.0029 (−0.89)
Mkt	1.1326*** (9.74)	1.0309*** (11.57)	1.1204*** (15.67)	1.0148*** (15.10)	1.0924*** (8.26)	1.0143*** (10.17)	0.9612*** (10.67)	0.9546*** (14.41)	0.8871*** (9.19)	0.9252*** (10.80)
SMB	0.8406*** (4.85)	0.2862** (2.03)	0.9811*** (5.94)	0.3460*** (2.75)	0.9558*** (4.61)	0.2740 (1.21)	0.3406** (2.10)	−0.0185 (−0.12)	0.3811* (1.97)	−0.0159 (−0.08)
HML	0.8674*** (3.44)	0.4833* (1.83)	0.7366*** (3.54)	0.3030 (1.49)	0.7161 (1.46)	0.4315 (0.92)	0.5978*** (2.80)	0.7024*** (3.45)	0.4202*** (2.65)	0.5353** (2.36)
RMW	0.1151 (0.36)	0.5080* (1.76)	0.6157* (1.81)	0.8869*** (2.97)	0.8350** (2.14)	1.0528** (2.34)	−0.2433 (−0.84)	−0.1092 (−0.33)	−0.3027 (−0.87)	−0.2889 (−0.73)
CMA	−0.3178 (−0.90)	−0.0045 (−0.01)	−0.6125** (−1.98)	−0.0971 (−0.42)	−1.4360*** (−3.56)	−0.5962 (−1.62)	0.0734 (0.26)	0.3187 (1.23)	0.3321 (1.57)	0.5801** (2.15)
Adj. R^2	0.514	0.427	0.644	0.558	0.785	0.713	0.693	0.722	0.714	0.724
Difference Portfolio										
α	−0.0108 (−1.56)	−0.0024 (−0.36)	−0.0058 (−0.96)	0.0029 (0.52)	−0.0038 (−0.59)	0.0046 (0.90)	−0.0028 (−0.54)	0.0008 (0.21)	0.0052 (0.92)	0.0082** (1.98)
Mkt	0.2796* (1.78)	0.3564 (1.64)	0.5000*** (4.29)	0.3952*** (3.85)	0.4274** (2.49)	0.2980 (1.65)	0.2056** (2.48)	0.2981*** (2.89)	0.2120* (1.88)	0.2256** (2.35)
SMB	0.5530** (2.38)	0.1930 (0.89)	0.6000*** (3.49)	0.1403 (0.76)	0.4591* (1.87)	−0.2624 (−0.88)	0.6217*** (2.71)	0.6254** (2.39)	0.7857*** (2.67)	0.8894*** (3.22)

Table B.2: Full regression results for the Fama–French (2015) five-factor model (*continued*)

	<i>Dependent variable: Excess Return</i>									
	1996–2005		1996–2010		2006–2015		2011–2026		2016–2026	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
HML	−0.0987 (−0.30)	0.3786 (1.10)	−0.1268 (−0.53)	0.3880 (1.49)	−0.2965 (−0.92)	−0.0167 (−0.05)	−0.6050** (−2.36)	−0.6219* (−1.96)	−0.6832*** (−2.64)	−0.7552** (−2.42)
RMW	−0.1204 (−0.23)	−0.4025 (−0.75)	0.1221 (0.33)	−0.1560 (−0.44)	−0.5172** (−2.06)	−0.9706*** (−3.03)	−0.4563 (−1.28)	−0.5334 (−1.08)	−0.2675 (−0.63)	−0.3145 (−0.56)
CMA	−0.0510 (−0.10)	−0.2241 (−0.39)	−0.0403 (−0.10)	−0.5460 (−1.10)	−0.6312 (−1.29)	−1.6529*** (−3.04)	−0.0548 (−0.14)	0.0969 (0.24)	0.1380 (0.40)	0.3283 (0.96)
Adj. R^2	0.054	0.060	0.150	0.133	0.271	0.293	0.158	0.127	0.184	0.124
N	119	119	179	179	120	120	180	180	120	120

Note: Newey–West HAC t-statistics are reported in parentheses. Adj. R^2 is the adjusted coefficient of determination. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

B.3 Full regression results for the Fama–French (2018) five-factor model

This table reports full estimation results for the Fama–French (2018) six-factor model across five subperiods (1996–2005, 1996–2010, 2006–2015, 2011–2026, and 2016–2026). Results are reported for equal-weighted (EW) and value-weighted (VW) portfolios of critical minerals, fossil fuel, and their difference (CM – FF).

