Sustainability and Commodity Price

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Abstract

In this research, I first aim to construct several green-minus-brown commodity factors based on carbon and water consumption during the production process, followed by research on the diversification benefits of the portfolio after adding the green commodities in the light of sustainability performance. With small average returns and negligible alphas, little evidence is found that sustainability is priced in the cross-sections of commodities. However, substantial asset allocation benefits occur when including green (long) commodity portfolios to diversify equity and bond allocations. The annualized risk-adjusted performance can be increased by up to 27% when the commodity pocket accounts for 20% of the composition. With regard to environmental impact, portfolios composed of metal futures have much larger raw footprint compared to agricultural goods. Additionally, I intend to examine how ESG disclosure impacts the firm value of commodity producers. The last topic concentrates on the potential role of sustainability in the resilience of firm value during times with turbulent crude oil prices caused by geopolitical tensions.

Keywords: Sustainable Finance, Commodity, Portfolio Management, Corporate Finance.

1. Introduction

Sustainability and Environmental, Social and Governance (ESG) factors have become prevalent in investments (Oestreich & Tsiakas, 2015; Cornell, 2021; Flammer, 2021; Coqueret, 2022; Zerbib, 2022; Hsu et al., 2023; Y. Wang & Xu, 2023). It is also under serious scrutiny by regulatory bodies in the U.S. and Europe, as well as the focus of several initiatives led by major financial industry players. In this regard, the Securities and Exchange Commission (SEC) has recently heightened its requirements on climate-related disclosures and broadened effort to oversee the sustainability claims of asset managers and index providers. In Europe, the Sustainable Finance Disclosure Regulation (SFDR) will progressively impose sustainability-related reporting in the financial services sector. It complements the EU taxonomy of sustainable activities which serves as a classification grid for disclosure by corporations. Initiatives in this direction, taken by financial institutions and investors, date back to 2000 with the Carbon Disclosure Project (CDP) and to 2015 with the Taskforce for Climate-related Financial Disclosures (TCFD).

However, with most of the research and practice in sustainable finance having focus on securities in equity and bond class, commodities, as a prominent asset class, have been largely overlooked in the sustainable finance realm. In 2023, a handful of index providers have broadened their offer and introduced green commodity investment solutions,[1] but academic research on the matter seems to be lagging. There exist a limited quantity of literature that study the role of commodity under the sustainability context. Some papers focus on the financial contribution brought by commodities, with efforts spent to address the connectedness between commodities and green assets in other classes (Arfaoui et al., 2023, Naeem et al., 2021).

Other studies shed lights on the relationship between commodity (mainly energy) price risk or uncertainty and sustainability (Phan et al., 2021, Hasan et al., 2022). Recent Ukraine crisis brings this topic back to table, which is followed by an oil crisis posing threats to most of the companies. The volatile energy price further evokes trends of increasing sustainability level and decreasing the dependence level of fossil fuels. This could have potential effect on sustainable asset market. A few studies such as Mertzanis & Tebourbi, 2024 investigate the role of such geopolitical events on the sustainability or related securities. However, a detailed clarification of the mechanism still remains deficient.

In this research, I first aim to construct several *green* commodity factors based on carbon and water consumption during the production process, followed by research on the diversification benefits of the portfolio after adding the newly-built commodities in the light of sustainability performance. Additionally, I intend to examine how ESG disclosure impacts the firm value of commodity producers. The last topic concentrates on the role of sustainability in the linkage between oil price risk and firm value during energy crises.

This thesis would fill the literature void with respect to sustainable commodity investment by assessing the significance of a novel factor construction strategy. It would be of substantial interest to market participants such as banks, mutual funds, and insurance companies. In addition, it will evaluate the importance of sustainability performance in maximizing the firm value, which has been a concern for private companies and regulatory authorities.

Chapter 1 quantifies metal and agricultural commodities' sustainability and constructs a commodity factor based on each product's *green* performance. I consider 3 cohorts of the factor: GreenHouse Gas (GHG) emission, water consumption throughout their production process and contribution to energy transition (considered only when the metal family is involved). 21 metal and 20 agricultural products are considered. Based

[1] e.g. the Bloomberg Carbon-Tilted Commodity Index, the iShares Green Transition Metals ETF, the UBS carbon-compensated gold ETF, and the Han ETF Royal Mint Responsibly Sourced Physical Gold ETC.

on their GHG and water intensities over their prices, these commodities are grouped into *green* and *brown* according to the dimensions above. The sustainability factor is measured by the return of the Green-Minus-Brown (GMB) portfolio which is made up of the studied commodities. The GMB portfolio's return and risk profile is investigated with a prevalent commodity pricing multi-factor model by Bakshi et al., 2019a. This study extends this stream of literature by adding novel attributes to metals and agrarian goods: their environmental impact.

Chapter 2 is aimed at studying the diversification benefits of the green commodity portfolios in **Chapter 1**. By adding green commodities defined in Chapter 1 to benchmark portfolios, the variation of portfolio performance is observed. Benchmark portfolio is represented by the mixture of low-carbon equity bond indices with different weights assigned. Both financial performance represented by growing returns or reducing volatilities and environmental benefits are examined. This chapter views commodities from a sustainable investing standpoint, with a focus on the risk-adjusted performance of green portfolios. Finally, this study documents the reduction of the associated footprints at portfolio level. It sheds light on how commodities can participate to this trend by delivering diversification and performance, while at the same time contributing to reduce portfolios' related impacts in terms of carbon emissions and water consumption. This is a decisive issue, as the aggregate environmental impact of materials' production is both sizeable and increasing (Hertwich, 2021), but also hard to measure (Maus & Werner, 2024).

Chapter 3 switches the perspective to the corporate side. Focusing on commodity production companies, I investigate the relationship between ESG disclosure and firm performance (see, *e.g*, Lins et al., 2017, Albuquerque et al., 2019, Cornell & Shapiro, 2021, Menla et al., 2023). The list of those metal and agricultural commodity producers could be drawn from the GICS classification of commodities. As a more commodity-oriented study based on previous literature showing this impact in environmental-sensitive industries (Bachoo et al., 2013; Yoon et al., 2018), firm value, profitability, growth, and performance on the stock market will be compared from green and brown production groups as defined in previous chapters.

Chapter 4 examines the firm value variation during oil crises caused by geopolitical tenses. Regarding ESG orientation is a must-take path to energy transition and fossil fuel exiting process, the role of ESG in this linkage is also measured. Event study will be carried out to measure the firm value variation during several oil shocks, whilst the potential effect of ESG on firm value resilient will be further confirmed by a difference-in-difference analysis of several oil shocks in 2008, 2011 and, recently 2022 with the heterogeneous treatment effect model by Sun & Abraham, 2021. I hereafter apply the structural model by Shrout & Bolger, 2002 and Zhao et al., 2010 in order to test the indirect impact that the oil price risk has on corporate value with ESG performance as a mediator.

2. Chapter 1: Sustainability Commodity Factors

In this chapter, I define the climate sustainability of 41 chosen commodities based on their environmental performance, which are mainly represented by their carbon emission and water usage.

2.1 Literature Review

2.1.1 Climate Environmental Footprints of Commodities

The topic of the environmental footprint of commodities is central to this paper and the related literature underpins the construction of aggregate impact measures. Among articles and technical reports addressing the environmental impacts of metal and agricultural commodities, carbon emissions and water usage emerge as frequently calculated metrics.

Concerning carbon issues within the context of climate change, Life-Cycle-Assessment (LCA) is a widely used framework to measure the carbon emission of certain amounts of products from cradle to gate. For example, Nuss & Eckelman, 2014 have compiled carbon emission data on the from-cradle-to-gate global warming potentials possessed by 63 common metals including aluminum, zinc, copper, gold, etc. Under the same framework, Davidson et al., 2016 quantify the global warming impact of lead as 1.31kg carbon per ton of lead product. Similar studies are carried out to investigate other metals (e.g., iron studied by Gan & Griffin, 2018 and Haque, 2022, cobalt studied by Farjana et al., 2019 and nickel and zinc by Spanos et al., 2015). The LCA framework has also been applied to agricultural goods, with Beccali et al., 2009 presenting the carbon footprints of citrus products throughout their life cycles. Additionally, the carbon emissions associated with beet sugar and sugarcane sugar have been studied by Gonzalez & Björnsson, 2022 and Seabra et al., 2011, respectively. Further literature applies LCA to measure the environmental burden associated with other agricultural commodities, such as cotton (Hedayati et al., 2019), soybean (Jekayinfa et al., 2013), and cheese (Kim et al., 2013).

Synthesizing the carbon footprints can be approached from various perspectives, one of which involves case studies. This method is mostly employed by a wealth of studies focusing on agri-products. By accessing data from one or several certain farms or factories, the volume of production and GHG emission could be measured. For example, Canellada et al., 2018 track the environmental footprints of a small-sized cheese factory in Europe and successfully attain the carbon footprint of cheese as 10.2 kg per kg. In order to determine the factors that are driving and impeding the carbon emission of rubber manufacturing, Gunathilaka & Gunawardana, 2015 undertake ten unstructured interviews with pertinent experts, where they retrieve the non-organic rubber carbon footprint as 6.67 kg per kg and organic rubber as 3.34 kg per kg. Some studies also carry out case studies in more than one bases. From 22 cattle farms, Cerri et al., 2016 assess beef GHG emissions (range from 4.8 to 8.2 kg CO_2e per kg) in Brazil and the detailed gas percentage regarding the different GHGs. The second perspective involves obtaining the carbon footprint from a systematic view, which entails analyzing previous statistics (Clune et al., 2017) or conduct LCA simulations in software with existing data (Farjana et al., 2019). Different from the case study, this methodology could be commonly observed in research concentrating on both metals and agriculture. Based on various data sources, Gan & Griffin, 2018 approach carbon footprint results of iron with a self-built model considering carbons emitted from soil, vegetation, energy consumed and other possible sources. Northey et al., 2013 resort to various company sustainability or financial reports to gather data in production, energy, and GHG dimensions (2.6kg per kg). Along the same line, the carbon footprint range (0.7t-26.0t per ton) of palm oil is calculated by Lam et al., 2019. They base their analysis on land use data of palm oil plants, which is the direct cause of deforestation.

