Lisbon School of Economics & Management
Universidade de Lisboa

MASTER IN FINANCE

MASTER FINAL WORK

DISSERTATION

DIRECT VS. INDIRECT COMMODITY EXPOSURE: PORTFOLIO DIVERSIFICATION IN THE GLOBAL FORESTRY, PULP AND PAPER INDUSTRY

JULIANA COSTA GUERREIRO

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JUNE 2026

Abstract

This study aims to investigate whether direct commodity-futures or indirect commodity exposure via forestry, pulp and paper equities offer superior diversification benefits to a global equity portfolio for a euro-based risk-averse investor. The empirical analysis uses monthly data from January 2016 to December 2025 and compares a global industry-specific equity portfolio with a commodity basket containing wood, pulp and energy exposures, through fixed-weight and minimum-variance allocation rules, and benchmark-relative and downside-risk measures.

The results show that indirect commodity exposure, particularly through an equal-weighted industry portfolio composed of 198 firms from 33 countries, provides the strongest overall diversification outcome over the full sample. Direct commodity exposure generates higher average returns but also higher volatility and tail risk, although it becomes more attractive during high-inflation periods. Results also differ across regions and product-focus groups. Overall, the results indicate that direct and indirect commodity exposure are not interchangeable. Their diversification benefits depend on the portfolio construction, market conditions and firm characteristics.

JEL: C12; G11; G12

Keywords: Risk-averse; Commodities; Diversification; Forestry, Pulp and Paper

Resumo

Este trabalho tem como objetivo analisar se a exposição direta a futuros de matérias-primas ou a exposição indireta através de ações de empresas do setor florestal, de pasta e papel proporciona benefícios de diversificação superiores numa carteira global de ações na perspetiva de um investidor avesso ao risco e com o euro como moeda de referência. A análise empírica utiliza dados mensais de janeiro de 2016 a dezembro de 2025 e compara um portefólio de ações com um cabaz de matérias-primas composto por madeira, pasta e energia, através de regras de alocação de peso fixo e de variância mínima, bem como de medidas de desempenho relativo e de risco de perda.

Os resultados mostram que a exposição indireta, especialmente através de um portefólio setorial equiponderado composto por 198 empresas de 33 países, proporciona o resultado global de diversificação mais favorável na amostra total. A exposição direta a matérias-primas gera retornos médios mais elevados, mas também maior volatilidade e risco de perda, embora se torne relativamente mais atrativa durante períodos de elevada inflação. Os resultados também variam entre regiões e segmentos de atividade. No geral, os resultados indicam que as exposições diretas e indiretas a matérias-primas não são equivalentes, uma vez que os seus benefícios de diversificação dependem da construção do portefólio, das condições de mercado e das características das empresas expostas.

JEL: C12; G11; G12

Palavras-chave: Aversão ao risco; Matérias-primas; Diversificação; Silvicultura, Pasta e Papel

Acknowledgements

This work is first and foremost dedicated to my parents, Anabela Guerreiro and José Guerreiro, who have been my anchor throughout my life. I am deeply grateful to have parents who have always believed in me, invested in my education, and stood by my side at every difficult or joyful moment.

A special thank you to my sister, Adriana Guerreiro, for her design skills and support.

I would also like to express my appreciation to Professors Victor Barros and Pedro Sampayo Ramos. We shared a lot of work, challenges, wins, learning, and even some fun along the way. Thank you for always encouraging your students.

To my colleagues and professors from the Master's in Finance, thank you for making this such a special journey. To ISEG and all the friends I made along the way: five years at a place that I will always call 'home', and friendships that I know will last a lifetime. I am proud to be 'Iseguiana'.

To all my remaining friends and family, thank you for your support in every step of my journey.

Finally, I dedicate this work to my boyfriend, João. After my high-school and bachelor's graduation, another important chapter of my life by his side. A lot of hours feeling tired and demotivated, and many others unavailable for our life at home. His partnership, patience and support made everything easier.

Abbreviations

BHKP	Bleached Hardwood Kraft Pulp
BICS	Bloomberg Industry Classification System
CVaR	Conditional Value at Risk
EM-DAT	Emergency Events Database
EUR	Euro
EW	Equally Weighted
GDP	Gross Domestic Product
IR	Information Ratio
MCW	Market-Capitalization Weighted
MSCI	Morgan Stanley Capital International
MV	Minimum-Variance
NBSK	Northern Bleached Softwood Kraft
U.S.	United States
VaR	Value at Risk

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1 Introduction

Portfolio diversification remains one of the central concerns in asset allocation, especially for investors seeking protection against periods of market stress and unexpected inflation. Commodities have thus long been regarded as a logical complement to most traditional financial assets (Bodie & Rosansky, 1980), given that their prices are more directly related to fluctuations in production conditions and availability of inputs than to macroeconomic shocks. However, this intuition has become less clear in recent years, since commodity markets have been increasingly financialized (Tang & Xiong, 2012; Cheng & Xiong, 2014; Basak & Pavlova, 2016). Consequently, the rationale for commodities being a structurally stable source of diversification has been diminished, which raises the following question: do investors obtain commodity-related diversification benefits when holding commodity-exposed equities, or can similar benefits only be achieved through direct commodity holdings?

This dissertation considers this question within the context of the global forestry, pulp, and paper industry, a rich setting in which commodity-related inputs, ranging from wood to pulp and energy, are critical. At the same time, operating models within the industry vary widely by product focus, geography, and sourcing structure. Accordingly, this industry is well suited for direct and indirect commodity exposure comparisons within a single commodity-sensitive basket, whereas prior studies compare large indices composed of firms that vary widely in terms of their business models and cost structures.

The analysis is conducted from the perspective of a euro-based risk-averse investor holding a global equity portfolio. A diversified range of equity and commodity portfolio configurations – including industry-specific equity exposure, direct commodity exposure and combinations of both - are benchmarked against a global equity portfolio. These configurations are evaluated under fixed-weight and minimum variance allocations, and the empirical analysis considers benchmark-relative instruments and downside measures of risk, besides the traditional average return and volatility. On top of the established baseline results, three extensions are introduced: how product focus, geography, and inflation regimes impact diversification benefits. Finally, the empirical framework analyses a country-level physical-risk extension related to wildfire and extreme-temperature events.

The baseline results indicate that, on average, the best diversification benefit is obtained through indirect commodity exposure via an equal-weighted industry portfolio, while direct commodity exposure becomes more attractive in high inflation environments. These results also suggest that the portfolio role of commodity-exposed companies varies across business segments and geographies, as physical climate shocks may weaken diversification metrics in specific cases.

Overall, this study contributes to the literature by providing an industry-specific analysis that compares direct and indirect commodity exposure through commodity-exposed firms and by showing that the portfolio role of both depends on firm characteristics, macroeconomic conditions, and physical-risk exposure. The remainder of the dissertation is organized as follows: literature review, empirical analysis (data and methodology), results, and conclusions.

2 Literature Review

For decades, commodities have been a natural complement to diversified portfolios, mainly because their prices are influenced by drivers that differ from those affecting traditional assets, including weather conditions, geopolitical events, supply shocks and event risks. In earlier evidence, this translated into low correlation with stocks and bonds, providing a source of inflation hedging, and improved risk-return trade-offs (Bodie & Rosansky, 1980; Jensen, Johnson, & Mercer, 2000; Gorton & Rouwenhorst, 2006). However, these conclusions are no longer viewed as unconditional, with recent studies pointing to such benefits as dependent on the sample, the allocation rules, or the market regime (Daskalaki & Skiadopoulos, 2011; Gao & Nardari, 2018; Ruano & Barros, 2022).

The traditional argument is therefore that commodities’ distinct return drivers can improve the portfolio opportunity set. Earlier studies reported lower risk for a given expected return and stronger risk-return trade-offs when commodity futures were added to equity and bond portfolios (Jensen, Johnson, & Mercer, 2000; Gorton & Rouwenhorst, 2006). The inflation-hedging argument was also important: commodity prices were expected to respond differently to shocks to production costs and to restrictive phases of the monetary cycle (Jensen, Johnson, & Mercer, 2000).

Several studies challenged the empirical relevance of these mechanisms after considering higher moments, estimation error, and out-of-sample implementation. Daskalaki & Skiadopoulos (2011) show that the classical result weakens when performance is evaluated in a mean-variance world, while Yan & Garcia (2017) find limited improvements in Sharpe ratios for several commodity asset classes. The remaining evidence is consequently more conditional: diversification benefits may exist, but their strength depends on the commodity set, portfolio design, and inflation regime.

A central explanation is the financialization of commodity markets, namely the expansion of futures-based investment products. This process has been associated with higher commodity volatility and stronger co-movement with traditional asset classes, thereby weakening the diversification and hedging potential emphasized in earlier research (Buyuksahin, Haigh, & Robe, 2008; Tang & Xiong, 2012; Cheng & Xiong, 2014; Basak & Pavlova, 2016). Evidence on the magnitude and persistence of this change remains mixed: Daskalaki & Skiadopoulos (2011) and Yan & Garcia (2017) report limited out-of-sample gains, whereas Ruano & Barros (2022) find that commodities can still protect against downside risk, although their benefits are time-dependent and have declined over time.

The financialization debate also matters for the comparison between direct and indirect exposure. When commodity futures become more equity-like, commodity-related stocks may become a relatively more attractive route to commodity sensitivity, but they still retain the valuation, financing and operating risks of equities. Daskalaki (2021) therefore distinguishes the diversification role of commodity stocks from that of futures, while

Carter, Rogers, Simkins, & Treanor (2017) highlights how firms adjust their commodity-price exposure through production, hedging and financing choices.

The risk-averse investor perspective, for whom volatility control and protection against large losses are central concerns, strengthens the relevance of this debate. Mean-variance analysis alone may be insufficient when returns are non-normal and investors are concerned with severe losses. Accordingly, recent work complements Sharpe-ratio evidence with downside measures such as VaR and CVaR (Daskalaki & Skiadopoulos, 2011; Ruano & Barros, 2022). This is particularly important for commodity markets, where the relative tail-risk ranking of commodities and their relationship with equity-market tail risk can change across periods (Powell, Vo, Pham, & Singh, 2017).

Investors can obtain commodity-related exposure not only through futures, but also through commodity-exposed equities. These firms are influenced by underlying commodity-price dynamics, yet their returns also incorporate firm-specific and broader equity-market risks. Daskalaki (2021) finds that commodity-stock investing became relatively more attractive after financialization, while Han, Laing, Lucey, & Vigne (2023) and Carter, Rogers, Simkins, & Treanor (2017) show that commodity exposure depends on firm characteristics, operating choices, hedging policy, financing conditions and market structure. Commodity-related equities are therefore neither a perfect substitute for futures nor a homogeneous asset class.

The global forestry, pulp and paper industry offers a relevant setting in which to compare these two forms of exposure. First, input-price exposure is economically central, as firms are strongly exposed to commodities such as wood/pulp and energy. Chemicals are also relevant, but are excluded from the final commodity basket because sufficiently comparable continuous market series are unavailable (Corcelli, Fiorentino, Vehmas, & Ulgiati, 2018; Sousa, Pinto, Machado, Gando-Ferreira, & Quina, 2023; Lipiäinen, Kuparinen, Sermyagina, & Vakkilainen, 2022; Li, Xu, Yin, Wang, & Liu, 2023). Second, that exposure is not uniform across firms, since companies differ substantially in terms of product focus, geographic footprint, sourcing structure, and operational profile. Taken together, these features make the industry a suitable context in which to compare direct commodity exposure with indirect exposure through commodity-related equities.