	<i>Dependent variable: Excess Return</i>									
	1996–2005		1996–2010		2006–2015		2011–2026		2016–2026	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Critical Mineral Portfolio										
α	−0.0092 (−1.50)	−0.0031 (−0.51)	−0.0047 (−0.82)	0.0021 (0.39)	−0.0097 (−1.16)	−0.0003 (−0.04)	−0.0086* (−1.66)	−0.0018 (−0.49)	0.0015 (0.27)	0.0060* (1.78)
Mkt	1.3880*** (9.27)	1.3839*** (5.74)	1.6100*** (12.49)	1.4150*** (11.29)	1.5168*** (6.23)	1.3064*** (5.03)	1.1368*** (9.48)	1.1928*** (10.66)	1.1275*** (8.02)	1.1205*** (10.34)
SMB	1.4659*** (8.50)	0.4893* (1.81)	1.6132*** (7.91)	0.4711* (1.71)	1.3798*** (5.65)	−0.0561 (−0.16)	0.9404*** (3.56)	0.5631*** (3.08)	1.2074*** (3.69)	0.8303*** (4.24)
HML	0.6916* (1.78)	0.8510* (2.01)	0.5543* (1.41)	0.7173* (1.81)	0.5720 (1.41)	0.7094 (1.78)	−0.1524 (−0.41)	−0.2097 (−0.56)	−0.1496 (−0.41)	−0.3404 (−0.86)