Apart from absolute carbon footprints, Bueb & To, 2020 of France Stratégie also propose a parameter to unveil the internal economic cost of carbon. In their technical report, they measure carbon emissions per ton during the production of 17 metals and furthermore introduce the dollar footprint (carbon emission per ton metal divided by metal price per ton) as a measure of metal externality.

Compared with endeavors to estimate carbon footprints, studies vary significantly from one study to another regarding the water scope which should be included in ultimate footprints. The most widely-accepted taxonomy is blue water, green water and grey water (Rost et al., 2008, Mekonnen & Hoekstra, 2010a, Shu et al., 2021). [2] However, few papers synthesize water footprints across different commodity classes in a homogeneous scope. For metal goods, Gunson, 2013 quantifies worldwide mine water withdrawals and calculates water consumption for unit ores. For agri-commodities, Mekonnen & Hoekstra, 2010b and Mekonnen & Hoekstra, 2010a summarize water footprints of both animal products and crops from a combination of large data sources. Based on a multi-level water usage database, food products' water footprints are well presented in Petersson et al., 2021.

To conclude this subsection, previous literature provide the possibility to quantify commodities' climate environmental sustainability by granting accessible carbon and water footprint data. These data are further gathered in Table 1 and Table 2 in subsection 2.2.1 to help with the sustainable commodity definition.

2.1.2 Commodity Pricing Factors

Numerous research works have focused on explaining the evolution of commodity prices, which could be divided into two groups, depending on whether they adopt a factor approach or not. Indeed, many factors have been identified to characterize the cross-section

[2]Blue water refers to surface water and groundwater resources that are readily available for human use, including rivers, lakes, reservoirs, and aquifers. Green water encompasses rainwater that is absorbed by soil and vegetation, where it is utilized for plant growth and ecosystem functions, such as transpiration and evaporation. Grey water represents wastewater generated from households, industry, and agriculture, containing pollutants from human activities, which requires treatment before it can be safely reused or discharged into the environment to prevent contamination of water sources.

of commodity futures' returns: **hedging pressure** (Basu & Miffre, 2013),[3] **slope** based on the basis spread (F. Yang, 2013), **skewness** (Fernandez-Perez et al., 2018), **carry** (Bakshi et al., 2019b), **momentum** (Bakshi et al., 2019b, Qian et al., 2024), **basis momentum** (Boons & Prado, 2019), and **fear of hazards** (Fernandez-Perez et al., 2020). To sort things out in this nascent factor zoo, Hollstein et al., 2021 review and systematically test anomalies present in commodity markets. They identify momentum, skewness and jump risk as being those that generate the most significant risk premia. Szymanowska et al., 2014 also confirm that several of the aforementioned factors are priced: they report significant premia for futures basis, return momentum, volatility, inflation, hedging pressure, and liquidity.

Outside factor models, several contributions have sought to explain commodity price patterns based on various variables. For instance, in their empirical study on soybean prices, Geman & Nguyen, 2005 find that the **scarcity, measured as inverse inventory level,** drives the volatility of prices and the shape of the forward curve. Frankel & Rose, 2010 propose a commodity pricing model that includes both macroeconomic variables (global output and and inflation) and microeconomic factors (volatility, inventories, and the spot-forward spread). Hong & Yogo, 2012 shed light on the link between movements in **open interest** (the amount of futures contracts outstanding) and commodity returns, but also with other asset classes. Le Pen & Sévi, 2018 document excess co-movement patterns that remain even after controlling for the impact of fundamentals.[4] Another potential driver of commodity prices is the **roll yield**: according to Bessembinder, 2018, it helps explain the deviations between future returns and spot price changes. Finally, S. Wang & Zhang, 2023 use machine learning algorithms to predict commodity returns. They argue that feature importance shows which are the most important predictors, and the latter vary substantially across commodities.

Beyond the literature that *explains* commodity returns, several contributions propose trading strategies that *exploit* salient features in commodity markets. For instance, Miffre & Rallis, 2007 documents momentum patterns in commodity futures. Inspired by Basu & Miffre, 2013, Miffre, 2016 reviews of the performance of long-short strategies built from inventory levels and hedging pressure. In a similar vein, Sakkas & Tessaromatis, 2020 propose a multi-factor commodity strategy that is found to outperform benchmarks, with a focus on factors such as momentum, basis and hedging pressure. Furthermore, in commodity markets, Rad et al., 2020 find that risk-based allocations dominate equally-weighted and utility-maximizing portfolios. Finally, Bianchi et al., 2023 develop trading strategies based on the level, slope and curvature of the term-structure of commodity futures.

The present study extends this stream of literature by adding novel attributes to

[3]For a theoretical foundation that links hedging pressure and level of storage with equilibrium prices, I refer to Ekeland et al., 2018.

[4]These fundamentals are: futures basis, prior futures returns, prior spot returns, and spot price volatilities are such fundamentals, see G. B. Gorton et al., 2012.

metals and agrarian goods: their environmental impact. Moreover, it views commodities from a sustainable investing standpoint, with a focus on the risk-adjusted performance of green portfolios. Finally, our study documents the reduction of the associated footprints at portfolio level.

2.2 Data

Chapter 1 and Chapter 2 rely on two sets of data. First, in Section 2.2.1 I detail the material on which our portfolio sorts will be based, which is essentially hand-collected estimates of commodities' impact with respect to GHGs and water consumption. Second, in Section 2.3.2, I clarify the data sources and processing that we used to calculate returns for commodity future strategies.

2.2.1 Commodity Environmental Footprints

In this study, 21 metal commodities and 20 agricultural goods are selected. The complete list is presented in Table 1 and 2. For the considered metals, footprints are usually computed as ratios of aggregate quantities (emission or consumption over production). In Glaister & Mudd, 2010, it is clearly shown that depending on companies or projects, the intensity can vary substantially. In the case of platinum, they report intensities between 2,300 and 78,300 tons of CO_2 equivalent required to extract one ton of metal. Moreover, GHG intensities are not constant in time, as better technologies are employed for mining (see Ulrich et al., 2020 in the case of gold). In addition, some reports compute carbon emissions and omit methane, for instance, which is the other important GHG beyond CO_2. Nevertheless, the reproduced values show some marked disparities between certain types of metals (e.g., precious ores versus common ones like iron, steel or lead). This is necessary to establish the rankings from which I craft groups based on resource-intensity. For each metal and footprint, the rankings I use are based on the average of intensities obtained from the available sources.

In particular, the footprint is often reversely related to the production: the precious ores are harder to extract and require more energy, which explains both the small production amounts and the higher prices. This is less pronounced for agrarian goods, for which the intensities in Table 2 are gathered. The aggregate results listed in Tables 1 and 2 were hand-collected and compiled from more than 80 bibliographic sources. The exhaustive list of all the references we used is postponed to Appendices.

Finally, it is noted that discrepancies in terms of production, prices and footprints are less marked for agrarian goods. There is at most a factor 20 between the smallest and the largest water intensity in Table 2. For metals, in Figure 1, the ratio is above 600,000 (platinum versus aluminum). Similar conclusions hold for GHG intensities (see Figure 1), as well as for prices (gold is roughly 90,000 times more expensive that steel on average in our sample).

Metal	log(P)	$\bar{p}$	GHG footprint				Water footprint		
			Source 1	Source 2	Source 3	Average	Source 4	Source 5	Average
Industrial and rare metals:									
Iron	22	0.10	-	-	0.1	0.1	1.4	0.4	0.9
Steel	21	0.52	2	-	2.2	2.1	-	2.5	2.5
Aluminum	20	2.00	17	8.2	15.4	13.5	0.4	0.4	0.4
Manganese	17	2.39	-	1.0	2.1	1.5	1.4	-	1.4
Chromium	17	9.25	5	2.4	-	3.7	-	4.8	4.8
Copper	17	6.94	4	2.8	4.6	3.8	43.2	81.2	62.2
Zinc	16	2.51	4	3.1	3.6	3.5	11.9	8.5	10.2
Lead	16	2.08	-	1.3	1.9	1.6	6.6	4.4	5.5
Titanium	16	9.51	30	8.1	35.7	24.6	-	43.4	43.4
Nickel	15	15.47	11	6.5	13.3	10.3	193.8	117.7	155.8
Magnesium	14	2.87	36	5.4	28.7	23.4	-	185.3	185.3
Molybdenum	13	41.95	11	5.7	7.2	8.0	240.9	107.1	174.0
Cobalt	12	40.99	3	8.3	15.2	8.8	208.4	452.3	330.4
Lithium	12	134.32	-	7.1	3.4	5.2	1,892.7	450.0	1,171
Tungsten	11	43.87	29	12.6	-	20.8	-	258.0	258.0
Vanadium	11	18.01	-	33.1	39.1	36.1	-	-	-
Neodymium	9	78.36	33	17.6	75.8	42.1	-	1,230	1,230
Precious metals:									
Silver	10	642.4	104	196	52	117	1,713	1,826	1,769.5
Gold	8	47,569	5,100	12,500	26,878	14,826	265,861	202,133	233,997
Palladium	5	40,827	-	3,880	9,380	6,630	210,713	59,274	134,994
Platinum	5	34,407	20,600	12,500	33,240	22,113	313,496	183,920	248,708

Table 1: **Environmental footprint of metal extraction**. I report the estimated GHG footprint required to produce one unit of metal by decreasing order of production, with precious metals listed last. The unit for carbon emissions is the number of tons of CO_2 equivalent generated to produce one ton of the corresponding metal. The unit for water consumption is the number of cubic meters of water per ton produced. Metals are ranked according to their log annual production (**log(P)**), in tons (from Survey, 2023, Table 5, and Idoine et al., 2023). I also provide the average long-term price of each metal, $\bar{\mathbf{p}}$, in U.S. dollars per kilogram - computed over the chronological range 2012-06 to 2023-09 (common to all metals). For carbon intensities, the first source is Bueb & To, 2020, the second is Nuss & Eckelman, 2014 and the third ones are listed in Appendix. For water intensities, the Source 4 is Meißner, 2021, except for lithium (Huang et al., 2021), and the Source 5 is Gunson, 2013, except that the water footprint of steel comes from Colla et al., 2017, that for neodymium comes from Haque et al., 2014, that for magnesium from Cherubini et al., 2008, that for titanium from Perks et al., 2022 and that for lithium from Vera et al., 2023. Intensities are averaged when several are proposed.