Within forestry, pulp and paper, this heterogeneity is especially material. Wood and pulp costs, energy intensity, sourcing arrangements, vertical integration and regional production footprints can affect how a firm transmits input-price shocks into cash flows and equity returns. The industry setting thus allows the study to move beyond the average commodity-sensitive firm and examine whether an indirect exposure retains a similar portfolio role across distinct segments of the same value chain.

A further dimension of this study concerns whether physical climate shocks may also affect the diversification properties of commodity-linked assets. Wildfire and extreme-temperature events may disrupt timber supply, and operating conditions, while their economic significance should be assessed relative to the size of the affected economy (Neumayer & Barthel, 2011; Tavor, 2024; Bousfield, et al., 2025). Yet, evidence directly linking such shocks to diversification properties remains limited.

A clear gap therefore remains in the literature. Existing studies provide valuable insights into direct commodity holdings and commodity-related equities but usually rely on broad market exposures and do not assess how diversification varies within a single commodity-sensitive industry. The present study addresses these gaps by comparing direct commodity holdings and commodity-exposed equities within the global forestry, pulp and paper industry, while also examining product-focus and geographic heterogeneity, inflation regimes and a country-level physical-risk extension.

Building on the previous literature, this dissertation tests four main hypotheses:

H1: In the aggregate sample, indirect commodity exposure through industry-specific equities provides stronger diversification benefits than direct commodity exposure.

H2: The diversification role of indirect commodity exposure differs across product-focus and geographic sub-portfolios.

H3: The diversification benefits of direct and indirect commodity exposure are time-varying and become stronger in high-inflation environments.

H4. Historical wildfire and extreme-temperature shocks are associated with changes in the diversification benefits of direct and indirect commodity exposure.

3 Empirical Analysis

3.1 Data

The empirical analysis combines (i) a risk-free rate, (ii) a global equity benchmark, (iii) a self-constructed industry equity portfolio, and (iv) an input-based commodity portfolio. Firm-level classifications support product-focus and geographic sub-portfolios, while monthly inflation and country-level disaster information support the regime and physical-risk extensions. This structure allows direct and indirect commodity exposure to be compared within the same industry and investor perspective.

3.1.1 Sample Period and Investor Perspective

All series are aligned in EUR terms. The risk-free rate is proxied by the yield on a long-term euro-denominated German government bond, converted into a monthly equivalent rate and used as a normalized benchmark input rather than as a historical monthly risk-free series (Fernandez, Habibian, & Acín, 2026). The sample runs from January 2016 to December 2025, although the minimum-variance portfolios begin only after the initial 36-month estimation window. Figure 1 reports the resulting data-availability restrictions.

3.1.2 Benchmark and Industry-Specific Equity Portfolio

The MSCI World Index represents the benchmark equity portfolio throughout the baseline and regional exercises. Retaining the same global benchmark allows each regional industry sub-portfolio to be assessed against the investment opportunity set of a global euro-based investor rather than against a local market index. Monthly returns are used throughout the analysis.

Indirect commodity exposure is proxied by a self-constructed portfolio of listed firms classified by Bloomberg BICS Level 3 as Forestry, Paper & Wood Products. After the price-coverage screen, the universe contains 198 firms. The portfolio is constructed under both equal-weighted and market-cap-weighted specifications, allowing the analysis to assess whether concentration in the largest firms changes the results. The resulting sample captures sectoral heterogeneity and supports the subsequent product-focus and geographic exercises. This construction is deliberately broader than a narrow single-product portfolio. It captures firms operating across forestry, pulp, paper and wood-product activities while maintaining a common industry classification. The equal-weighted specification gives the same importance to each included firm and is therefore better suited to identifying a broad industry effect, whereas the market-cap-weighted version reflects the investment opportunity set available through a more concentrated large-cap allocation.

3.1.3 Commodity Portfolio

Direct commodity exposure is represented by an input-based basket of wood, pulp and energy benchmarks. Wood exposure is proxied by LB1 Comdty until its discontinuation in August 2022, and by LBO1 Comdty as the successor contract. The transition-date return is excluded to avoid an artificial contract-change jump. Market pulp exposure uses NOREXECO Pulp NBSK Europe Futures and NOREXECO Pulp BHKP Europe Futures. Energy exposure uses TZT1 Comdty, LGOc1 and LCOc1, which proxy Dutch gas, low-sulphur gasoil and Brent crude oil, respectively.

Returns are first equally weighted within the wood, pulp and energy input blocks, after which the three blocks receive equal weights in the final commodity portfolio. This avoids mechanically over-weighting energy (three instruments available) and avoids preliminary assumptions about the relative weights. Chemicals are economically relevant but are excluded from the portfolio because continuous comparable market series are unavailable, and their selection is dependent on the production process. The selected series are used as nearest relevant monthly benchmark exposures and should be interpreted as proxy futures-price returns rather than fully collateralized futures returns including roll yield and collateral income. The selected contracts do not all share an identical continuation format. Wood and energy are represented through front-month or front-continuation benchmark series, whereas pulp is represented through monthly financially settled futures contracts. These differences remain a data limitation, but the maturity alignment is considered sufficient for a monthly industry-input portfolio. The series are nevertheless treated consistently as proxy price-return exposures rather than as a full decomposition of spot, roll and collateral returns.

3.1.4 Firm-Level Characteristics and Product-Focus Classification

Bloomberg BICS Level 4 and Level 5 classifications are used to divide the industry universe into Forestry & Logging, Wood Products and Paper & Pulp Mills. Regional sub-portfolios are constructed for Europe, the Americas, and Asia, which are the only regions with sufficient firm coverage and data availability to support meaningful empirical comparisons. The composition of these sub-portfolios is not uniform: Table 1 reports the number of firms, countries and the differences in size and internal concentration that should be considered when comparing results.

The regional classification is intentionally not treated as a set of directly comparable local-market portfolios. Europe, Asia and the Americas are evaluated against the same MSCI World benchmark so that the exercise asks whether each regional industry allocation improves the global investor's portfolio. The groups also differ in representation and country concentration: Asia is the broadest group, while European representation is concentrated in Poland and Sweden and the Americas are dominated by Canadian and U.S. firms. The sub-portfolio evidence should therefore be interpreted as a variation in the portfolio role of the available regional industry exposure, rather than as a pure test of regional market performance.

Within the product-focus classification, the largest group is Paper & Pulp Mills (106 firms), followed by Wood Products (64 firms), and Forestry & Logging (28 firms). This indicates that product-focus analysis compares groups with materially different levels of representation. The geographic classification is also unbalanced. Asia is the largest regional subsample, with 140 firms, followed by Europe with 27 firms and the Americas with 25 firms. In addition, the regional groups differ in internal diversification. Europe includes 11 countries, although the largest representations are concentrated in Poland and Sweden, while the Americas cover 7 countries and are dominated by Canadian and U.S. firms. Asia is the broadest regional group, spanning 15 countries, with particularly strong representation from India, China, Malaysia, Japan, and South Korea. These differences suggest that the geographic and product-focus sub-portfolios should not be interpreted as perfectly comparable in terms of scope or internal concentration, and this should be borne in mind when discussing their subsequent diversification performance.

3.1.5 Macroeconomic Inputs

Monthly world inflation is used both as macroeconomic control and to define high- and low-inflation regimes. This is consistent with the view that commodity diversification benefits are time-varying rather than constant across macroeconomic environments (Ruano & Barros, 2022).

3.1.6 Physical-Risk Exposure and Environmental Variables

A further data extension concerns physical climate risk. Each firm is linked to a main country using country of largest revenue as the preferred proxy, country of risk otherwise and country of domicile as a fallback proxy, extracted from Bloomberg. This provides the closest approximation of where the firm's economic activity is concentrated and supports a transparent and replicable mapping. However, the climate evidence remains an exploratory country-level approximation rather than a fully granular location-of-assets analysis. Table 2 reports the agreement rates between the alternative country identifiers.

Based on this country mapping, the environmental dataset is constructed using historical natural disaster information for wildfires and extreme temperature events, obtained from the EM-DAT International Disaster Database and matched to firms through this main country proxy. This analysis is designed to capture how realized physical shocks translate into financial outcomes over time, focusing on the empirical relationship between observed disaster events and portfolio diversification metrics. The key climate risk input is the severity of each disaster event. In this analysis, severity is defined as a financial-loss proxy, measured by the ratio of reported economic damage to the size of the affected country's economy. More specifically, for event e, in country c, hazard h, in month m, and year y, observed severity is defined as:

$$Observed\ Sev_{c,h,e,m} = \ln\left(1 + \frac{Damage_{c,h,e,m}}{GDP_{c,y}}\right),$$

where $Damage_{c,h,e,m}$ denotes reported disaster damage, in US dollars, and $GDP_{c,y}$ denotes annual nominal GDP, also in US dollars. The normalization by GDP follows the disaster-loss normalization literature, which argues that raw disaster losses are not directly comparable across countries of very different economic size. In particular, Neumayer & Barthel (2011) show that disaster-loss normalization is necessary when comparing economic losses across countries, while more recent macro-disaster work also treats asset damage as more directly linked to economic disruption than the number of affected people alone.

Although GDP is measured annually, each event is assigned to its EM-DAT start date so that country-hazard severity can be aligned with the monthly portfolio data. The logarithmic transformation reduces the influence of highly skewed loss data while retaining events with a severity equal to zero.

As EM-DAT damage data is incomplete, missing values of normalized damage are imputed on the subsample with observed damage using the auxiliary regression:

$$\ln\left(1 + \frac{Damage_{c,h,e,m}}{GDP_{c,y}}\right) = \propto + \beta_1 \ln\left(1 + Affected_{c,h,e}\right) + \beta_2 \ln(1 + Deaths_{c,h,e}) + \delta_h + u_{c,h,e}$$

where $Affected_{c,h,e}$ and $Deaths_{c,h,e}$ are used only to predict the financial-loss proxy and δ_h represents hazard-type fixed effects, included to account for systematic differences across hazard categories. In particular, (i) observed values are retained whenever damage data exist; (ii) imputed values are used only for event observations with missing damage but non-zero human impact; and (iii) non-event months are assigned a zero-severity value. The resulting measure should consequently be read as a standardized proxy for realized physical loss severity rather than as a complete valuation of firm-level climate exposure.

Event severity is then aggregated to the country-hazard-month level and matched to firms through the Main Country variable.

3.1.7 *Descriptive Statistics*

Table 3 reports the descriptive statistics for the benchmark, the two industry-specific equity portfolios, and the commodity portfolio. Monthly returns are computed from end-of-month price series as percentage changes between two consecutive monthly observations, while volatility is computed as the sample standard deviation of monthly returns over the corresponding period. The benchmark records a mean monthly return (annualized) of 1.02% (12.95%) and volatility of 3.93% (58.81%). The equal-weighted and market-cap weighted industry portfolios returns are 1.14% (14.57%) and 1.04% (13.22%), and presented volatilities of 4.29% (65.54%) and 4.66% (72.73%), respectively. Similarly, the commodity portfolio exhibits an average monthly return of 1.19% (15.25%) and a volatility of 7.36% (134.48%).

Regarding higher moments, the benchmark and industry portfolios show a slightly negative skewness, while the equal-weighted industry portfolio has the highest excess kurtosis. The commodity portfolio exhibits strong positive skewness, suggesting that its return distribution is more influenced by occasional large positive observations, but overall more volatile. These distributional features reinforce the use of downside-risk measures alongside conventional risk-return metrics. Table 4 shows that the benchmark is more strongly correlated with the industry-specific equity portfolios (0.69 and 0.72) than with the commodity portfolio (0.37). Correlations between the industry and commodity portfolios are moderate (0.48 and 0.46), meaning that direct and indirect exposure are therefore related but not interchangeable, motivating the portfolio-level comparison.