<i>Dependent variable: Excess Return</i>										
	1996–2005		1996–2010		2006–2015		2011–2026		2016–2026	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
	(1.94)	(1.73)	(1.70)	(1.97)	(0.87)	(1.10)	(−0.54)	(−0.69)	(−0.51)	(−1.15)
RMW	0.0872	0.1185	0.7828**	0.7096*	0.2358	−0.0763	−0.7439**	−0.7312**	−0.5182	−0.6587
	(0.26)	(0.26)	(2.08)	(1.71)	(0.46)	(−0.17)	(−2.07)	(−2.08)	(−1.16)	(−1.51)
CMA	−0.3847	−0.2309	−0.6313	−0.6533	−2.2388**	−2.5809***	0.1423	0.6630	0.3898	0.9936**
	(−0.85)	(−0.39)	(−1.25)	(−1.18)	(−2.45)	(−3.04)	(0.30)	(1.29)	(0.96)	(2.27)
UMD	−0.1305	−0.0184	−0.0688	0.0326	0.1365	0.2638*	−0.1798	−0.3595**	0.1639	−0.1742
	(−1.25)	(−0.14)	(−0.64)	(0.26)	(0.69)	(1.89)	(−0.84)	(−2.00)	(0.71)	(−0.94)
Adj. R^2	0.586	0.423	0.692	0.536	0.768	0.692	0.570	0.546	0.576	0.519
Fossil Fuel Portfolio										
α	0.0010	−0.0003	0.0010	−0.0008	−0.0059	−0.0049	−0.0068**	−0.0047*	−0.0035	−0.0033
	(0.28)	(−0.09)	(0.32)	(−0.37)	(−1.18)	(−1.41)	(−2.38)	(−1.80)	(−1.11)	(−1.02)
Mkt	1.1186***	1.0197***	1.1137***	1.0207***	1.0895***	1.0077***	0.9612***	0.9558***	0.9062***	0.9399***
	(9.21)	(10.89)	(14.60)	(14.96)	(8.14)	(10.03)	(10.18)	(13.65)	(8.58)	(10.23)
SMB	0.8825***	0.3197**	1.0018***	0.3279**	0.9212***	0.1973	0.3406**	−0.0177	0.4083**	0.0051
	(5.02)	(2.39)	(6.34)	(2.60)	(4.35)	(0.94)	(2.05)	(−0.12)	(2.08)	(0.03)
HML	0.8227***	0.4475*	0.7008***	0.3343*	0.8666*	0.7653	0.5980***	0.7082***	0.4962***	0.5939***
	(3.27)	(1.67)	(3.59)	(1.80)	(1.70)	(1.65)	(3.09)	(3.65)	(2.94)	(2.73)
RMW	0.1687	0.5509**	0.6448**	0.8615***	0.7540*	0.8732**	−0.2432	−0.1074	−0.2679	−0.2620
	(0.53)	(2.04)	(2.03)	(3.31)	(1.96)	(2.15)	(−0.85)	(−0.33)	(−0.77)	(−0.67)
CMA	−0.3270	−0.0119	−0.5986*	−0.1092	−1.6056***	−0.9721**	0.0732	0.3137	0.2783	0.5386**
	(−0.91)	(−0.03)	(−1.90)	(−0.44)	(−3.16)	(−2.44)	(0.28)	(1.26)	(1.32)	(2.07)
UMD	−0.0756	−0.0606	−0.0444	0.0388	0.1348	0.2989**	0.0002	0.0072	0.1099	0.0847
	(−0.81)	(−0.69)	(−0.46)	(0.41)	(1.07)	(2.51)	(0.00)	(0.10)	(1.40)	(1.20)
Adj. R^2	0.512	0.424	0.643	0.556	0.786	0.734	0.691	0.720	0.714	0.723
Difference Portfolio										
α	−0.0103	−0.0029	−0.0056	0.0029	−0.0038	0.0046	−0.0018	0.0029	0.0050	0.0093**
	(−1.46)	(−0.41)	(−0.96)	(0.54)	(−0.59)	(0.90)	(−0.39)	(0.81)	(0.92)	(2.37)
Mkt	0.2694*	0.3642	0.4963***	0.3943***	0.4274**	0.2987	0.1755*	0.2369**	0.2214*	0.1806*
	(1.68)	(1.63)	(4.14)	(3.71)	(2.49)	(1.65)	(1.97)	(2.39)	(1.94)	(1.85)
SMB	0.5835**	0.1697	0.6114***	0.1432	0.4586*	−0.2534	0.5997***	0.5807**	0.7991***	0.8253***
	(2.54)	(0.69)	(3.55)	(0.68)	(1.83)	(−0.81)	(2.67)	(2.54)	(2.74)	(3.70)
HML	−0.1311	0.4035	−0.1465	0.3830	−0.2947	−0.0559	−0.7504**	−0.9180***	−0.6458**	−0.9343**
	(−0.38)	(0.99)	(−0.55)	(1.22)	(−0.87)	(−0.15)	(−2.59)	(−2.68)	(−2.00)	(−2.58)
RMW	−0.0814	−0.4324	0.1380	−0.1519	−0.5182**	−0.9495***	−0.5007	−0.6238	−0.2503	−0.3966

<i>Dependent variable: Excess Return</i>										
	1996–2005		1996–2010		2006–2015		2011–2026		2016–2026	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
	(−0.16)	(−0.80)	(0.38)	(−0.41)	(−2.31)	(−3.16)	(−1.40)	(−1.31)	(−0.57)	(−0.71)
CMA	−0.0577	−0.2189	−0.0327	−0.5441	−0.6333	−1.6088***	0.0691	0.3493	0.1115	0.4550
	(−0.11)	(−0.38)	(−0.08)	(−1.07)	(−1.29)	(−2.78)	(0.17)	(0.78)	(0.30)	(1.12)
UMD	−0.0550	0.0422	−0.0244	−0.0062	0.0017	−0.0351	−0.1800	−0.3667**	0.0540	−0.2590
	(−0.47)	(0.31)	(−0.27)	(−0.06)	(0.01)	(−0.37)	(−1.06)	(−2.27)	(0.26)	(−1.33)
Adj. R^2	0.047	0.053	0.145	0.128	0.264	0.287	0.160	0.144	0.178	0.127
N	119	119	179	179	120	120	180	180	120	120