2.2.2 Commodity Price

Data for commodity contracts correspond to end-of-month futures prices obtained from Datastream. When the series are not available through Datastream they are obtained from Refinitiv Eikon (LSEG). For some metals, futures contracts are not traded, and in that case, our data correspond to spot prices.

Most of the studied futures are quoted in USD. Commodities denominated in other currencies are converted to USD, using end-of-month exchange rates obtained from Data-

Agri. Product	log(P)	$\bar{\mathbf{p}}$	GHG footprint				Water footprint
			Source 6	Source 7	Source 8	Average	Source 9
Corn	9.08	0.193	0.63	0.48	0.31	0.47	1,191
Rice	8.90	0.296	1.70	2.19	1.27	1.72	1,597
Wheat	8.89	0.222	0.65	0.57	0.63	0.62	1,639
Milk	8.87	0.386	-	1.19	1.31	1.25	1,261
Soybean	8.57	0.436	0.79	0.56	0.35	0.57	1,816
Soybean Meal	8.42	0.408	0.95	0.62	1.03	0.87	2,524
Sugar	8.22	0.378	0.71	0.78	0.45	0.65	1,295
Cotton	7.87	1.805	1.30	-	2.44	1.87	4,029
Palm oil	7.86	0.779	9.1	2.43	7.75	6.43	4,971
Cattle	7.86	2.817	-	-	13.07	13.07	7,477
Soybean Oil	7.79	0.949	2.06	1.79	2.19	2.39	4,190
Oats	7.35	0.232	0.67	0.67	0.63	0.66	1,788
Cheese	7.34	3.904	-	8.93	9.44	9.19	5,253
Rubber	7.15	2.358	4.10	-	3.40	3.75	13,748
Butter	7.05	4.554	-	8.48	9.11	8.79	5,659
Coffee	7.00	3.379	6.70	0.49	7.20	4.80	15,987
Cocoa	6.75	2.588	6.20	-	7.63	6.91	19,928
Dry Milk	6.68	2.712	-	-	9.88	9.88	4,750
Dry Whey	6.52	1,030	-	-	12.10	12.10	2,530
Orange Juice	6.35	3.324	2.97	0.46	6.00	3.14	1,019

Table 2: **Environmental footprint of agricultural production**. I present the estimated footprint needed for producing each agricultural product. The GHG metric is the amount of CO_2 equivalent (in tons) that is generated in order to produce one ton of the associated agricultural product. The water footprint is the number of cubic meters of water required to produce one ton of product. Agricultural goods are ranked according to their log annual production (**log(P)**), in tons (production data in 2021 from Food and Agriculture Organization, the Soybean Processors Association of India; United States Department of Agriculture and prediction by R&M, 2019)). The cattle production is substituted by that of beef. I also provide the average long-term price of each agricultural product, $\bar{\mathbf{p}}$, in U.S. dollars per kilogram for the period 2011-03 to 2023-09. For carbon intensities, the Source 6 is Carbon Cloud, Source 7 is Petersson et al., 2021, and the description of the products and references in Source 8 and Source 9 are listed in Appendix, where intensities are averaged when several are proposed.

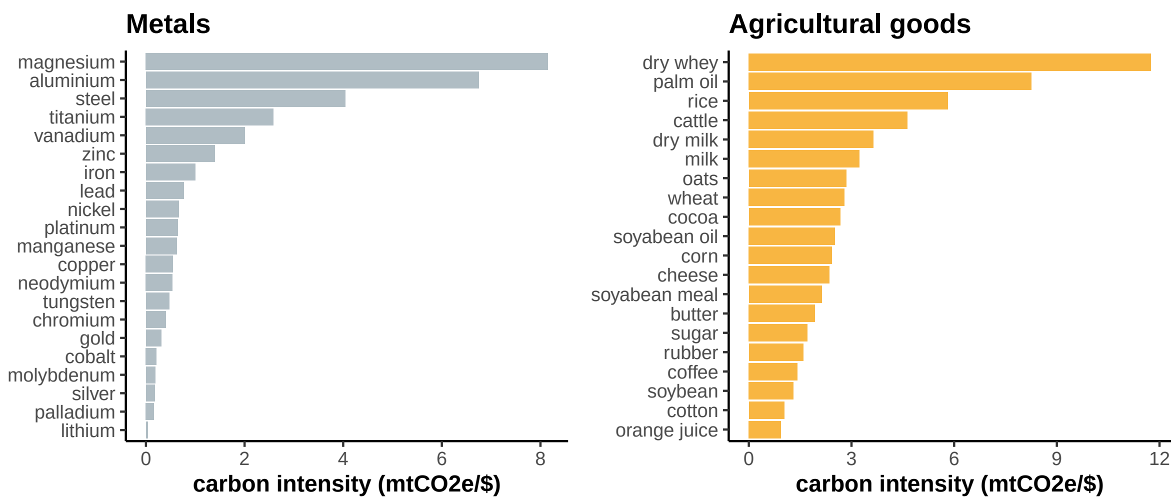

Figure 1: **Carbon intensities**. This figure shows the GHG intensity (dollar-scaled) of all commodities in our sample.

stream. Returns are then computed between USD quotes. In addition, for the purpose of computing footprint intensities, all quotes are converted to match prices for one kilogram of production.

For metals, data start in June 2012 and end in September 2023. For agricultural commodities, data are from March 2011 to September 2023. In this respect, this dataset covers interesting market periods: the Paris Agreement in 2015 (United Nations Climate Change Conference, COP21) and two recent periods and market-wide stress, namely 2020 and 2022.

This dataset encompasses 21 metals belonging to three categories: industrial metals (Iron, Steel, Aluminum, Copper, Zinc, Lead, Nickel), precious metals (Gold, Silver, Palladium, Platinum) and other, possibly rare, metals (Manganese, Chromium, Titanium, Magnesium, Molybdenum, Cobalt, Lithium, Tungsten, Vanadium, and Neodymium).

For agricultural products, the 20 commodities are split into the following categories: grains and oil seeds (Wheat, Corn, Rice, Oats, Soybeans, Soybean Meal, Soybean Oil), soft commodities (Cocoa, Coffee, Sugar, Cotton, Orange juice), cattle (Live Cattle) and dairy products (Dry Milk, Dry Whey, Butter, Cheese) as well as other slightly more exotic products (Palm oil, Rubber).

The time-series of prices corresponds to end-of-month nearby futures settlement prices, or spot prices when futures are not traded often enough (lacking liquidity). For each commodity, the returns are computed from these end-of-month prices and with respect to the settlement of the same contract at the end of the preceding month. In doing so, I implicitly assume a fully collateralized position in the futures. By computing fully-collateralized returns with respect to the same contract, the returns are tradeable and I avoid integrating "roll yields" to returns (see Bessembinder, 2018).

2.3 Sustainability Factors

2.3.1 Commodity Sustainability Definition

The binary classifications are summarized in Table 5 (green versus brown) for ores and agricultural products (detailed footprint rank are presented in Tables 3 and 4). Half of commodities with lower environmental burdens are defined as green commodities while the other half are defined as brown commodities. [5] It is underlined that these groups are well diversified with respect to major sub-classes of metals and agricultural goods. For example, precious metals and grains are present in both green and brown groups.

Figure 2 shows the cumulative of equally-weighted portfolios of green, brown and green-minus-brown (GMB) commodities, within each of the two subgroups (metals and agricultural goods). Both long-only legs display similar patterns of decrease (until 2016 for metals or 2020 for agrarian goods), followed by a sharp increase between 2020 and

[5] As there are 21 metals in this study, 10 metals with lower GHG emission or less water consumption are defined as green while the other 11 are placed in the brown family.

metal	returns				footprint		
	mean	sd	min	max	GHG $ intens.	Water $ intens.	Transition
lithium	0.012	0.077	-0.308	0.446	0.039 green	8.718 brown	✓
palladium	0.009	0.086	-0.231	0.249	0.162 green	3.306 green	
silver	0.000	0.080	-0.177	0.301	0.182 green	2.755 green	
molybdenum	0.005	0.053	-0.318	0.234	0.191 green	4.148 green	
cobalt	0.006	0.099	-0.382	0.358	0.215 green	8.061 brown	✓
gold	0.001	0.041	-0.121	0.105	0.312 green	4.919 brown	
chromium	0.001	0.053	-0.140	0.300	0.400 green	0.519 green	✓
tungsten	0.000	0.041	-0.120	0.184	0.474 green	5.881 brown	
neodymium	0.003	0.098	-0.213	0.440	0.537 green	15.697 brown	
copper	0.002	0.055	-0.125	0.199	0.548 green	8.963 brown	✓
manganese	0.003	0.093	-0.529	0.400	0.628 brown	0.586 green	✓
platinum	-0.003	0.062	-0.162	0.140	0.643 brown	7.228 brown	✓
nickel	0.004	0.089	-0.202	0.313	0.666 brown	10.071 brown	✓
lead	0.002	0.062	-0.151	0.180	0.769 brown	2.644 green	
iron	0.006	0.112	-0.268	0.309	1.000 brown	9.000 brown	
zinc	0.005	0.068	-0.189	0.153	1.394 brown	4.064 green	
vanadium	0.011	0.157	-0.447	1.177	2.004 brown		
titanium	-0.002	0.052	-0.316	0.209	2.587 brown	4.564 green	
steel	0.003	0.086	-0.276	0.213	4.038 brown	4.808 green	
aluminium	0.000	0.056	-0.130	0.134	6.750 brown	0.200 green	✓
magnesium	0.007	0.113	-0.294	0.993	8.153 brown	64.564 brown	

Table 3: **Summary table for metals**. I produce the descriptive statistics of metal price monthly returns (2012-06 to 2023-09), as well as the dollar intensity of their extraction with respect to GHG emissions and water consumption. The metals are ordered in decreasing order of carbon dollar intensity.