3.2 Variable Definition

This section groups the main variables into dependent, independent and control variables. This distinction is particularly relevant in the sub-portfolio and inflation analysis, and the climate-risk framework.

3.2.1 Dependent Variables

The main dependent variables are the performance and risk measures: Sharpe ratio, Information Ratio (IR), Value at Risk (VaR), and Conditional Value at Risk (CVaR). These measures are first evaluated over the full sample and then computed on a rolling basis using a 36-month window, consistent with the time-varying perspective emphasized by Ruano & Barros (2022). For the climate-risk analysis in particular, the dependent variables are defined as incremental diversification measures relative to the benchmark: Sharpe ratio differences, Information Ratio (benchmark-relative by definition), and reductions in VaR and CVaR. The selection of these measures is also consistent with the commodity-diversification literature, which evaluates augmented portfolios not only through conventional risk-adjusted performance measures, but also through benchmark-relative and downside-risk indicators (Bessler & Wolff, 2015; Ruano & Barros, 2022).

For the full-sample comparison, the measures show both absolute and benchmark-relative profile of each setup. In the dynamic extensions, a rolling approach is used because the study tests whether diversification shifts across macroeconomic conditions and physical shocks. The benchmark-relative changes in the climate analysis are therefore designed to quantify the incremental benefit or cost of adding direct or indirect commodity-related exposure.

3.2.2 Independent Variables

The main independent variables vary according to the dimension of the analysis being considered. In the cross-sectional extensions, the main factors examined are product focus and geographic exposure. Product-focus variables are based on Bloomberg BICS Level 4 and Level 5 classifications and are used to build sub-portfolios within the broader Forestry, Paper & Wood Products universe. Geographic exposure is shown through the Main Country variable.

In the climate-risk extension, the independent variables are portfolio-level shock measures, which are based on actual wildfire and extreme-temperature severity, that are then combined into country-hazard exposure of the firms in the portfolio. These variables are also considered with one- and three-month lags, once supply disruptions, operating changes, and financial-market responses may happen gradually instead of right after an event.

3.2.3 Control Variables

Inflation is the main macroeconomic control and is the basis for defining different market regimes in the time-series extensions of the analysis. Using inflation both as a macroeconomic control and as a regime-classification device is consistent with the literature (Ruano & Barros, 2022; Gaete & Herrera, 2023).

In addition, using the benchmark as a control is also key for interpretation, as all augmented portfolios are compared to the same reference portfolio. This means the Information Ratio and risk-gain measures show whether the added exposure improves an investor's global equity allocation, not just if it produces positive returns on its own.

Likewise, the use of alternative internal constructions of the industry-specific equity portfolio - equal-weighted and market-cap-weighted - serves as an additional robustness dimension. Finally, in the minimum-variance framework, the rolling 36-month estimation window and quarterly rebalancing frequency provide a consistent time structure that is maintained across the dynamic extensions of the analysis, while aligned with the literature.

3.3 Methodology

The empirical strategy starts by comparing how the benchmark, industry-specific, and commodity portfolios correlates within a baseline portfolio framework. Second, the augmented portfolios are evaluated under both fixed-weight and minimum-variance approaches. Third, the baseline framework is extended along three additional dimensions, namely firm-level heterogeneity, inflation periods, and a climate-related physical-risk extension.

3.3.1 Baseline Portfolio Construction

The correlation analysis is useful as an initial test of whether commodity-exposed equities behave as close substitutes for direct holdings. The strong benchmark-industry correlation confirms that commodity-exposed equities retain an important broader equity-market component, while the lower benchmark-commodity correlation suggests a more distinct direct exposure. At the same time, the moderate correlation between the industry portfolios and the commodity portfolio indicates that both forms of exposure are related but sufficiently differentiated to justify a deeper portfolio-level comparison of their respective diversification benefits.

Additionally, this correlation structure implies that any apparent diversification benefit from the industry-specific portfolio may partly reflect broader factor angles, such as sector composition or firm-size effects, rather than pure commodity exposure alone. That is why comparing portfolios gives the most important evidence.

The empirical analysis considers four portfolio configurations:

- Portfolio 1 contains only the benchmark equity portfolio and serves as the base case.
- Portfolio 2 combines the benchmark equity portfolio with the industry-specific equity portfolio, thereby capturing indirect commodity exposure through sector equities.
- Portfolio 3 combines the benchmark equity portfolio with the commodity portfolio, thus reflecting direct commodity exposure.
- Portfolio 4 combines the benchmark equity portfolio with both the industry-specific equity portfolio and the commodity portfolio, allowing the joint contribution of direct and indirect commodity exposure to be evaluated within the same framework.

For each configuration, if R_t^B, R_t^{IND} and R_t^{CMDTY} denote the returns of the benchmark, industry-specific, and commodity portfolios, respectively, the return of a generic augmented portfolio (k) at time (t) is given by:

$$R_t^k = w_{B,t} R_t^B + w_{IND,t} R_t^{IND} + w_{CMDTY,t} R_t^{CMDTY},$$

subject to the relevant portfolio configuration and the corresponding asset-allocation rule. The comparison across portfolios is intended to isolate the incremental diversification value of indirect exposure, direct exposure, or both.

3.3.2 Asset-allocation rules

The weights assigned to the benchmark, industry-specific, and commodity portfolio blocks within each augmented portfolio depend on the asset-allocation rule adopted. First, the industry block is built using both equal-weight and market-cap-weight methods. The four portfolio setups are then tested with fixed weights and minimum-variance optimization. Fixed-weight portfolios serve as a transparent benchmark. A 50/50 allocation is used in Portfolios 2 and 3, while Portfolio 4 divides its allocation equally among all three components.

Minimum-variance portfolios aim to minimize total portfolio variance by using a rolling 36-month covariance matrix. Portfolio weights are recomputed at a quarterly frequency. The optimization is subject to a full-investment constraint, and no short positions are allowed. Accordingly, the optimizer is free to assign zero weight to a given portfolio block whenever this contributes to minimizing total variance. This approach is consistent with the objective of evaluating diversification benefits from a pure risk-minimization perspective under realistic portfolio constraints.

Taken together, these two allocation rules make it possible to compare a simple and transparent benchmark with a risk-minimizing strategy, while remaining consistent with the perspective of a risk-averse investor. Since the industry-specific equity portfolio is constructed both on an equal-weighted and market-cap-weighted basis, the portfolio analysis is performed under both specifications.

3.3.3 Performance and Risk Evaluation

The performance of the four portfolio configurations is evaluated using Sharpe ratio, Information Ratio, VaR and CVaR. This combination is important because a portfolio that improves average risk-adjusted performance may still be unattractive for a risk-averse investor if it increases exposure to large losses, while a portfolio that performs well in absolute terms may not necessarily outperform the benchmark on a relative basis. The Sharpe ratio relates the average portfolio return in excess of the risk-free rate to the volatility of portfolio returns:

$$Sharpe_k = \frac{\mathbb{E}\,(R_k - R_f)}{\sigma\,(R_k)}$$

where R_k is the return of portfolio k, R_f is the risk-free rate, and $\sigma(R_k)$ is the standard deviation of portfolio returns. This measure captures the excess return earned per unit of total risk, while Information Ratio relates the average active return of a given portfolio over the benchmark to tracking error, defined as:

$$\mathrm{IR}_k = \frac{\mathbb{E}\,(R_k - R_\mathrm{B})}{\sigma\,(R_k - R_\mathrm{B})}$$

where R_B denotes the return of the benchmark portfolio. This metric is particularly useful because the main portfolio configurations are constructed by augmenting the benchmark with direct and/or indirect commodity exposure.

VaR and CVaR are computed at the 95% confidence level using the historical distribution of monthly returns and are reported as positive percentage loss measures. VaR is the loss threshold in the worst 5% of outcomes, while CVaR is the average loss conditional on being beyond that threshold. Their inclusion is especially relevant because the descriptive analysis already suggests that return distributions deviate from normality, which reinforces the importance of using downside-risk measures. In the baseline portfolio comparison, these performance and risk measures are first reported over the full sample, providing a clear summary of the overall risk-return profile of each portfolio.

3.3.4 Extended Analysis: Sub-Portfolios, Inflation Regimes, and Climate Risk

The baseline framework is repeated to both product-focused and geographic sub-portfolios. Namely, the same portfolio-construction, asset-allocation, and performance-evaluation procedures used in the baseline analysis are then repeated for these sub-portfolios. Moreover, since the literature review made clear that the diversification benefits of commodities are not expected to remain constant over time, the goal of the inflation analysis is to compare whether rolling diversification measures are stronger during high or low inflation. High-inflation months are defined as those above the sample median of global inflation, while low-inflation months are at or below the median.

The climate analysis has a similar approach. By aggregating shocks at the country level and using rolling results, the study tests if real physical events are linked to changes in diversification. A key practical issue in this extension is that the dependent variables are portfolio-level rolling time series, whereas the underlying climate shocks are observed initially at the country-hazard-event level. To address this mismatch, event-level severity is first converted into country-hazard-month observations and then aggregated to the portfolio level using the Main Country mapping of constituent firms. This produces, for each month, a portfolio-level wildfire shock and a portfolio-level extreme-temperature shock, associated with the firms in the portfolio.

The analysis then considers rolling Sharpe-ratio gains, rolling benchmark-relative VaR and CVaR gains, and the rolling Information Ratio. Additionally, to allow for delayed transmission from physical disruptions to financial returns, the empirical model includes one-month and three-month lags of the portfolio-level hazard shocks. The baseline regression for portfolio (k) is therefore given by:

$$\Delta M_{k,t} = \alpha + \beta_1 WFShock_{t-l} + \beta_2 ETShock_t + \gamma Inflation_t + \varepsilon_t, \qquad l \in \{0,1,3\}$$

where:

- $\Delta M_{k,t}$ is the relevant rolling diversification metric for portfolio k at time t.
- $WFShock_t$and $ETShock_t$ are wildfire and extreme-temperature shocks at lag l.
- $Inflation_t$ is the inflation control measured at time t.

Inflation controls for a key macroeconomic driver of time-varying diversification. Accordingly, the climate-risk coefficients can be interpreted as the association between hazard-specific financial shocks and diversification metrics.

A forward-looking forecast is left to future research as this exercise would be more speculative than informative, considering the historical response evidence is selective rather than broad-based.

3.3.5 Robustness Tests

Finally, to ensure that the main conclusions are not driven by specific modelling choices, the dissertation includes two robustness checks. First, the dynamic analysis is repeated under alternative rolling-window and rebalancing specifications, namely a 30-month rolling window with quarterly rebalancing, a 42-month rolling window with quarterly rebalancing, and a 36-month rolling window with rebalancing every four months. Second, the baseline commodity portfolio is decomposed into its three underlying input blocks - wood, pulp, and energy - and the portfolio analysis is repeated by considering each block separately. Together, these exercises assess whether the main findings remain stable under reasonable alternative dynamic specifications and alternative constructions of the direct commodity exposure measure.

4 Results

This chapter presents evidence for both the benchmark portfolio and augmented portfolios defined in the Data and Methodology chapters, under the two asset-allocation rules considered in methodology section. It then covers extensions based on geography, product focus, inflation and climate risk. Mean return, volatility, VaR, and CVaR are reported in percent. VaR and CVaR represent positive 5% loss measures, so higher values indicate worse downside risk. Sharpe and Information Ratios are unitless. Table 5 reports the full-sample performance and risk measures for all baseline portfolio configurations. Figures 2 and 3 provide a visual summary of the fixed-weight baseline results, while Figure 4 compares the realized volatility of fixed-weight and minimum-variance portfolios over the common sample.