Note: Heteroskedasticity and autocorrelation consistent standard errors following Newey–West (1987) are reported in parentheses. Adj. R^2 is the adjusted coefficient of determination * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

B.4 Full regression results for the Hou et al. (2021) q-factor model

This table reports full estimation results for the Hou et al. (2021) q-factor model across five subperiods (1996–2005, 1996–2010, 2006–2015, 2011–2026, and 2016–2026). Results are reported for equal-weighted (EW) and value-weighted (VW) portfolios of critical minerals, fossil fuel, and their difference (CM – FF).

<i>Dependent variable: Excess Return</i>										
	1996–2005		1996–2010		2006–2015		2011–2026		2016–2026	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Critical Mineral Portfolio										
α	−0.0043	0.0020	0.0013	0.0065	−0.0060	0.0012	−0.0130**	−0.0048	−0.0014	0.0042
	(−0.43)	(0.27)	(0.16)	(0.96)	(−0.60)	(0.16)	(−1.98)	(−1.00)	(−0.21)	(0.84)
Mkt	0.8054***	0.9759***	1.1694***	1.2090***	1.4312***	1.3927***	0.9357***	0.9581***	0.8795***	0.8690***
	(5.02)	(5.41)	(5.69)	(6.13)	(7.57)	(7.15)	(8.58)	(8.14)	(6.86)	(7.77)
Me	0.4622***	0.1062	0.3699**	0.0333	−0.3395	−0.3946	−0.0775	−0.2797	0.0203	−0.2095
	(2.62)	(0.68)	(2.38)	(0.21)	(−1.41)	(−1.49)	(−0.36)	(−1.32)	(0.07)	(−0.88)
I/A	0.4385*	0.5261*	0.3559	0.2278	−1.3641**	−1.7034***	0.0241	0.2107	0.1840	0.4576**
	(1.81)	(1.83)	(1.32)	(0.74)	(−2.24)	(−3.32)	(0.10)	(0.74)	(0.99)	(2.16)
ROE	−0.3628*	0.0442	−0.2614	0.1258	−0.6603*	−0.2081	−0.1542	−0.1555	−0.2554*	−0.3750**
	(−1.77)	(0.16)	(−1.11)	(0.48)	(−1.74)	(−0.53)	(−0.75)	(−0.61)	(−1.91)	(−2.24)

Table B.4: Full regression results for the Hou et al. q-factor model (*continued*)