2022 - and a relative stability in 2023.

The long-short strategies (factors), on the other hand, do not exhibit clear common trends. Both metal factors (upper panels) oscillate around zero, as does the one based on GHG for agrarian goods. However, the last factor based on water for agricultural goods experiences mostly positive cumulative returns over the period of our sample.

Figure 3 shows the average return and volatility of all possible combinations of equally-weighted portfolios of 10 commodities. In addition, I locate within these clouds of points the eight long-only portfolios depicted in Figure 2. This shows whether the environment-based sorting generates a tilt towards low or high return commodities - or whether the sorting induces more or less risk. The samples in this case are such that data is available for all assets. The evidence suggests that brown factors are clearly riskier but not particularly more profitable. It is especially clear for GHG-based factors for which the green portfolio dominates the brown one on both criteria (return and volatility). For metals and agricultural goods, the green GHG factors deliver returns that are among the best that is possible to span for the corresponding level of risk: the associated points lie close to the upper frontiers of the clouds.

agri. products	returns				footprint	
	mean	sd	min	max	GHG $ intens.	Water $ intens.
orange juice	0.010	0.096	-0.210	0.276	0.945 green	0.307 green
cotton	0.000	0.075	-0.252	0.195	1.036 green	2.232 green
soybean	0.008	0.062	-0.191	0.198	1.307 green	4.165 green
coffee	-0.004	0.088	-0.209	0.436	1.421 green	4.731 brown
rubber	-0.017	0.077	-0.196	0.224	1.590 green	5.830 brown
sugar	-0.001	0.075	-0.263	0.223	1.720 green	3.426 green
butter	0.004	0.082	-0.338	0.399	1.930 green	1.243 green
soyabean meal	0.013	0.080	-0.204	0.301	2.132 green	6.186 brown
cheese	0.000	0.091	-0.372	0.466	2.354 green	1.346 green
corn	0.001	0.076	-0.228	0.311	2.435 green	6.171 brown
soyabean oil	0.005	0.077	-0.149	0.407	2.518 brown	4.415 brown
cocoa	0.005	0.078	-0.201	0.312	2.670 brown	7.700 brown
wheat	-0.007	0.085	-0.252	0.289	2.793 brown	7.383 brown
oats	0.012	0.091	-0.214	0.258	2.845 brown	7.707 brown
milk	-0.001	0.063	-0.254	0.272	3.238 brown	3.267 green
dry milk	-0.005	0.060	-0.238	0.170	3.643 brown	1.751 green
cattle	0.002	0.042	-0.129	0.160	4.640 brown	2.654 green
rice	-0.001	0.058	-0.157	0.222	5.811 brown	5.395 brown
palm oil	0.004	0.091	-0.230	0.292	8.254 brown	6.381 brown
dry whey	0.000	0.068	-0.194	0.162	11.748 brown	2.456 green

Table 4: **Summary table for agricultural products**. I produce the descriptive statistics for monthly returns for agricultural commodities, as well as the dollar intensity of their extraction with respect to GHG emissions and water consumption. The agricultural products are ordered in decreasing order of carbon dollar intensity.

Panel A: Metals		
	Green metals	**Brown metals**
GHG	palladium, lithium, silver, copper, molybdenum, cobalt, gold, chromium, tungsten, neodymium	manganese, platinum, nickel, lead, zinc, vanadium, titanium, aluminum, magnesium, iron, steel
Water	palladium, silver, molybdenum, chromium, manganese, lead, zinc, aluminium, titanium, steel	lithium, cobalt, gold, tungsten, neodymium, platinum, nickel, magnesium, iron, copper
Panel B: Agricultural goods		
	Green goods	**Brown goods**
GHG	cotton, orange juice, soyabean, sugar, rubber, butter, coffee, cheese, soyabean meal	corn, cocoa, oats, wheat, milk, dry milk, soyabean oil, cattle, rice, palm oil, dry whey
Water	cotton, orange juice, sugar, butter, cheese, milk, dry milk, cattle, dry whey, soyabean	coffee, rubber, soyabean meal, soyabean oil, corn, cocoa, oats, wheat, rice, palm oil

Table 5: **Classifications for commodity products.**

2.3.2 Sustainable Factor Performance in Commodity Pricing

A factor analysis is followed to better explain the sources of risk and return of these portfolio. Based on the empirical results by Bakshi et al., 2019b, three explanatory

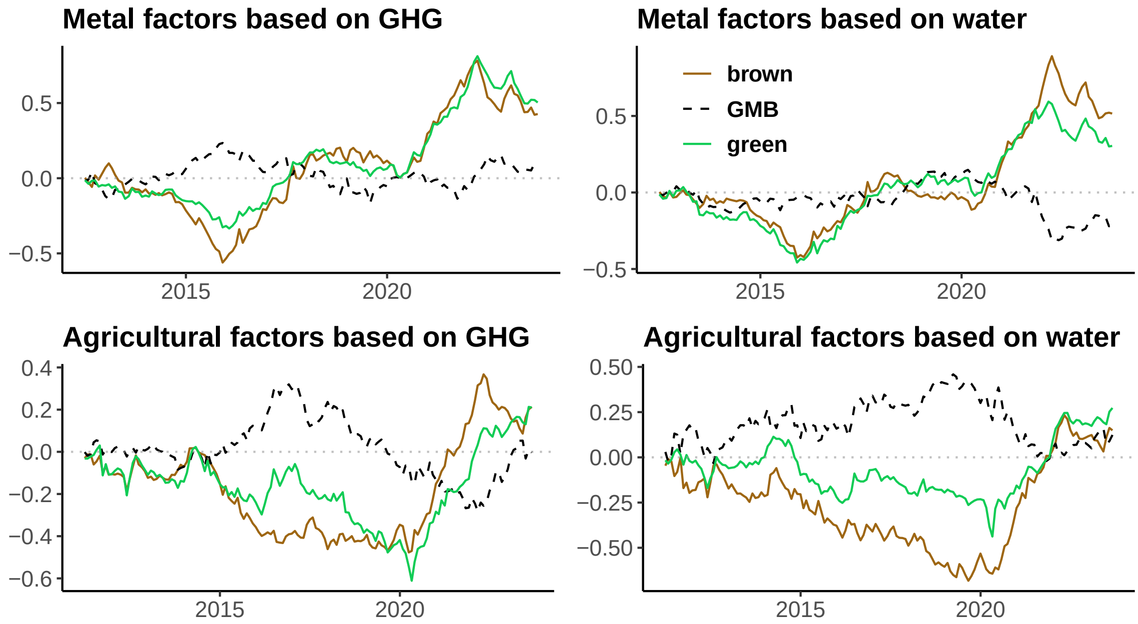

Figure 2: **Cumulative returns of commodity factors**. I plot the monthly cumulative returns of the factors based on GHG dollar intensity (left) and water dollar intensity (right). The products are metals (upper panels) and agricultural goods (lower panels). The long leg is in green, the short one in brown and the green-minus-brown (GMB) one in dotted **black**. The exact compositions of the legs are given in Table 5. The samples start in June 2012 for metals and in March 2011 for agrarian goods; they end in September and August 2023, respectively.

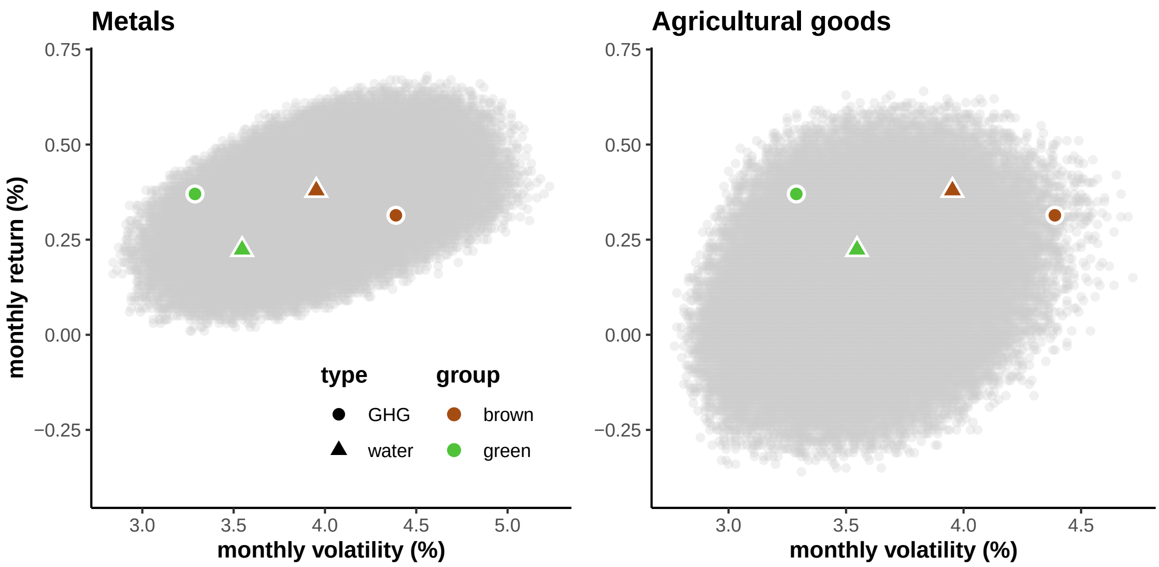

Figure 3: **Spanning the risk-return relationship**. I plot the average monthly returns (y-axis) and volatility (x-axis) of all possible long portfolios of 10 commodities for both types (equally weighted). This makes $\binom{21}{10} = 352,716$ combinations for metals and $\binom{20}{10} = 184,756$ for edibles. I position the green and brown brown portfolios shown with circles (•) for the GHG-based sorts and triangles (▲) for the portfolios based on water consumption. The samples start in June 2012 for metals and in November 2013 for agrarian goods; they end in September and August 2023, respectively.

commodity pricing factors are introduced: **average** (proxy for market), **momentum**, and **carry**. They are constructed as follows.