4.1.1 Baseline fixed-weight portfolio results

The baseline comparison begins with the fixed-weight portfolios, which provide the clearest benchmark for evaluating diversification benefits. The first result to emerge from

Table 5 is that the equal-weighted version of Portfolio 2 provides the most balanced outcome in the baseline specification. Relative to the benchmark alone, this portfolio increases the mean monthly return from 1.02% to 1.08%, while also reducing volatility from 3.93% to 3.78%. It also improves the downside-risk profile, with VaR declining from 6.46% to 5.92% and CVaR from 8.65% to 8.54%. In addition, it records the highest Sharpe ratio among the fixed-weight portfolios and a positive Information Ratio. Taken together, these results indicate that, at the aggregate level, indirect commodity exposure through the industry-specific equity portfolio provides the clearest diversification gain under the fixed-weight allocation rule. This result is also visible in Figure 2, where Portfolio 2 EW lies in a more favourable risk-return position than the benchmark, and in Figure 3, where it displays a better downside-risk profile than the benchmark and the other augmented fixed-weight portfolios.

The benchmark-commodity portfolio (Portfolio 3) produces a more mixed result. As Table 5 shows, it records a slightly higher average monthly return than both the benchmark and Portfolio 2, reaching 1.10%. However, this improvement comes together with materially higher volatility, which rises to 4.76%, and with weaker downside-risk measures, with VaR and CVaR increasing to 7.14% and 9.50%, respectively. Its Sharpe ratio is also lower than that of the equal-weighted version of Portfolio 2. This suggests that direct commodity exposure may strengthen the return profile, but not in the most efficient way once total and downside risk are taken into account. This trade-off is also evident in Figures 2 and 3.

When both direct and indirect exposure are included simultaneously, the strongest return result among the fixed-weight strategies is obtained. In particular, the equal-weighted version of Portfolio 4 reaches a mean monthly return of 1.12%, above both Portfolio 2 and Portfolio 3. However, Table 5 also shows that this stronger return profile is not matched by equally strong improvements in risk-adjusted or downside-risk measures. Volatility rises to 4.26%, remaining above the benchmark and Portfolio 2, while VaR and CVaR, at 6.50% and 8.76%, are also weaker than in the equal-weighted version of

Portfolio 2. Portfolio 4 therefore appears more attractive from a pure return perspective than from a broader risk-return perspective.

These findings should nevertheless be interpreted with some caution. Since the industry-specific equity portfolio remains strongly correlated with the benchmark, part of its diversification benefit may reflect sector composition or differences in firm size rather than commodity exposure itself. Therefore, the fact that the industry portfolio performs better than the commodity portfolio in the baseline comparison does not by itself establish that it is a full substitute for direct commodity exposure. Rather, the baseline evidence suggests that indirect commodity exposure through sector equities may provide a more attractive diversification profile than direct commodity exposure in the aggregate sample.

A further insight from Table 5 is that the internal construction of the industry-specific equity portfolio matters. In the aggregate sample, the equal-weighted industry portfolio produces stronger diversification outcomes than the market-cap weighted version. This is visible in Portfolio 2, where the market-cap weighted specification records a weaker return-volatility combination and less favourable downside-risk measures than the equal-weighted one. A similar pattern appears in Portfolio 4. This suggests that the diversification role of commodity-exposed equities is broader-based and may be weakened when exposure is concentrated in the largest firms. Accordingly, the strongest baseline fixed-weight result is specifically the equal-weighted version of Portfolio 2.

4.1.2 Baseline minimum-variance portfolio results

While fixed-weight portfolios provide the clearest benchmark comparison, they impose exogenous weights on the constituent blocks. For this reason, minimum-variance portfolios are also considered, using a rolling 36-month covariance matrix and quarterly rebalancing. This second stage allows the portfolio comparison to be reassessed from a pure risk-minimization perspective and therefore tests whether the baseline fixed-weight conclusions remain valid when portfolio weights are chosen endogenously. Table 5 reports the corresponding minimum-variance portfolio performance measures, while

Figure 4 compares the realized volatility of fixed-weight and minimum-variance portfolios over the common January 2019-December 2025 sample.

Before interpreting the optimized results, one comparability issue must be made explicit. The fixed-weight results in Table 5 are reported over the full available sample, whereas the minimum-variance portfolios are only available after the initial 36-month estimation window. As a result, the minimum-variance portfolios are evaluated over a shorter subsample. This distinction is important because realized volatility and other performance measures can differ across sample periods. Therefore, the minimum-variance portfolios should not be interpreted as minimizing variance over the full sample reported in Table 5, but rather as minimizing ex-ante variance at each rebalancing date on the basis of the preceding 36 months of returns. Figure 4 is especially useful in this regard, as it compares the realized volatility of the fixed-weight and optimized portfolios over the same effective sample.

This point helps explain why some optimized portfolios do not appear dramatically less volatile than their fixed-weight counterparts. Minimum-variance optimization minimizes variance only conditionally on the estimated covariance matrix available at each point in time. It does not guarantee that ex-post realized volatility over the evaluation sample will always be lower than that of a simpler fixed-weight strategy. In practice, the optimized portfolios remain exposed to estimation error and to changes in covariance patterns over time. Accordingly, a fixed-weight allocation may occasionally display similar, or even slightly lower realized volatility, simply because it is more robust to noisy covariance estimates. This distinction is illustrated in Figure 4.

With this constraint in mind, Table 5 shows that the optimized portfolios do not dominate the fixed-weight ones, and their benchmark-relative performance is weaker. Although minimum-variance optimization is designed to reduce total variance, the realized return profiles of these portfolios are generally less attractive than those of the strongest fixed-weight alternatives. In particular, the Information Ratios of the minimum-variance portfolios are negative in the aggregate sample. This indicates that, despite generating positive absolute returns, the optimized portfolios underperform the benchmark on a tracking-error-adjusted basis. This result is economically plausible, since the optimizer is minimizing variance rather than maximizing benchmark-relative return.

Among the optimized portfolios, the strongest case is the market-cap weighted version of Portfolio 2. As Table 5 shows, this portfolio records an average monthly return of 1.09%, above both the benchmark and the equal-weight minimum-variance version of Portfolio 2, while maintaining volatility at 4.11%. It also presents the most favorable CVaR among the minimum-variance portfolios, at 8.34%. Nevertheless, its Information Ratio remains negative, confirming that even this comparatively stronger optimized case does not outperform the benchmark on a benchmark-relative basis.

The minimum-variance version of Portfolio 3 improves on some risk dimensions relative to its fixed-weight counterpart. Its volatility falls to 4.34% and its CVaR to 8.69%, but this comes together with a lower mean monthly return, at 1.03%, and with a strongly negative Information Ratio. A similar pattern appears in Portfolio 4: the optimized versions achieve some degree of risk control, but at the cost of weaker return performance and clearly negative benchmark-relative results. Therefore, while minimum-variance optimization succeeds in controlling risk to some extent, it does not overturn the central fixed-weight finding that indirect commodity exposure through the industry-specific equity portfolio provides the most attractive aggregate diversification profile.

Taken together, the baseline results suggest that indirect commodity exposure through sector equities provides the most attractive diversification outcome in the main sample, especially under the equal-weighted industry specification. Direct commodity exposure is able to increase return, but only at the cost of materially higher volatility and weaker downside-risk performance. At the same time, these findings should not be interpreted as proving that commodity-exposed equities are equivalent to direct commodity exposure. Rather, they indicate that, from a portfolio-construction perspective, indirect commodity exposure appears to provide stronger diversification gains than direct commodity exposure in the aggregate baseline analysis.

4.1.3 Geographic sub-portfolio results

The geographic sub-portfolio analysis extends the baseline framework by examining whether the diversification role of indirect commodity exposure differs across regional equity subsamples. To preserve consistency with the baseline specification, the MSCI World Index is retained as the benchmark in all regional exercises. Accordingly, the results should be interpreted as showing whether each regional industry sub-portfolio improves diversification relative to the same global benchmark, rather than relative to a purely local market index. Table 6 summarizes the geographic fixed-weight results, Figure 5 plots the benchmark and regional Portfolio 2 specifications in mean-volatility space, and Figure 6 compares fixed-weight and minimum-variance volatilities for the Americas Portfolio 2 specifications over the common sample.

The European subsample provides the weakest case for indirect commodity exposure. In the fixed-weight results, neither version of Portfolio 2 improves the benchmark in a convincing way. The equal-weighted version records a mean monthly return of 0.92%, below the benchmark's 1.02%, while volatility rises to 4.13% and the Information Ratio turns negative. The market-cap weighted version performs only slightly better in absolute terms, with a mean monthly return of 1.00%, but still fails to generate a meaningful benchmark-relative gain. Within Europe, direct commodity exposure remains comparatively stronger from a return perspective, as Portfolio 3 reaches 1.10%, although at the cost of materially higher volatility and weaker downside-risk measures. The combined portfolios also fail to deliver a clear improvement. Overall, the European results suggest that regional industry exposure does not provide a strong diversification case relative to the global benchmark. This weaker positioning is also visible in Figure 5.

By contrast, the Asian subsample offers the clearest support for indirect commodity exposure. The strongest fixed-weight result is the equal-weighted version of Portfolio 2, which increases the mean monthly return to 1.06% while also reducing volatility to 3.71%, below the benchmark's 3.93%. It also improves the downside-risk profile, with VaR falling to 5.15% and CVaR to 8.15%, and delivers a positive Information Ratio. This is a particularly strong result because it combines return enhancement with lower total and downside risk. The market-cap weighted version is weaker, but still broadly comparable to the benchmark. Portfolio 4 also performs reasonably well, especially in its equal-weight version, but the most balanced outcome in Asia remains Portfolio 2 EW. Taken together, these results suggest that indirect commodity exposure is most effective in the Asian subsample. Figure 5 reinforces this interpretation by showing that Asia occupies the most favorable risk-return position among the regional Portfolio 2 specifications.

The Americas subsample presents a different pattern. Here, the regional industry portfolios generate strong return enhancement, but only at substantially higher risk. In the fixed-weight results, the equal-weighted version of Portfolio 2 records the highest mean monthly return among the regional Portfolio 2 specifications, at 1.31%, and a strongly positive Information Ratio. However, this comes together with a sharp increase in volatility to 5.26% and markedly weaker downside-risk measures. The market-cap weighted version shows the same general pattern. In other words, for the Americas, indirect commodity exposure seems to offer higher return potential, but this comes at the cost of considerably greater risk rather than providing clear diversification benefits. This interpretation becomes more nuanced once minimum-variance optimization is considered. Under the optimized rule, both Portfolio 2 specifications retain high average returns while substantially reducing volatility relative to their fixed-weight counterparts. In this sense, the Americas results suggest that indirect commodity exposure can become more attractive when its allocation is disciplined by optimization, even though the fixed-weight evidence is considerably riskier. Figure 6 supports this comparison directly.

Taken together, the geographic analysis reveals substantial heterogeneity across regions. Asia provides the strongest and cleanest case for indirect commodity exposure, Europe the weakest, and the Americas a more aggressive profile in which return enhancement is present but accompanied by materially greater risk. Therefore, the diversification role of commodity-exposed equities does not appear uniform across geographies but instead depends on the regional composition of the industry portfolio.