<i>Dependent variable: Excess Return</i>										
	1996–2005		1996–2010		2006–2015		2011–2026		2016–2026	
	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
EG	0.1050 (0.31)	−0.0311 (−0.10)	0.0151 (0.05)	0.0266 (0.10)	−1.1582** (−2.06)	−1.1952* (−1.92)	−0.7534*** (−3.26)	−0.8201** (−2.52)	−0.5187*** (−3.33)	−0.4387* (−1.98)
Adj. R^2	0.303	0.241	0.400	0.350	0.563	0.561	0.492	0.442	0.535	0.440
Fossil Fuel Portfolio										
α	0.0070 (1.01)	0.0054 (1.10)	0.0056 (1.22)	0.0042 (1.32)	−0.0009 (−0.21)	−0.0008 (−0.25)	−0.0060* (−1.79)	−0.0034 (−1.12)	−0.0015 (−0.39)	−0.0007 (−0.18)
Mkt	0.7518*** (6.63)	0.7197*** (9.39)	0.9215*** (7.92)	0.8555*** (10.62)	0.9811*** (8.67)	0.9917*** (8.81)	0.7743*** (10.03)	0.8019*** (14.04)	0.6974*** (8.15)	0.7409*** (11.07)
Me	0.3277* (1.68)	0.0225 (0.15)	0.3057* (1.70)	0.0003 (0.00)	−0.1104 (−0.44)	−0.2953 (−1.34)	0.0301 (0.25)	−0.0423 (−0.41)	0.1528 (1.49)	0.0743 (0.74)
I/A	0.3791 (1.51)	0.3490* (1.94)	0.2198 (0.81)	0.1402 (0.67)	−1.0738*** (−2.76)	−0.8490** (−2.59)	0.4613*** (3.30)	0.7067*** (4.70)	0.5456*** (4.95)	0.7807*** (5.70)
ROE	0.2007 (1.08)	0.2981* (1.74)	0.1398 (0.66)	0.3198** (2.07)	−0.5949* (−1.73)	−0.1152 (−0.44)	−0.2105 (−1.03)	−0.1640 (−0.94)	−0.1911 (−1.32)	−0.1136 (−0.70)
EG	−0.2744 (−1.18)	−0.2475 (−1.31)	−0.1282 (−0.78)	−0.0753 (−0.45)	−0.7988** (−2.39)	−0.4337 (−1.43)	−0.5439*** (−3.06)	−0.4616*** (−3.00)	−0.3920** (−2.33)	−0.3706** (−2.16)
Adj. R^2	0.299	0.294	0.404	0.390	0.628	0.602	0.656	0.685	0.734	0.725
Difference Portfolio										
α	−0.0113 (−1.46)	−0.0034 (−0.51)	−0.0043 (−0.64)	0.0023 (0.40)	−0.0051 (−0.70)	0.0020 (0.37)	−0.0071 (−1.22)	−0.0014 (−0.32)	0.0001 (0.01)	0.0049 (0.98)
Mkt	0.0536 (0.53)	0.2562 (1.45)	0.2479** (2.08)	0.3535** (2.38)	0.4500*** (2.91)	0.4010** (2.47)	0.1614 (1.63)	0.1563 (1.57)	0.1821 (1.44)	0.1281 (1.29)
Me	0.1345 (0.87)	0.0837 (0.64)	0.0642 (0.45)	0.0330 (0.28)	−0.2291 (−1.42)	−0.0993 (−0.49)	−0.1076 (−0.60)	−0.2374 (−1.25)	−0.1325 (−0.54)	−0.2838 (−1.17)
I/A	0.0594 (0.29)	0.1771 (0.74)	0.1361 (0.73)	0.0875 (0.45)	−0.2903 (−0.88)	−0.8544** (−2.53)	−0.4373*** (−3.02)	−0.4960** (−2.55)	−0.3616** (−2.48)	−0.3231* (−1.82)
ROE	−0.5635*** (−2.92)	−0.2538 (−1.20)	−0.4013** (−2.30)	−0.1940 (−1.06)	−0.0654 (−0.29)	−0.0930 (−0.32)	0.0563 (0.41)	0.0085 (0.04)	−0.0643 (−0.44)	−0.2615 (−1.29)
EG	0.3794 (1.43)	0.2164 (0.88)	0.1433 (0.55)	0.1019 (0.39)	−0.3594 (−0.95)	−0.7614 (−1.30)	−0.2095 (−1.09)	−0.3585 (−1.05)	−0.1266 (−0.60)	−0.0681 (−0.21)
Adj. R^2	0.032	0.012	0.070	0.070	0.141	0.188	0.049	0.047	0.053	0.029
N	119	119	179	179	120	120	168	168	108	108

Table B.4: Full regression results for the Hou et al. q-factor model (*continued*)

Dependent variable: Excess Return									
1996–2005		1996–2010		2006–2015		2011–2026		2016–2026	
EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Note: Heteroskedasticity and autocorrelation consistent standard errors following Newey–West (1987) are reported in parentheses. Adj. R^2 is the adjusted coefficient of determination *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.									