- **average**: the average return of all commodities in the sample (i.e., equally-weighted portfolio). For all three factors, the average can be performed within commodity types (metals versus ores separately), or across types (i.e., when all commodities are blended together);
- **momentum**: the return on a portfolio that is long in the N commodities with the highest returns over the previous J months and short in the ones with the lowest returns over the previous J months. In Bakshi et al., 2019b, the authors recommend $J = 6$ months and $N = 5$ assets. In addition to these default parameters, I also test the combination of $J = 12$ months with $N = 10$ assets.
- **carry**: the return on a portfolio that is long in the N commodities that are most backwardated (i.e., the lowest $\log(y_t)$) and short the ones that are most in contango (i.e., the reverse), where $y_t = F_t^{(1)}/F_t^{(0)}$ is the slope of the futures curve.

The carry factor y_t is computed using two adjacent futures contracts and scaled with respect to the difference between times to expiry of the contracts. When the exact date of expiry is not available, the month of expiry is taken instead (implicit day-count convention 30/360). And when the expiry month is also missing, I recover it from the calendar of contract expiry provided by the exchange under the contract definition or specification sections.

I construct six variations of these factors. The first difference in factor construction is the 6 months lookback period and 5 assets versus 12 months and 10 assets options. The second difference is the sets of retained assets. Three sets are considered here: metals, agricultural sets, and the union of both (all commodities in the sample).

Table 6 presents the 5%, 50% and 95% of bootstrapped returns of these three factors, for all configurations: one line pertains to one configuration. In particular, it is noted that signs are mostly unchanged within columns, with the momentum and carry factors experiencing mostly negative returns. The confidence intervals depart substantially from those in Bakshi et al., 2019b and I can put forward at least two reasons for why it is the case.

First, the universe of commodities is not the same. While I naturally omit energy commodities (oil and gas notably) because they fall out of the scope of the paper, many products are also included which are absent from the empirical study of Bakshi et al., 2019b. One reason for this is simply that quotes for futures on these commodities is simply not available because the products have only been on the market for one decade or so. The second related reason that explains the discrepancies between the results and those of Bakshi et al., 2019b is sample depth. While theirs starts in 1970, the data in this study is much more recent. Hence, fluctuations of commodities in the most recent period may have differed from those prior to the sample.

factor		market (EW)			momentum			carry		
type	spec	5%	median	95%	5%	median	95%	5%	median	95%
agri	12/10	-0.002	0.003	0.008	-0.015	-0.009	-0.003	-0.038	-0.033	-0.027
agri	6/5	-0.001	0.005	0.010	-0.029	-0.020	-0.011	-0.066	-0.057	-0.049
metal	12/10	-0.004	0.003	0.010	-0.001	0.004	0.009	-0.021	-0.013	-0.006
metal	6/5	-0.005	0.002	0.009	-0.006	0.002	0.011	-0.008	-0.003	0.001
both	12/10	-0.003	0.003	0.009	-0.013	-0.008	-0.002	-0.040	-0.034	-0.028
both	6/5	-0.003	0.003	0.009	-0.015	-0.008	-0.001	-0.068	-0.059	-0.049

Table 6: **Bootstrapped quantiles of factor returns**. I report the 5%, median and 95% quantiles of bootstrapped returns for the three asset pricing factors. The number of samples is 10,000 and the block size is 6, which corresponds to the number of months in the sample raised to the power 1/3, as is recommended in Politis & White, 2004. Quantiles are evaluated for three cases: when the cross-section of commodities for the construction of the asset pricing factors consists either of metals, edibles, or both (horizontal sub-panels). I also allow for two sizes of the long/short legs (5 versus 10 commodities) and two lookback windows (6 or 12 months). This corresponds to the **spec** column. For example, the 12/10 label means 12-month windows and 10 commodities in each leg.

Equipped with these $K = 3$ factors, the following regressions are carried out:

$$r_t - r_f = \alpha + \sum_{k=1}^{K} \beta^{(k)} f_t^{(k)} + e_t, \tag{1}$$

and the resulting coefficients are gathered in Table 7. The risk-free rate r_f (annualized one month T-Bill) is equal to 0.9% over the span of the sample. Note that I impose $r_f = 0$ in the above equation when regressing the returns of the long-short portfolios. All results are compiled in Table 7.

In the upper half of the table, the factors $f_t^{(k)}$ are computed within commodity group, i.e., the metal portfolios are analyzed with average, momentum and carry factors based on metal futures - and likewise for the agrarian futures' returns. In the lower half of the table, the average, momentum and carry factors are evaluated with the *whole* cross-section of commodities, i.e., ores and agricultural goods are blended in the construction of explanatory factors. A second dichotomy is also proposed in the crafting of these factors: in the leftmost columns, factors are constructed exactly as in Bakshi et al., 2019b, with $J = 6$ months periods for momentum and $N = 5$ assets for carry and momentum. But in the rightmost columns, I test an alternative configuration with $J = 12$ and $N = 10$. This is for the sake of completeness to assess and confirm the robustness of conclusions.

The first striking pattern is the negative coefficients for the intercept (α) in a majority of models. This confirms the visual impression from Figure 2 that long-short factors do not earn substantial returns. In fact, if the risk-free rate and regress returns are removed instead of excess returns for the long factors, all statistical significance vanishes.

A second takeaway is that the market factor has by far the best explanatory power

Factors	Baseline explanatory factors					Alternative explanatory factors				
	α	Factors			R^2	α	Factors			R^2
		market (EW)	mom	carry			market (EW)	mom	carry	
Within commodity type factors										
Panel A: Metal factors from greenhouse gas emissions										
green	-0.008 (***)	0.827 (***)	0.009	0.053	0.745	-0.008 (***)	0.84 (***)	-0.023	0.032	0.747
brown	-0.01 (***)	1.145 (***)	0.013	-0.003	0.778	-0.01 (***)	1.137 (***)	0.055	0.003	0.780
GMB	0.002	-0.318 (***)	-0.004	0.056	0.086	0.002	-0.297 (***)	-0.078	0.029	0.095
Panel B: Metal factors from water consumption										
green	-0.010 (***)	0.895 (***)	-0.019	-0.046	0.706	-0.010 (***)	0.895 (***)	-0.075 (*)	0.001	0.71
brown	-0.009 (***)	1.026 (***)	0.041 (*)	0.039	0.797	-0.009 (***)	1.034 (***)	0.049	-0.004	0.795
GMB	-0.001	-0.131 (*)	-0.06	-0.085	0.04	-0.001	-0.139 (*)	-0.123 (*)	0.005	0.045
Panel C: Agricultural factors from greenhouse gas emissions										
green	-0.012 (***)	1.021 (***)	-0.002	-0.031	0.689	-0.011 (***)	1.031 (***)	0.027	-0.020	0.686
brown	-0.01 (***)	0.961 (***)	0.047 (*)	-0.011	0.733	-0.01 (***)	0.955 (***)	0.064 (*)	-0.012	0.734
GMB	-0.002	0.06	-0.049	-0.020	0	-0.001	0.075	-0.037	-0.008	-0.011
Panel D: Agricultural factors from water consumption										
green	-0.01 (***)	0.789 (***)	0.006	-0.019	0.486	-0.009 (***)	0.798 (***)	0.054	-0.005	0.490
brown	-0.012 (***)	1.193 (***)	0.039	-0.023	0.707	-0.012 (***)	1.189 (***)	0.038	-0.026	0.705
GMB	0.002	-0.405 (***)	-0.033	0.005	0.057	0.003	-0.391 (***)	0.016	0.021	0.056
Across commodity type factors										
Panel A: Metal factors from greenhouse gas emissions										
green	-0.01 (***)	0.948 (***)	0.038	-0.025	0.592	-0.011 (***)	0.954 (***)	-0.003	-0.053	0.590
brown	-0.011 (***)	1.302 (***)	0.030	-0.010	0.623	-0.01 (***)	1.298 (***)	0.005	0.017	0.622
GMB	0.001	-0.354 (***)	0.008	-0.015	0.065	-0.001	-0.345 (***)	-0.008	-0.071	0.074
Panel B: Metal factors from water consumption										
green	-0.012 (***)	0.994 (***)	0.057 (*)	-0.023	0.563	-0.011 (***)	0.990 (***)	0.032	-0.02	0.553
brown	-0.012 (***)	1.217 (***)	0.017	-0.031	0.673	-0.013 (***)	1.226 (***)	-0.005	-0.083 (*)	0.680
GMB	0.000	-0.223 (*)	0.04	0.008	0.032	0.002	-0.236 (*)	0.037	0.063	0.038
Panel C: Agricultural factors from greenhouse gas emissions										
green	-0.011 (***)	0.895 (***)	-0.013	-0.024	0.424	-0.012 (***)	0.887 (***)	0.046	-0.063	0.428
brown	-0.01 (***)	0.830 (***)	-0.039	0.000	0.457	-0.009 (**)	0.827 (***)	-0.027	0.033	0.453
GMB	-0.001	0.065	0.026	-0.024	-0.013	-0.003	0.059	0.073	-0.096	0.005
Panel D: Agricultural factors from water consumption										
green	-0.008 (*)	0.630 (***)	-0.044	0.022	0.251	-0.009 (**)	0.628 (***)	-0.010	-0.005	0.243
brown	-0.013 (***)	1.095 (***)	-0.008	-0.046	0.496	-0.011 (***)	1.086 (***)	0.029	-0.024	0.491
GMB	0.006	-0.465 (***)	-0.036	0.068	0.078	0.002	-0.457 (***)	-0.038	0.019	0.068

Table 7: **Factor exposures**. This table gathers the loadings estimated via Equation (1). The horizontal panels pertain to the dependent variable (i.e., which commodity factor is explained). In the leftmost columns of results, the **baseline** independent variables are the factors recommended in bakshi2019understanding: $N = 5$ assets in both legs of momentum and carry and a backward looking window of $J = 6$ months for momentum returns. In the rightmost columns (**alternative factors**), I allow for $N = 10$ assets in both legs and use a $J = 12$ month window for momentum returns. In the **upper half** of the table, explanatory factors are *within* commodity universe, i.e., they are constructed from metals for metals and likewise for agricultural goods. In the **lower half**, explanatory factors are built with the two types of commodities mixed. In this case, the independent variables are the same for all four panels, from A to D. Significance levels for p-values are: (***)<0.001<(**)<0.01<(*)<0.1.

over factor returns. This is somewhat surprising for the long-short factors because the market portfolio, by construction, is long-only. The momentum factors are found to be less efficient at explaining sustainability-driven returns, but emerges as significant in some cases. However, the carry factor has only one coefficient for which the null can be reasonably rejected, which implies that it has only marginal pricing power for the studied portfolios.