4.1.4 Product-focus sub-portfolio results

The product-focus analysis refines the baseline results by asking whether the diversification role of indirect commodity exposure varies across different business segments within the broader Forestry, Paper & Wood Products universe. Three product-oriented subsamples are considered: Wood Products, Paper & Pulp Mills, and Forestry & Logging. The results show that the main baseline conclusion is not equally strong across all business lines. Table 7 reports the full-sample fixed-weight results for the product-focus sub-portfolios, while Figures 7 and 8 summarize, respectively, the mean monthly return and the risk profile of Portfolio 2 across the three business segments.

Among the three product categories, Paper & Pulp Mills provides the strongest support for indirect commodity exposure. In the fixed-weight results, the equal-weighted version of Portfolio 2 stands out as the most attractive specification. It raises the mean monthly return to 1.12% while reducing volatility to 3.80%, slightly below the benchmark. It also improves the downside-risk profile, with VaR falling to 5.24% and CVaR to 8.28%, and records the highest Sharpe ratio within this product-focus exercise together with a clearly positive Information Ratio. This is the cleanest sub-portfolio result in the product-focus analysis, since it combines higher return, lower volatility, and stronger downside-risk performance. The combined portfolio (Portfolio 4) also performs reasonably well, especially in its equal-weighted version, but the evidence points most clearly to the Paper & Pulp Mills industry portfolio on its own as the most efficient form of indirect exposure. This pattern is also visible in Figures 7 and 8.

The Wood Products subsample produces a more mixed result. Here, the equal-weighted version of Portfolio 2 does not improve materially on the benchmark, while the market-cap weighted version delivers stronger mean returns, reaching 1.15%, but only with substantially higher volatility and weaker downside-risk indicators. A similar pattern holds for Portfolio 4, where the market-cap weighted version also produces the strongest return result, but again at the cost of higher risk. This suggests that this business segment appears to be able to raise returns, but not to do so while simultaneously preserving the more defensive characteristics observed in the Paper & Pulp Mills subsample. Figures 7 and 8 illustrate this trade-off.

The Forestry & Logging subsample is the weakest of the three product categories. The equal-weight version of Portfolio 2 produces only a modest improvement in mean return relative to the benchmark, while volatility remains higher and the Information Ratio is only slightly positive. The market-cap weighted version performs worse. Direct commodity exposure through Portfolio 3 remains competitive in this segment, while the combined portfolios do not deliver a clear improvement over the simpler alternatives. Under minimum-variance optimization, some of the regional forestry portfolios improve in absolute terms, particularly in mean return, but benchmark-relative performance remains weak. The Forestry & Logging results therefore do not provide strong support for indirect commodity exposure as a superior diversification channel.

Overall, the product-focus analysis suggests that the main baseline result is concentrated in specific industry segments rather than being common to the entire sector. In particular, the strongest evidence in favour of indirect commodity exposure comes from Paper & Pulp Mills, while Wood Products offers a more return-seeking profile and Forestry & Logging remains comparatively weak. This reinforces the idea that firm and business-model heterogeneity matter for the portfolio role of commodity-exposed equities.

4.1.5 Inflation-regime analysis

The inflation extension introduces a time-varying dimension to portfolio comparisons and examines whether diversification gains depend on different macroeconomic environments. Months with world inflation above the sample median are considered high-inflation regimes, while those at or below the median are considered low-inflation regimes. Table 8 reports the rolling 36-month performance and risk measures, Figures 9 and 10 plot world inflation against selected diversification metrics, and Figure 11 summarizes regime differences in excess mean return over the benchmark. This is therefore a conditional analysis of diversification gains that vary over time, and it does not replace the conclusions drawn from a full-sample analysis in the baseline specification.

A first result is that inflation, across the augmented portfolios, is positively associated with benchmark-relative performance. Indeed, correlations between world inflation and rolling excess mean return, Sharpe-ratio-based diversification gains, and the rolling Information Ratio are generally positive, particularly for fixed-weighted Portfolio 2 EW, Portfolio 3, and Portfolio 4 EW. The regime comparison confirms the following result: excess mean return over the benchmark is higher under high-inflation periods for every portfolio. The strongest fixed-weight effects occur in Portfolio 3 and the combined portfolios, especially Portfolio 4 EW, indicating that direct commodity and combined exposure become relatively more attractive when inflation is elevated. Portfolio 2 EW also improves, although by less than the commodity-based portfolios. Figures 9 and 10 illustrate these patterns, while Figure 11 shows the regime differences directly.

Minimum-variance portfolios point to similar results, although with smaller gains than fixed-weight portfolios. Even so, high inflation is associated with higher excess returns, stronger Sharpe-based diversification gains, and less negative benchmark-relative performance across optimized specifications. Overall, the results confirm that commodity-related diversification benefits are not constant across macroeconomic conditions, and while the full-sample analysis continues to favour indirect exposure through sector equities, high-inflation environments strengthen the relative attractiveness of direct commodity and combined exposure more markedly.

4.1.6 Climate-risk extension results

This subsection examines whether historical physical-risk shocks are associated with changes in the diversification benefits of the augmented portfolios. The analysis focuses on wildfire and extreme-temperature shocks constructed from the country-level disaster severity measure described in the methodology subsection and matched to firms through the Main Country variable. Given the time-varying nature of the dependent variables, the regressions use rolling diversification metrics as outcomes and include both current and lagged hazard shocks, together with inflation as a macroeconomic control.

Table 9 reports the main results for the fixed-weight portfolios. Overall, the evidence is selective rather than broad-based. At the 5% significance level, at least one of the two hazard shocks is significant in 39 out of 80 regressions, while this number rises to 50 at the 10% level. Inflation is itself highly significant, appearing at the 5% level in 62 out of 80 regressions, which confirms that macroeconomic conditions remain an important driver of time variation in diversification metrics. Accordingly, the climate-risk results should be interpreted conditionally on a strong inflation channel, rather than as a dominant independent source of portfolio variation.

A first result is that wildfire shocks are more strongly associated with the rolling Information Ratio and, to a lesser extent, the Sharpe-ratio gain. In these regressions, the wildfire coefficient is typically negative when statistically significant, suggesting that wildfire shocks tend to weaken benchmark-relative and risk-adjusted diversification benefits. This pattern is especially visible in the Information Ratio results, where wildfire is the only consistently significant hazard, and in some Sharpe-gain regressions, where the negative coefficient appears more at the three-month lag than at the one-month lag.

By contrast, extreme-temperature shocks are more relevant in the downside-risk dimension. Their effects are most visible in the CVaR-gain regressions, and in a smaller set of VaR-gain regressions. In most of these cases, the coefficient is positive, indicating that, conditional on inflation, extreme-temperature shocks are associated with an improvement in benchmark-relative downside-risk performance. Accordingly, as VaR and CVaR are reported as positive loss measures, the gain variables are defined relative to the benchmark, so that a positive gain denotes lower downside risk. This result is not uniform across all portfolios, but it suggests that the response of downside-risk metrics to physical shocks may differ from the response of return-efficiency measures.

The lag structure also provides useful information, with the three-month lag generally more informative than the one-month lag, particularly for wildfire in the Sharpe-gain and

Information Ratio regressions and for extreme temperature in several VaR- and CVaR-based regressions. This suggests that the transmission from physical shocks to portfolio diversification is not purely immediate but may emerge with some delay or persistence over subsequent months.

Comparing the fixed-weight portfolio specifications, the strongest climate-sensitive results appear in Portfolio 3 and 4, which show several significant responses in both the return-efficiency and downside-risk metrics. However, the signs are not uniform across measures. The climate-risk evidence therefore does not support the view that physical shocks systematically strengthen or weaken all forms of commodity-related diversification. Instead, it suggests that the effect depends on the hazard considered, the metric used, and the time horizon at which the effect is measured. The corresponding minimum-variance regressions are generally weaker.

Taken together, the climate-risk extension provides evidence that historical physical shocks may affect diversification metrics, but the relationship is not uniform across hazard types or performance dimensions. Wildfire shocks are more clearly associated with weaker risk-adjusted and benchmark-relative diversification benefits, whereas extreme-temperature shocks are more often linked to changes in downside-risk measures. The results are therefore best interpreted as selective and hazard-specific rather than as evidence of a single general climate effect on portfolio diversification.

4.1.7 Robustness tests results

The rolling baseline analysis is repeated using alternative estimation windows and rebalancing rules. The main conclusions remain unchanged: Portfolio 2 EW continues to provide the strongest and most consistent benchmark-relative diversification performance, while Portfolio 3 and the combined portfolios deliver higher average returns at the cost of higher volatility and weaker downside-risk profiles. Changes are most visible in the optimized portfolios. Under the shorter 30-month window, the mean monthly return of Portfolio 2 MCW declines from 1.09% to 0.97%, suggesting greater sensitivity to short-term estimation noise. In contrast, the 42-month window and four-month rebalancing produce slightly smoother results; for example, Portfolio 3 MCW rises from 1.03% to 1.08% under four-month rebalancing. Nevertheless, Portfolio 2 MCW remains the strongest minimum-variance result, and the main findings are not driven by the baseline 36-month window or quarterly rebalancing.

As an additional test, the commodity basket is decomposed into wood, pulp, and energy portfolios. Indirect exposure continues to provide the strongest and most consistent benchmark-relative diversification performance, but the block-level analysis reveals substantial heterogeneity in direct exposure. Wood increases Portfolio 3 EW's mean monthly return from 1.10% to 1.34% but also raises volatility from 4.76% to 8.77% and CVaR from 9.50% to 16.96%. Pulp produces the opposite pattern, reducing mean return to 0.73%, volatility to 3.07%, and VaR and CVaR to 4.01% and 5.44%, respectively, although its benchmark-relative performance is weaker. Energy is closest to the baseline commodity basket, increasing mean return to 1.25% alongside higher volatility (6.00%) and CVaR (12.82%). Overall, wood amplifies the return-seeking dimension of direct exposure, pulp provides a more defensive profile, and energy most closely preserves the baseline result.

5 Conclusions

This study compares direct and indirect commodity exposure through listed forestry, pulp, and paper equities from a euro-based risk-averse investor. The analysis was assessed using a global equity benchmark, an industry equity portfolio, and a commodity basket. The performance-risk measures (Sharpe ratio, Information Ratio, VaR, and CvaR) were used for both fixed-weight and minimum-variance asset-rule allocations. Sensitivity analyses were performed to check if the main analysis results differ by product focus, geographic sub-portfolios, periods of inflation, and country-level climate shocks.

Overall, results support the hypothesis that indirect commodity exposure through industry-specific equities provides stronger diversification benefits than direct commodity exposure. In the case of fixed weights, Portfolio 2 EW provides the best diversification: it increases the average monthly return from 1.02% to 1.08% while reducing volatility, VaR, and CVaR. Portfolio 3 has a slightly higher return of 1.10% but brings higher volatility and risk. This results in the highest return for combined exposure (Portfolio 4) but not the best risk-adjusted result. Therefore, indirect exposure through an equal-weighted industry portfolio is generally preferable, although industry equities cannot be considered a perfect substitute for direct commodities.

This conclusion remains true even when minimum-variance optimization is applied. It is important to keep in mind that these results should be interpreted as risk-minimization estimates for the future rather than a guarantee of lower realized volatility. Portfolio 2 MCW is the best among the optimized portfolios. Still, its negative Information Ratio indicates that volatility control does not imply better performance than the benchmark. For this investor, the simple fixed-weight allocation rule is more straightforward and more efficient in the primary sample.

The analysis supports the hypothesis that diversification role of indirect commodity exposure differs across product-focus and geographic sub-portfolios. Paper & Pulp Mills and the Asian sub-portfolios exhibit the best diversification profile, with higher returns and lower risk than the benchmark. Wood Products and the Americas sub-portfolios show greater return potential but with much higher volatility and risk. Europe and Forestry & Logging sub-portfolios offer weaker evidence. These differences, therefore, add value in studying industry segments separately rather than considering all commodity-sensitive equities as a whole group.

Further testing supports the hypothesis that diversification benefits of direct and indirect commodity exposure are time-varying and become stronger in high-inflation environments but introduces some nuance to the overall ranking. The diversification benefits of direct and indirect exposure are more significant in times of high inflation, with the most significant improvement in Portfolio 3 and 4. Direct commodity exposure becomes relatively more attractive in times of high inflation, although indirect exposure remains the best overall diversifier. An investor's best choice depends on its view of the economy and risk tolerance.

This study conclusions are not robust enough to fully support the hypothesis that historical wildfire and extreme-temperature shocks are associated with changes in the diversification benefits of direct and indirect commodity exposure.

Wildfire shocks have generally been associated with weaker diversification compared to the benchmark, especially over three months, while extreme temperature shocks have been more often linked with changes in CVaR and sometimes VaR. Inflation remains the more consistently significant driver of the rolling metrics. In general, the climate-risk analysis suggests that physical shock responses in commodity-related portfolios vary by hazard type, metric, and time horizon rather than a straight-forward climate effect.

The robustness checks confirm the main results. The superior benchmark-relative performance of Portfolio 2 EW remains under alternative estimation windows and rebalancing rules, while optimized results are more sensitive to shorter periods. Decomposing the commodity basket suggests direct exposure varies: (i) wood seeks high returns, but it is high-risk; (ii) pulp is more defensive but underperforms the benchmark; and (iii) energy is the closest portfolio to the overall commodity profile.

For a risk-averse euro-based investor, this study points to a pragmatic rather than a singular best choice: a diversified, equal-weighted portfolio of forestry, pulp, and paper equities is the best overall addition to the global benchmark. Direct commodity exposure is less efficient across the whole sample but can have a special tactical role during high inflation. Different exposures play different roles, depending on the industry segment, region, economic conditions, and specific risks that investors want to manage.

There are a set of limitations that need to be consider when interpretating these results: (i) commodity returns are proxied by futures prices and do not represent fully collateralized futures returns; (ii) the contracts used restrict the sample balance; (iii) geographic exposure is proxied with a single main country for each firm, while the climate analysis relies on country-level disaster data; and (iv) equity results are driven by commodity sensitivity and other factors, such as sector, size, management, and operations.

In this sense, there is still some room for improvement, while future research can improve the matching rule of countries and assets, better consider transaction costs and investability, and test the methodology with forward-looking climate-risk data.

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7 Appendix

Table 1 – Descriptive characteristics of the sub-portfolios

	Number of firms	Number of countries	Average market-cap	Median market-cap
Product-focus sub-portfolios				
Wood Products	64	25	527,769,407	53,599,429
Forestry & Logging	28	12	318,597,992	22,617,226
Paper & Pulp Mills	106	27	551,508,455	66,251,706
Geographic sub-portfolios				
Europe	27	11	1,144,474,831	56,337,564
Americas	25	7	936,956,491	96,642,881
Asia	140	15	324,389,081	40,808,677

Note: Number of countries refers to the count of distinct country identifiers represented in each sub-portfolio. Average and median market capitalization are computed across the constituent firms included in each group, based on the market-capitalization values extracted directly from Bloomberg.

Table 2 – Pairwise agreement across alternative country identifiers

Pairs of identifiers	% identical assignment
Country of Risk vs. Country of Domicile	98.99%
Country of Domicile vs. Country of Largest Revenue	75.25%
Country of Risk vs. Country of Largest Revenue	74.75%

Note: The table reports pairwise agreement rates across the alternative country identifiers available for the 198 firms included in the final equity portfolio. Reported percentages correspond to the share of firms for which the two identifiers coincide.

Table 3 – Descriptive statistics of the main portfolios

Portfolio	**Mean monthly return (%)**	**Volatility (%)**	**Skewness**	**Excess kurtosis**
Benchmark equity portfolio	1.02%	3.93%	-0.45	1.47
Industry-specific equity portfolio (Equally Weighted)	1.14%	4.29%	-0.57	2.61
Industry-specific equity portfolio (Market-Cap Weighted)	1.04%	4.66%	-0.52	0.91
Commodity portfolio	1.19%	7.36%	2.24	0.58

Note: Mean monthly returns and volatility are reported in percent; skewness and excess kurtosis are unitless.

Table 4 – Correlation matrix of the main portfolios

Portfolio	Benchmark equity portfolio	Industry-specific equity portfolio (Equally Weighted)	Industry-specific equity portfolio (Market-Cap Weighted)	Commodity portfolio
Benchmark equity portfolio	1.00			
Industry-specific equity portfolio (EW)	0.69***	1.00		
Industry-specific equity portfolio (MCW)	0.72***	0.78***	1.00	
Commodity portfolio	0.37***	0.48***	0.46***	1.00

Note: The table reports correlations of monthly returns of the base portfolios. *** indicates statistical significance at the 1% level.

Table 5 – Full-sample performance of the benchmark and augmented portfolios

	Mean monthly return (%)	Volatility (%)	Skewness	Excess kurtosis	Sharpe ratio	Information ratio	VaR (5%, monthly loss)	CvaR (5%, monthly loss)
Portfolio 1	1.02%	3.93%	-0.45	1.47	0.19		6.46%	8.65%
Portfolio 2 EW	1.08%	3.78%	-0.73	3.13	0.22	0.04	5.92%	8.54%
Portfolio 2 MCW	1.03%	3.98%	-0.60	1.55	0.20	0.01	7.04%	8.80%
Portfolio 3	1.10%	4.76%	-0.17	2.14	0.18	0.03	7.14%	9.50%
Portfolio 4 EW	1.12%	4.26%	-0.54	3.02	0.20	0.04	6.50%	8.76%
Portfolio 4 MCW	1.08%	4.34%	-0.45	1.94	0.19	0.02	6.97%	9.19%
MV Portfolio 2 EW	0.98%	4.17%	-0.62	2.68	0.17	-0.23	6.41%	8.84%
MV Portfolio 2 MCW	1.09%	4.11%	-0.44	1.37	0.20	-0.14	6.50%	8.34%
MV Portfolio 3	1.03%	4.34%	-0.51	1.61	0.18	-0.29	6.84%	8.69%
MV Portfolio 4 EW	0.89%	4.22%	-0.66	2.83	0.15	-0.32	6.41%	8.88%
MV Portfolio 4 MCW	0.97%	4.21%	-0.55	2.00	0.17	-0.24	6.53%	8.71%

Note: Mean monthly return and volatility are reported in percent. Sharpe ratio and Information Ratio are unitless. VaR and CVaR are reported as positive percentage loss measures at the 5% level, so higher values indicate worse downside risk.

Table 6 – Geographic sub-portfolio performance of fixed-weight portfolios

	Mean Monthly Return (%)	Volatility (%)	Sharpe ratio	Information ratio	VaR (5%, monthly loss)	CVaR (5%, monthly loss)
Benchmark	1.02%	3.93%	0.19		6.46%	8.65%
EUROPE						
Portfolio 2 EW	0.92%	4.13%	0.16	-0.05	6.91%	9.05%
Portfolio 2 MCW	1.00%	4.15%	0.18	-0.01	7.41%	8.63%
Portfolio 3	1.10%	4.76%	0.18	0.03	7.14%	9.50%
Portfolio 4 EW	1.01%	4.34%	0.18	0.00	6.44%	8.95%
Portfolio 4 MCW	1.06%	4.33%	0.19	0.02	6.68%	8.55%
ASIA						
Portfolio 2 EW	1.06%	3.71%	0.22	0.02	5.15%	8.15%
Portfolio 2 MCW	1.00%	3.90%	0.19	-0.01	6.14%	8.65%
Portfolio 3	1.10%	4.76%	0.18	0.03	7.14%	9.50%
Portfolio 4 EW	1.10%	4.19%	0.20	0.03	6.17%	8.66%
Portfolio 4 MCW	1.06%	4.23%	0.19	0.01	6.89%	9.03%
AMERICAS						
Portfolio 2 EW	1.31%	5.26%	0.20	0.10	7.60%	11.06%
Portfolio 2 MCW	1.14%	5.54%	0.16	0.04	7.60%	10.85%
Portfolio 3	1.10%	4.76%	0.18	0.03	7.14%	9.50%
Portfolio 4 EW	1.27%	5.10%	0.20	0.08	6.91%	10.34%
Portfolio 4 MCW	1.16%	5.28%	0.17	0.04	6.66%	10.53%

Note: The table reports full-sample performance and downside-risk measures for the fixed-weight geographic sub-portfolio specifications. Mean monthly return and volatility are reported in percent. VaR and CVaR are expressed as positive percentage loss measures at the 5% level, so higher values indicate worse downside risk. Information Ratios are unitless.

Table 7 – Product-focus sub-portfolio performance of fixed-weighted portfolios

	Mean Monthly Return (%)	Volatility (%)	Sharpe ratio	Information ratio	VaR (5%, monthly loss)	CVaR (5%, monthly loss)
Benchmark	1.02%	3.93%	0.19		6.46%	8.65%
WOOD PRODUCTS						
Portfolio 2 EW	1.03%	4.11%	0.19	0.01	6.47%	9.04%
Portfolio 2 MCW	1.15%	4.83%	0.19	0.06	7.64%	9.83%
Portfolio 3	1.10%	4.76%	0.18	0.03	7.14%	9.50%
Portfolio 4 EW	1.08%	4.47%	0.19	0.02	6.63%	9.08%
Portfolio 4 MCW	1.16%	4.89%	0.19	0.05	6.69%	9.86%
PAPER & PULP MILLS						
Portfolio 2 EW	1.12%	3.80%	0.23	0.05	5.24%	8.28%
Portfolio 2 MCW	0.98%	3.77%	0.19	-0.02	6.88%	8.58%
Portfolio 3	1.10%	4.76%	0.18	0.03	7.14%	9.50%
Portfolio 4 EW	1.14%	4.22%	0.21	0.04	6.08%	8.71%
Portfolio 4 MCW	1.05%	4.19%	0.19	0.01	6.83%	8.88%
FORESTRY & LOGGING						
Portfolio 2 EW	1.05%	4.12%	0.19	0.02	6.10%	8.67%
Portfolio 2 MCW	0.85%	4.95%	0.12	-0.04	7.04%	9.69%
Portfolio 3	1.10%	4.76%	0.18	0.03	7.14%	9.50%
Portfolio 4 EW	1.10%	4.37%	0.19	0.03	6.45%	8.72%
Portfolio 4 MCW	0.97%	4.52%	0.16	-0.01	7.04%	9.05%

Note: The table reports full-sample performance and downside-risk measures for the fixed-weight product-focus sub-portfolio specifications. Mean monthly return and volatility are reported in percent. VaR and CVaR are expressed as positive percentage loss measures at the 5% level, so higher values indicate worse downside risk. Information Ratios are unitless.