In terms of fit, all models do a good job at explaining the returns of the long portfolios because the R^2 lie between 40% and 80%, because there is a strong market effect: the market returns explain a substantial share of individual futures' returns. If the EW factor is removed, the R^2 shrink dramatically. These levels are in line with those of Bakshi et al., 2019b. The values are nevertheless much lower for the GMB factors.

This analysis is completed with Fama-MacBeth regressions (Fama & MacBeth, 1973). The first pass estimations (in the cross-section of the 41 commodities) are performed on expanding windows, starting in July 2012. This gives the first estimates $\hat{\beta}_{i,f,t}$, where i is the index of the commodity, f the index of the factor (carry, EW and momentum) and t the index of the month. For the second pass, on a date-by-date basis, individual returns are regressed against the coefficients of the first pass. Two methods are tested. The first one is the simple OLS estimator, and the second one, following Bakshi et al., 2019b and Bryzgalova, 2015, leverages L^1-type selection (LASSO) to account for potentially spurious factors. Many penalization intensities are tested and the retained model is the one that minimizes the Bayesian Information Criterion. The second pass yields the estimated risk premia $\hat{\gamma}_{t,f}$, with $\gamma_{.,f}$ being the risk premium associated with factor f. In Table 8 below, I report the premia $\bar{\gamma}_f$ averaged across all dates, with the corresponding t-statistics.

		LASSO			Simple OLS		
type	**spec**	**carry**	**ew**	**mom**	**carry**	**ew**	**mom**
agri	12/10	0.664 (1.440)	0.198 (0.872)	-0.002 (-0.004)	0.899 (1.396)	0.128 (0.419)	0.094 (0.121)
agri	6/5	1.023 (1.250)	0.263 (1.159)	-0.532 (-0.555)	1.426 (1.272)	0.214 (0.666)	-0.079 (-0.061)
both	12/10	0.353 (0.490)	-0.098 (-0.392)	0.275 (0.434)	0.210 (0.208)	-0.029 (-0.087)	0.611 (0.719)
both	6/5	0.836 (0.761)	0.030 (0.134)	1.013 (1.061)	0.012 (0.007)	0.028 (0.079)	0.837 (0.648)
metal	12/10	0.330 (0.582)	0.152 (0.597)	0.668 (1.179)	0.489 (0.556)	0.039 (0.119)	0.902 (1.281)
metal	6/5	-0.038 (-0.095)	0.074 (0.311)	1.546 (1.729)	0.151 (0.273)	0.081 (0.251)	2.156 (1.872)

Table 8: **Risk premia of asset pricing factors** via Fama-MacBeth regressions. The returns of the cross-section of commodities are first regressed against the three factors. Then, date-by-date, the returns are regressed against the coefficients obtained in the first pass, possibly with a penalty (LASSO case). I provide results when the cross-section of commodities for the construction of the asset pricing factors consists either of metals, edibles, or both (horizontal sub-panels). I also allow for two sizes of the long/short legs (5 versus 10 commodities) and two lookback windows (6 or 12 months). This corresponds to the **spec** column. The reported figures are the averages $\bar{\gamma}_f$, in percents (%). The numbers between parentheses are the t-statistics associated with the null that the average premia are zero.

The premia in the table are all associated with insignificant test statistics across all specifications and estimation methods. Again, this marks a contrast with the results of Bakshi et al., 2019b. Furthermore, smaller sample sizes (e.g., $N \approx 100$) are likely to reject the null less often, compared to the larger ones ($N \geq 500$) used in Bakshi et al., 2019b.

3. Chapter II: Portfolio Diversification Benefits with Sustainable Commodities

This chapter is dedicated to the potential gains that can be obtained when including sustainable commodity factors to green portfolios comprising stocks and bonds, in terms of financial performance and environmental impact.

3.1 Literature Review: The Diversification Benefits of Commodities

Modern portfolio management theory by Markowitz, 1952 emphasizes diversification to achieve optimal risk-adjusted returns. Commodities, as a heterogeneous asset class, could potentially affect the portfolio risk-return profile by increasing the diversification level in portfolios merely consisting of equities and bonds. Some studies, such as those by G. Gorton & Rouwenhorst, 2006 and Tang & Xiong, 2012, find empirical evidence supporting that adding commodities to portfolios can increase risk-adjusted returns and reduce portfolio volatility. Based on benchmark portfolios with equity or bond indices, Belousova & Dorfleitner, 2012 confirm the diversification benefits brought by various types of commodities including metals, agricultural goods, livestock commodities and energies.

On the contrary, other literature (e.g., Daskalaki & Skiadopoulos, 2011, Erb & Harvey, 2016, Ruano & Barros, 2022) present mixed evidence regarding the risk-reducing properties of commodities. These studies emphasize the complexity of the linkage between commodities and other asset types, with the effectiveness of diversification varying across different market conditions or time periods.

In green finance field, the diversification contributions brought by commodities have been studied by a few works. The first set of papers examine the diversification benefits by including green commodities or related assets in traditional equity, bond or real-estate portfolios (e.g., Kuang, 2021, Naqvi et al., 2022). However, most of these literature shed lights on energy commodities or clean energy producers, leaving a research blank for diversification contributions of metals and agri-goods. The second perspective is to study the connectedness between general commodities and green equity or bond market (e.g., Naeem et al., 2021, Nguyen et al., 2021, Arfaoui et al., 2023).

In conclusion, under certain periods or conditions, commodities' diversification benefits (whether it is enhancing return or reducing volatility of portfolios) exist. Nevertheless, research regarding green commodities remains limited. This is due to the lack of green commodity definition, which is given in Chapter 1. Hereafter, I delve into the diversification advantages of green commodities based on the definition in the last chapter.

3.2 Financial performance

Indeed, Anson, 1999, G. Gorton & Rouwenhorst, 2006 and Bhardwaj et al., 2015 have documented that commodity futures not only have appealing raw performance on their own, but are also negatively correlated with the other two asset classes, thereby providing hedging opportunities. This is further reported in Rad et al., 2022 who show that incorporating a factor-based commodity component in a strategic asset allocation improves its risk-adjusted performance. With respect to sustainable investing, Lei et al., 2023 find hedging power of both palladium and gold for ESG indices, but the latter are precious metals and not particularly environment-friendly.

In this subsection, I investigate these properties for low carbon indices. As building blocks for the standard asset classes, I choose, for equities, the MSCI ACWI Low Carbon Target Index, which is tradable via an iShares ETF (Code CRBN) and, for fixed income securities, the S&P 500 Bond Investment Grade Carbon Efficient Index. With respect to the commodity components, I resort to both the GHG portfolios presented in the previous section and the transition metals portfolio.

In Table 9, the summary statistics of returns are provided over the period for which these carbon indices are available, i.e., from September 2015 to October 2023. The equity index, with a return of 8.9%, performs much better than the bond index (1.7%). With respect to the long-only carbon factors, some heterogeneity is found. The metal factors have higher returns than the one based on agricultural goods. The portfolio based on low carbon ores even has a return above that of equities on the period. Moreover, it is also associated with lower risk (12.3% volatility, versus 15.6% for equities). In terms of extreme risk, it is noted the high drawdown endured by the agricultural factor. It is visually confirmed in Figure 2.

Over the 2015-2023 period, I report a very high correlation between the low carbon equity and bond indices (0.59). One possible explanation may be the high inflation experienced towards the end of the period. Indeed, J. Yang et al., 2009 and Molenaar et al., 2023 find that the stock-bond correlation increases in times of high inflation. The diversification potential brought by the low carbon commodity portfolios is not evident ex-ante. Indeed, only the factor based on agricultural goods is (weakly) negatively linked to bond returns, and also weakly linked to stock returns. The factors from low GHG ores exhibit higher correlations, especially between the two metal-based portfolios.

The full sample correlations mask local chronological patterns shown in Figure 4. Twelve months correlations reveal more striking fluctuations, except for the two metal-based indices which remain highly correlated. Over smaller periods, even the stock-bond correlation oscillates much more, sometimes well below zero. While most points are located above zero, there are instances when the commodity indices are negatively related to either bonds or stocks. This signals chronological pockets of strong diversification opportunities for the low carbon commodity indices.