Table 8 – Summary of rolling 36-month performance and risk measures

	Avg. rolling mean return (%)	Avg. rolling volatility (%)	Avg. rolling Sharpe Ratio	Avg. rolling Information Ratio	Avg. rolling VaR	Avg. rolling CvaR	Nº rolling windows
Portfolio 1	1.03%	4.25%	0.19		6.49%	8.63%	85
Portfolio 2 EW	1.16%	4.02%	0.23	0.07	5.72%	8.60%	85
Portfolio 2 MCW	1.07%	4.20%	0.19	0.03	6.57%	8.55%	85
Portfolio 3	1.24%	5.09%	0.18	0.01	6.79%	9.73%	85
Portfolio 4 EW	1.26%	4.51%	0.21	0.02	6.27%	9.16%	85
Portfolio 4 MCW	1.20%	4.61%	0.19	0.01	6.22%	9.33%	85
MV Portfolio 2 EW	0.97%	4.17%	0.17	-0.05	6.22%	8.25%	49
MV Portfolio 2 MCW	0.95%	4.11%	0.17	-0.04	6.15%	7.95%	49
MV Portfolio 3	0.95%	4.30%	0.16	-0.25	6.41%	8.29%	49
MV Portfolio 4 EW	0.92%	4.19%	0.16	-0.14	6.32%	8.47%	49
MV Portfolio 4 MCW	0.92%	4.15%	0.16	-0.12	6.29%	8.22%	49

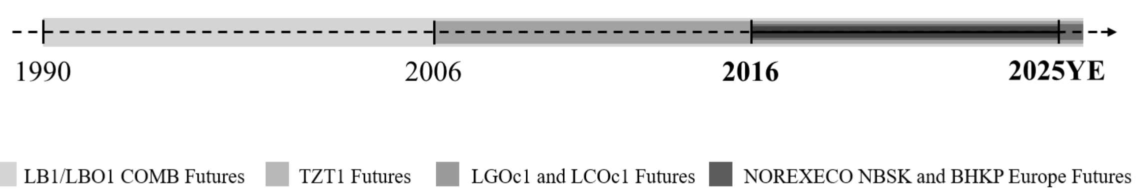
Note: This table reports the average values of the rolling 36-month performance and risk measures for each portfolio. Mean return and volatility are reported in percent. Sharpe ratio and Information Ratio are unitless. VaR and CVaR are reported in percent as positive percentage loss measures at the 5% level, so higher values indicate worse downside risk. The last column reports the number of rolling windows available for each portfolio.

Table 9 – Summary of the most relevant climate-risk regressions results for fixed-weight portfolios

Portfolio	Metric	Lag	Wildfire	Extreme temperature	Inflation
Portfolio 2 EW	Sharpe gain	1 month	Negative (5%)	Positive (10%)	Positive (5%)
Portfolio 2 EW	Sharpe gain	3 months	Negative (5%)	n.a.	Positive (5%)
Portfolio 2 EW	CVaR gain	1 month	n.a.	Positive (5%)	Negative (5%)
Portfolio 2 EW	CVaR gain	3 months	n.a.	Positive (5%)	Negative (5%)
Portfolio 2 EW	Information Ratio	3 months	Negative (5%)	n.a.	Positive (5%)
Portfolio 2 MCW	Sharpe gain	3 months	Negative (5%)	n.a.	Positive (5%)
Portfolio 2 MCW	CVaR gain	1 month	Negative (5%)	Negative (5%)	n.a.
Portfolio 2 MCW	CVaR gain	3 months	n.a.	Negative (5%)	n.a.
Portfolio 2 MCW	Information Ratio	1 month	Negative (5%)	n.a.	Positive (5%)
Portfolio 2 MCW	Information Ratio	3 months	Negative (5%)	n.a.	Positive (5%)
Portfolio 3	Sharpe gain	1 month	Negative (5%)	n.a.	Positive (5%)
Portfolio 3	Sharpe gain	3 months	Negative (5%)	Positive (10%)	Positive (5%)
Portfolio 3	VaR gain	3 months	Negative (5%)	n.a.	Negative (5%)
Portfolio 3	CVaR gain	1 month	Negative (5%)	Positive (5%)	Negative (5%)
Portfolio 3	CVaR gain	3 months	Negative (5%)	Positive (5%)	Negative (5%)
Portfolio 3	Information Ratio	1 month	Negative (5%)	n.a.	Positive (5%)
Portfolio 3	Information Ratio	3 months	Negative (5%)	n.a.	Positive (5%)
Portfolio 4 EW	Sharpe gain	1 month	Negative (5%)	n.a.	Positive (5%)
Portfolio 4 EW	Sharpe gain	3 months	Negative (5%)	Positive (10%)	Positive (5%)
Portfolio 4 EW	CVaR gain	1 month	n.a.	Positive (5%)	Negative (5%)
Portfolio 4 EW	CVaR gain	3 months	n.a.	Positive (5%)	Negative (5%)
Portfolio 4 EW	Information Ratio	1 month	Negative (5%)	n.a.	Positive (5%)
Portfolio 4 EW	Information Ratio	3 months	Negative (5%)	n.a.	Positive (5%)
Portfolio 4 MCW	Sharpe gain	1 month	Negative (5%)	n.a.	Positive (5%)
Portfolio 4 MCW	Sharpe gain	3 months	Negative (5%)	n.a.	Positive (5%)
Portfolio 4 MCW	CVaR gain	1 month	n.a.	Positive (5%)	Negative (5%)
Portfolio 4 MCW	CVaR gain	3 months	n.a.	Positive (10%)	Negative (5%)
Portfolio 4 MCW	Information Ratio	1 month	Negative (5%)	n.a.	Positive (5%)
Portfolio 4 MCW	Information Ratio	3 months	Negative (5%)	n.a.	Positive (5%)

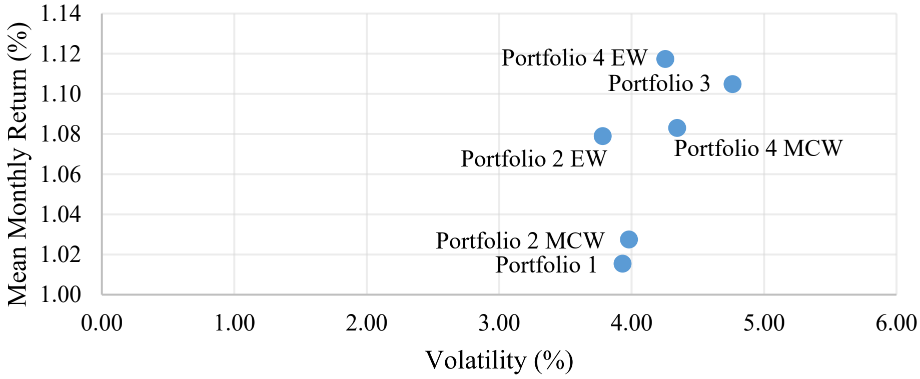
Note: This table summarizes the sign and statistical significance of the estimated coefficients in the climate-risk regressions for the fixed-weight portfolios. “Positive” and “Negative” indicate the sign of the coefficient, while values in parentheses report the significance level at 5% or 10%; insignificant coefficients are omitted. Wildfire and extreme temperature denote the hazard-specific shock variables, and inflation is included as a macroeconomic control. Results are reported for the one-month and three-month lag specifications.

Figure 1 – Data Restrictions Timeline



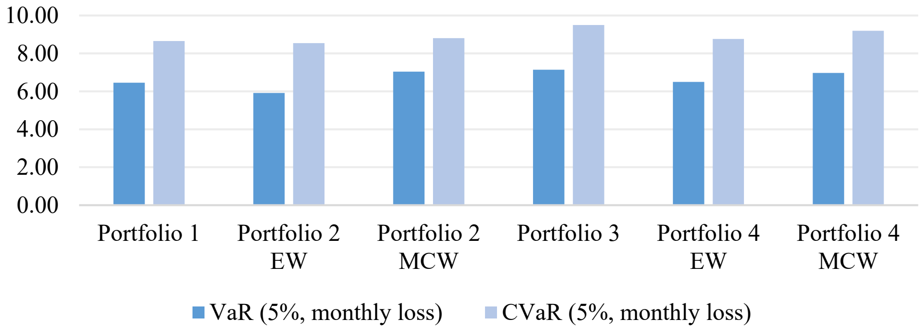
Source: Author’s compilation based on Bloomberg, Refinitiv, and contract availability constraints

Figure 2 – Risk-return positioning of fixed-weight portfolios



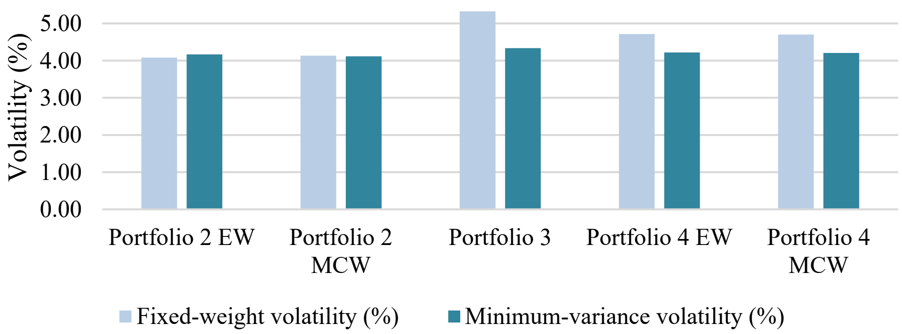
Note: The figure plots the fixed-weight portfolio configurations in mean-volatility space using full-sample monthly data. The horizontal axis reports monthly volatility, while the vertical axis reports mean monthly return. Both measures are expressed in percent. The figure is intended to provide a visual summary of the overall risk-return trade-off across the baseline fixed-weight portfolios.

Figure 3 – Downside-risk comparison of fixed-weight portfolios



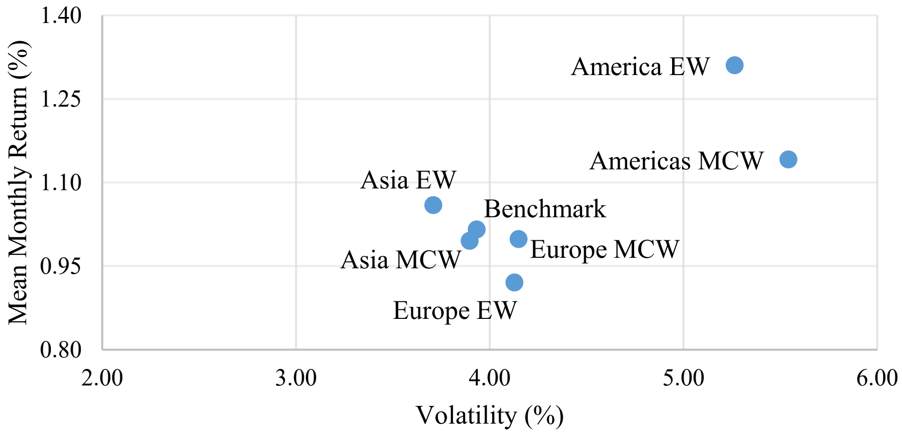
Note: The figure compares the 5% monthly VaR and CVaR of the fixed-weight portfolio configurations using full-sample monthly data. VaR and CVaR are reported in percent as positive percentage loss measures, so higher values indicate worse downside risk. The figure is intended to highlight differences in tail-risk exposure across the baseline fixed-weight portfolios.

Figure 4 – Volatility comparison of fixed-weight and minimum-variance portfolios over the common sample



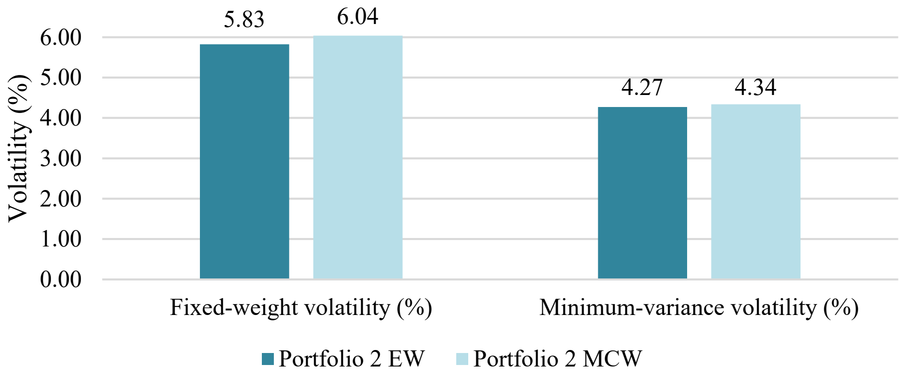
Note: The figure compares realized monthly volatility for fixed-weight and minimum-variance portfolios over the common January 2019-December 2025 sample, corresponding to the period for which minimum-variance portfolios are available after the initial 36-month estimation window. Volatility is reported in percent. The figure is intended to support the comparability discussion between the fixed-weight and optimized portfolio specifications.

Figure 5 – Risk-return positioning of regional industry portfolios



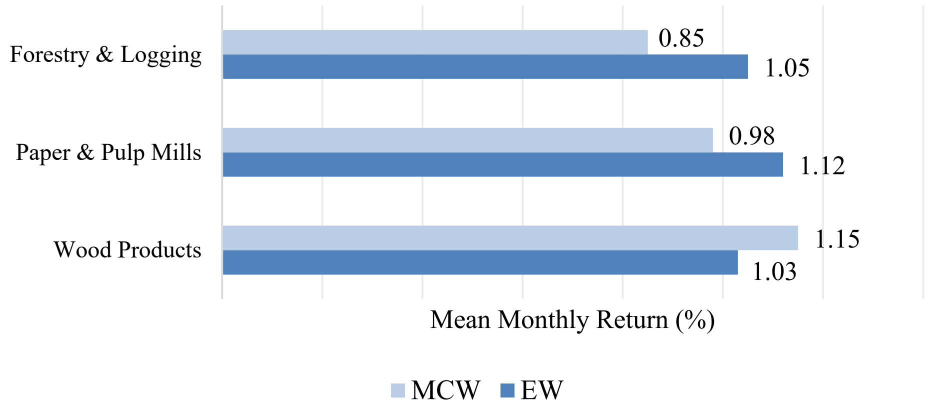
Note: The figure plots the benchmark and the regional Portfolio 2 specifications in mean-volatility space using full-sample monthly data. The horizontal axis reports monthly volatility, while the vertical axis reports mean monthly return. Both measures are expressed in percent. For improved visualization, the scales of both axes have been adjusted and do not start at zero. The figure is intended to summarize the trade-off between return enhancement and risk across the European, Asian, and Americas industry portfolios.

Figure 6 – Americas Portfolio 2: fixed-weight versus minimum-variance volatility over the common sample



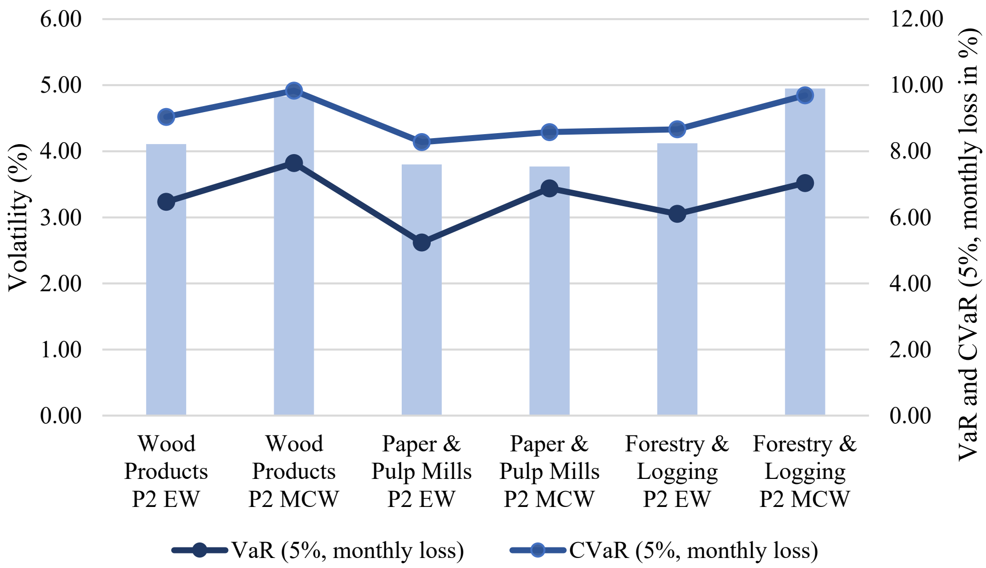
Note: The figure compares realized monthly volatility for the fixed-weight and minimum-variance versions of the Americas Portfolio 2 specifications over the common January 2019-December 2025 sample. Volatility is reported in percent. The figure is intended to illustrate whether optimization improves the volatility profile of the Americas industry portfolio once both strategies are evaluated over the same period.

Figure 7 – Mean monthly return of the fixed-weight version of Portfolio 2 across product-focus groups: equal-weighted vs. market-cap weighted



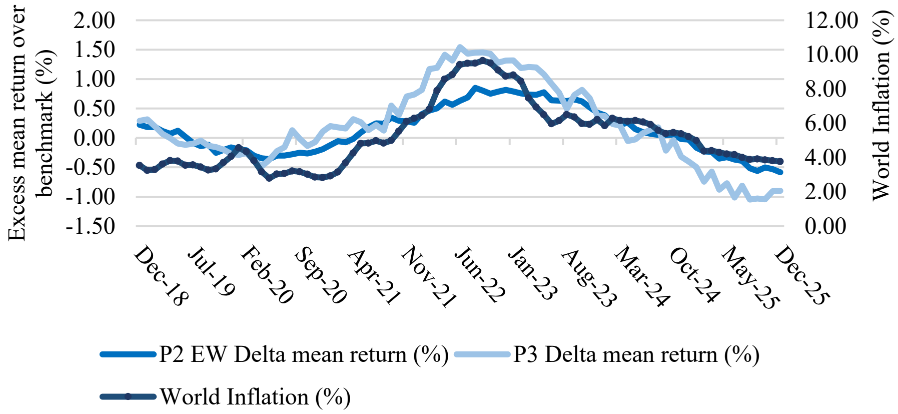
Note: The figure compares the mean monthly return of the equal-weighted and market-cap-weighted versions of Portfolio 2 across the three product-focus sub-portfolios. Mean monthly return is reported in percent. The figure is intended to show how the return profile of indirect commodity exposure varies across business segments and according to the internal weighting scheme of the industry portfolio.

Figure 8 – Risk profile of the fixed-weighted version of Portfolio 2 across product-focus sub-portfolios



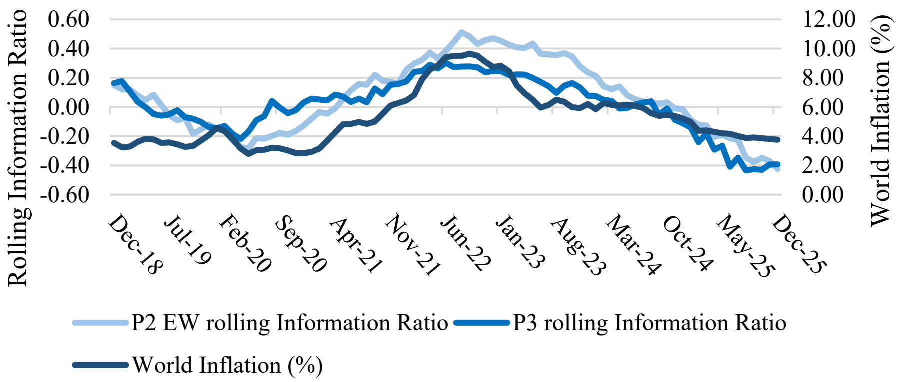
Note: The figure compares the volatility, 5% monthly VaR, and 5% monthly CVaR of the Portfolio 2 specifications across the three product-focus sub-portfolios: Wood Products, Paper & Pulp Mills, and Forestry & Logging. Results are shown for both the equal-weighted (EW) and market-cap weighted (MCW) constructions of the industry-specific equity portfolio. Volatility is reported in percent on the left axis, while VaR and CVaR are reported in percent as positive percentage loss measures on the right axis, so higher values indicate worse downside risk. The figure is intended to show whether the total-risk and downside-risk profile of indirect commodity exposure differs across business segments and according to the internal weighting scheme of the industry portfolio.

Figure 9 – World inflation and rolling excess mean return over the benchmark



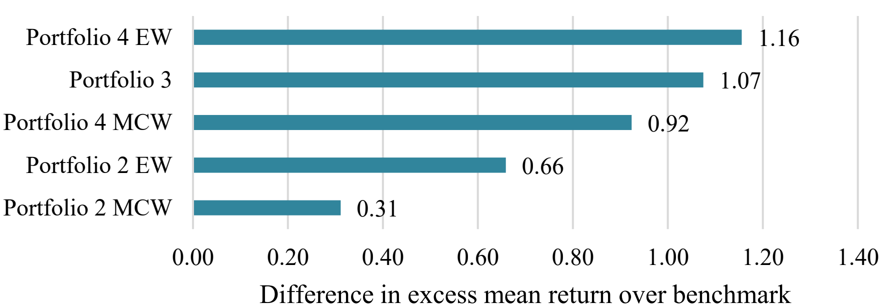
Note: The figure plots world inflation together with the rolling 36-month excess mean return over the benchmark for two portfolio specifications. Excess mean return is reported in percent on the left axis, while world inflation is reported in percent on the right axis. The figure is intended to illustrate whether periods of higher inflation coincide with stronger benchmark-relative return gains from indirect and direct commodity exposure.

Figure 10 – World inflation and rolling Information Ratio



Note: The figure plots world inflation together with the rolling 36-month Information Ratio for the Portfolio 2 EW and fixed-weight Portfolio 3 specifications. The Information Ratio is reported on the left axis, while world inflation is reported in percent on the right axis. The figure is intended to illustrate whether benchmark-relative performance tends to strengthen during periods of higher inflation.

Figure 11 – Inflation-regime differences in excess mean return over the benchmark



Note: The figure reports the difference between the average rolling excess mean return over the benchmark in high-inflation periods and the corresponding average in low-inflation periods. Results are shown for the fixed-weight portfolio specifications. Positive values indicate that the excess mean return over the benchmark is higher in high-inflation environments than in low-inflation environments. Values are reported in percentage points.

8 Disclosures and Disclaimers

AI Disclosure

This project was developed with strict adherence to the academic integrity policies and guidelines set forth by ISEG, Universidade de Lisboa. The work presented herein is the result of my own research, analysis, and writing, unless otherwise cited. In the interest of transparency, I provide the following disclosure regarding the use of artificial intelligence (AI) tools in the creation of this thesis/internship report/project:

I disclose that AI tools were employed during the development of this thesis as follows:

- AI-based research tools were used to assist in the literature review and data collection.
- AI-powered software was utilized for data analysis and visualization.
- Generative AI tools were consulted for brainstorming and outlining purposes. However, all final writing, synthesis, and critical analysis are my own work. Instances where AI contributions were significant are clearly cited and acknowledged.

Nonetheless, I have ensured that the use of AI tools did not compromise the originality and integrity of my work. All sources of information, whether traditional or AI-assisted, have been appropriately cited in accordance with academic standards. The ethical use of AI in research and writing has been a guiding principle throughout the preparation of this thesis.

I understand the importance of maintaining academic integrity and take full responsibility for the content and originality of this work.

Juliana Costa Guerreiro, June 30th, 2026