To formally assess the impact of the inclusion of such indices in asset allocation, a

asset	$\bar{r}$	σ	SR	VaR	MDD	correlations				
						bond	equity	metal GHG	metal transi	agri GHG
bond	0.019	0.061	0.164	-0.029	0.189	1.000	0.583	0.155	0.207	-0.042
equity	0.093	0.157	0.535	-0.070	0.265	0.583	1.000	0.304	0.408	0.126
metal GHG	0.096	0.123	0.707	-0.050	0.280	0.155	0.304	1.000	0.872	0.286
metal transition	0.079	0.148	0.473	-0.065	0.356	0.207	0.408	0.872	1.000	0.307
agri GHG	0.054	0.125	0.360	-0.053	0.438	-0.042	0.126	0.286	0.307	1.000

Table 9: **Summary statistics**. I report the full sample mean return ($\bar{r}$), volatility (σ), Sharpe ratio (SR), Value-at-Risk (95%, 1-month horizon) and maximum drawdown (MDD) of asset classes, as well as correlations. All metrics are computed on monthly returns and the first three are annualized. The risk-free rate is 0.9%. The sample runs from September 2015 to October 2023.

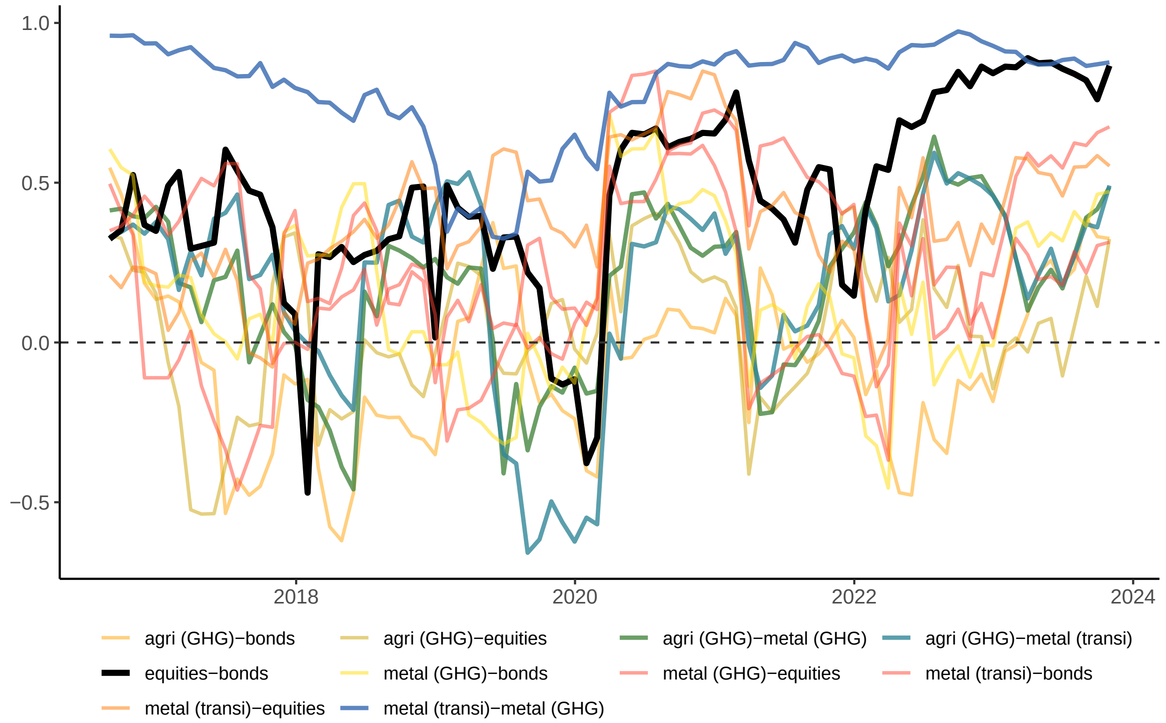

Figure 4: **Dynamic correlations**. This figure presents the realized correlations computed over rolling windows of 12 months. The **black** line shows the stock-bond correlation. The ones in **blue** to **green** represent the correlations within commodity indices. The links between commodities and stocks or bonds are depicted with lines in pale yellow to **red**. The sample starts from September 2009 (hence the time-series start one year later) and ends in September 2023.

simple exercise is performed. In the sample, portfolios with weights w_c for commodities and weights $w_b = 0.4(1 - w_c)$ for bonds and $w_e = 0.6(1 - w_c)$ for equities are crafted. Hence, when $w_c = 0$, I recover the traditional 60/40 allocation and when $w_c > 0$, the ratio between equities and bonds is fixed to 60/40.

Figure 5 depicts the gains brought by the commodity pocket in terms of volatility reduction and risk-adjusted performance. The reduction in volatility is modest, yet real, from 11% to roughly 10% on average when the proportion of commodities is close to 15% - a reasonable level in asset management. With regard to risk-adjusted returns, the improvement is more pronounced, yet dependent on the commodity index. In the best, case, the improvement is between 0.49 (annualized) and 0.62 when the share of commodity is 20%. Even in the least favorable scenario of a 10% share with the transition metals, the ratio increases to 0.56.

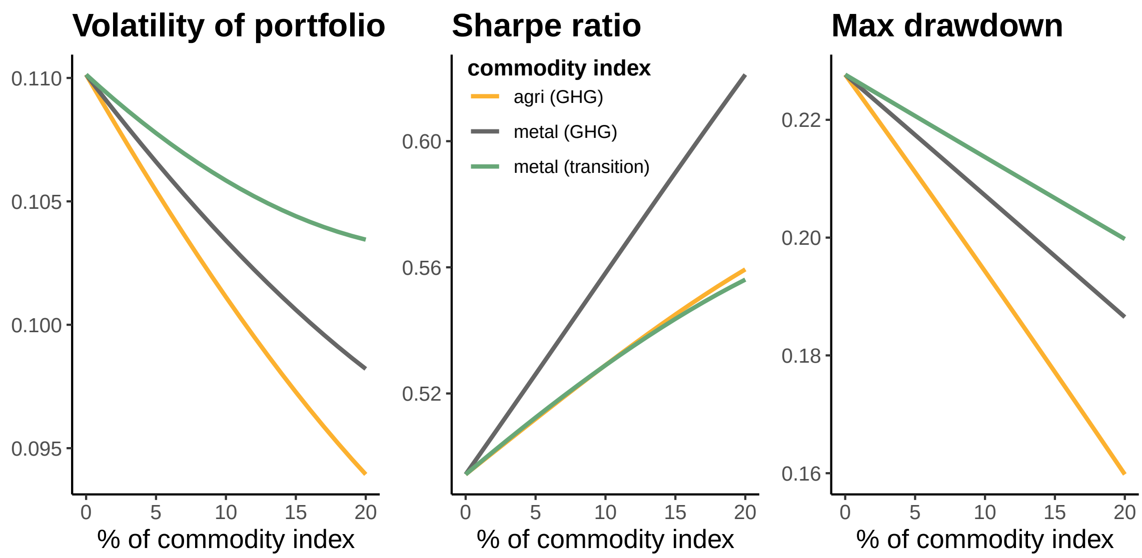

Figure 5: **Diversification benefits**. The left panel demonstrates the volatility of the asset allocation that includes a proportion of w_c (x-axis) in the portfolio and $0.4(1-w_c)$ to bonds and $0.6(1-w_c)$ to equities. The right panel shows the risk-adjusted return (average return scaled by volatility). The sample starts from September 2009 and ends in September 2023.

Perhaps, the diversification potential is maybe best illustrated with extreme risk. The maximum draw-down of the portfolio is efficiently mitigated when adding the commodity factor. In detail, this is particularly salient in the recent period: when the stock market fell sharply in the beginning of 2022, the green metal portfolio experienced high positive returns, thereby compensating the equity losses in the diversified portfolio.

Lastly, the analysis is extended to all combinations of commodities to see if the low-GHG sorting is responsible for the improvement in risk-adjusted performance. Figure 6 depicts the distribution of the Sharpe ratio of portfolios with a 20% pocket of commodities. The distribution spans all combinations of ten metal (left) or agricultural (right) futures. The equity and bond allocations are fixed to 48% and 32%, respectively. The histograms demonstrate that the enhancement does not stem from the particular choice of low-carbon futures. Indeed, almost all of the portfolios that include *any* combination of commodities improve on the commodity-free allocation (dotted vertical line). This corroborates the diversification benefits brought by commodities documented in G. Gorton & Rouwenhorst, 2006 and Rad et al., 2022. However, the magnitude of the increase in Sharpe ratio does depend on the choice of futures. As seen in Figure 5, the low-GHG metals bring the most sizable improvement.

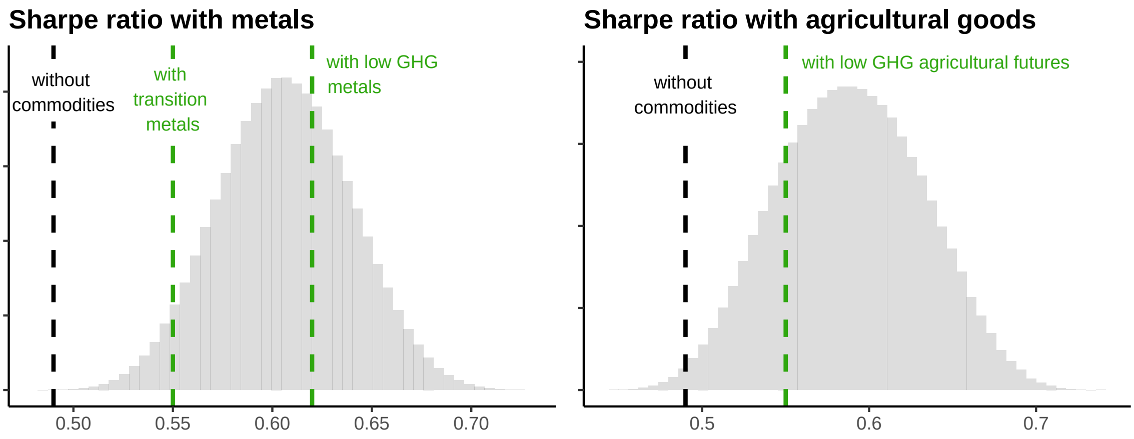

Figure 6: **Sharpe ratios across all commodity portfolios**. I plot the distribution of Sharpe ratios when the commodity pocket of the allocation spans all combinations of ten commodities. In the left (*resp.* right) plot, the metal (*resp.* agricultural) futures are used as diversification asset class. Vertical lines show the benchmark values, with the black line marking the Sharpe ratio of the pure equity-bond portfolio. Trading occurs between August 2015 and September 2023.

3.3 Environmental Impact

The reduction of carbon emissions is a major goal worldwide since the Paris Agreement in 2015. In this section, I quantify the gains that can be expected in terms of portfolio footprint when switching from brown to green commodities. Of course, this is a purely prospective perspective, as actual reductions will require economic shifts and re-allocations of production from higher intensity goods to lower intensity ones. But positive price pressure from investors can favor and accelerate such trends.

Table 10 gathers the average footprint of the different type of commodity indices. I split the analysis in four panel groups: ores and agrarian goods for the overarching panels and GHG versus water impact for the sub-panels.

Plainly, average intensities are rather homogeneous across the table, whereas raw emissions and water consumption are thousands of times larger for metals. This comes at least partly from the price disparity between ores and agrarian goods. One thousand dollars can buy a large amount of edibles, but only small quantities of precious metals. Hence, $1,000 invested in ores or agricultural goods will have comparable impacts, even though the activities that are being financed have inherently contrasted footprints.

A favorable feature of the sorting of metals on the GHG criterion is that the strong reduction in GHG intensity is also associated with a decline in water intensity. This also holds for agricultural futures, albeit in a less pronounced fashion. The reverse however is not true and the futures sorted on water intensity do not gain in GHG performance.

	GHG Intensity	GHG Emission	Water Intensity	Water Consumption
Panel A.1: Metal futures based on GHG				
all metals	1.5	2090.2	8.5	31155.2
brown	2.8	2,222.8	11.9	27,679.1
green	0.3	1,969.7	5.8	33,999.3
Panel A.2: Metal futures based on water consumption				
all metals	1.5	2090.2	8.5	31155.2
brown	1.3	3,705.3	14.3	48,609.9
green	1.7	680.5	2.8	13,700.6
Panel B.2: Agricultural futures based on GHG				
all goods	3.3	4.5	4.2	5.1
brown	4.8	5.5	4.9	5.0
green	1.7	3.4	3.6	5.3
Panel B.2: Agricultural futures based on water consumption				
all goods	3.3	4.5	4.2	5.1
brown	3.2	2.9	6.2	6.8
green	3.3	6.1	2.3	3.5

Table 10: **Footprint of portfolios**. This table provides the average footprint of portfolios based on greenhouse gases or water consumption. It further provides averages of intensities, but also actual GHG emissions and raw water consumption. The categorization green versus brown is provided in Tables 3 and 4.

Results above well quantifies the reduction in carbon intensity for the three asset portfolios. For equities, the reported intensity for the sustainable index is 57.35 tCO2e/\$M, versus 129.27 tCO2e/\$M for the equivalent non-carbon driven ETF,[6] which makes a ratio of 0.44 and a reduction of 56%. For the bond component, things are less straightforward, as S&P only communicates on the low carbon index, with a carbon to value ratio of 117.75tCO2e/\$M,[7] but they do not disclose on their business-as-usual indices. According to De Jong & Nguyen, 2016, it is possible to reduce the carbon intensity of bond portfolios by 50% to 65% without sacrificing tracking error performance. More recently, in their use case on high yield bonds, MSCI reports ratios between 0.41 and 0.47, implying reductions of the same magnitude as for equities.[8] Henceforth, I assume a reduction of 55% for equities and 50% for bonds. Note that according to Panel A.1 in Table 10, the reduction potential for the GHG-based metal index is five-fold, from 1.5 to 0.3, that is, a relative decrease of 80%, which is larger than that of the other two asset classes. The decline brought by the agricultural factor is close to 50%, i.e., similar to that of bonds or equities.

[6] See the documentation of the iShares MSCI ACWI ETF.

[7] See the documentation of the S&P500 Investment Grade Corporate Bond Index.

[8] Moreover, in their analysis on data providers and carbon intensity measurement, Swinkels & Markwat, 2024 find numbers that are very similar between developed equity markets and investment grade corporate bonds (when including Scope 3 emissions, see their Table 6). For an analysis of carbon intensity for these two asset classes, I further point to Wilson & Caldecott, 2023.

Figure 7 shows the GHG intensity reduction potential when including the GHG-driven commodity indices. With the agrarian factor, the intensity is stable and barely increasing as the proportion of commodities grows. With the metal index, the intensity shrinks from 47% (an already sizeable reduction) to below 42% if 20% of commodities in the allocation are included. It is feasible to further curtail the intensity by increasing the proportion of the metal index in the composition, but such levels (beyond 20%) are rare in practice.

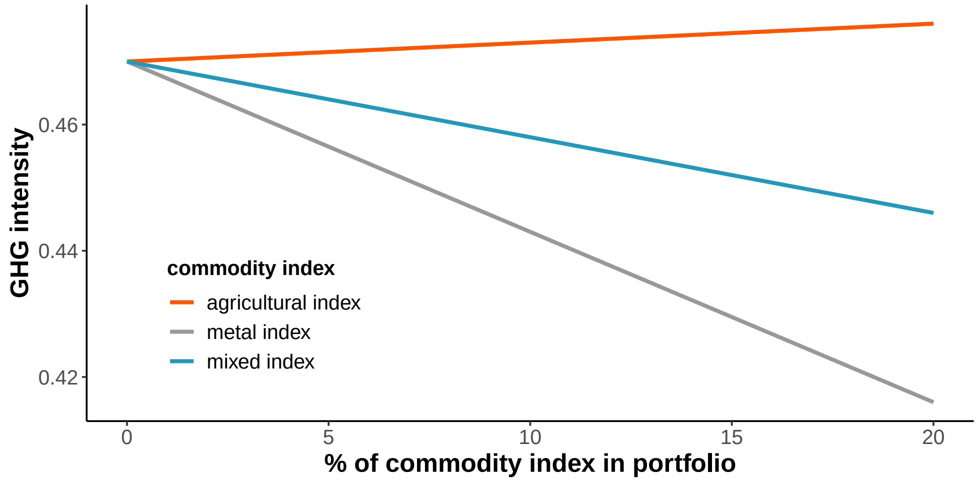

Figure 7: **Carbon intensity reduction**. I plot the GHG intensity of a three asset class allocation for three types of commodity pockets, shown with colors. The y-axis is scaled such that the unit intensity is that of a standard portfolio that ignores carbon concerns. The intensity reduction levels are 55% for equities, 50% for bonds and the agricultural index, and 80% for the GHG-based metal index. The mixed index consists of 50% of each commodity factors.

4. Chapter III: Green Commodity Producers' Firm Value

[Work-in-Due-Progress]

5. Chapter IV: Oil Shocks and Sustainability

[Work-in-Due-Progress]

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References

Albuquerque, R., Koskinen, Y., & Zhang, C. (2019). Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science*, 65(10), 4451–4469.

Anson, M. J. (1999). Maximizing utility with commodity futures diversification. *Journal of Portfolio Management*, 25(4), 86–94.

Arfaoui, N., Naeem, M. A., Boubaker, S., Mirza, N., & Karim, S. (2023). Interdependence of clean energy and green markets with cryptocurrencies. *Energy Economics*, 120, 106584.

Bachoo, K., Tan, R., & Wilson, M. (2013). Firm value and the quality of sustainability reporting in australia. *Australian Accounting Review*, 23(1), 67–87.

Bakshi, G., Gao, X., & Rossi, A. G. (2019a). Understanding the sources of risk underlying the cross section of commodity returns. *Management Science*, 65(2), 619–641.

Bakshi, G., Gao, X., & Rossi, A. G. (2019b). Understanding the sources of risk underlying the cross section of commodity returns. *Management Science*, 65(2), 619–641.

Basu, D., & Miffre, J. (2013). Capturing the risk premium of commodity futures: The role of hedging pressure. *Journal of Banking and Finance*, 37(7), 2652–2664.

Beccali, M., Maurizio, C., Maria, I., & Marina, M. (2009). Resource consumption and environmental impacts of the agrofood sector: Life cycle assessment of italian citrus-based products. *Environmental Management*, 43, 707–724.

Belousova, J., & Dorfleitner, G. (2012). On the diversification benefits of commodities from the perspective of euro investors. *Journal of Banking Finance*, 36(9), 2455–2472.

Bessembinder, H. (2018). The "roll yield" myth. *Financial Analysts Journal*, 74(2), 41–53.

Bhardwaj, G., Gorton, G., & Rouwenhorst, G. (2015). *Facts and fantasies about commodity futures ten years later* (tech. rep.). National Bureau of Economic Research.

Bianchi, R. J., Fan, J. H., Miffre, J., & Zhang, T. (2023). Exploiting the dynamics of commodity futures curves. *Journal of Banking & Finance*, 154, 106965.

Boons, M., & Prado, M. P. (2019). Basis-momentum. *Journal of Finance*, 74(1), 239–279.

Bryzgalova, S. (2015). Spurious factors in linear asset pricing models. *LSE Manuscript*, 1(3).

Bueb, J., & To, E. (2020). *Comment évaluer l'externalité carbone des métaux* (tech. rep.). France Stratégie (Report from the French Government).

Canellada, F., Laca, A., Laca, A., & Díaz, M. (2018). Environmental impact of cheese production: A case study of a small-scale factory in southern europe and global overview of carbon footprint. *Science of the Total Environment*, 635, 167–177.

Cerri, C. C., Moreira, C. S., Alves, P. A., Raucci, G. S., de Almeida Castigioni, B., Mello, F. F., Cerri, D. G. P., & Cerri, C. E. P. (2016). Assessing the carbon footprint of beef cattle in Brazil: A case study with 22 farms in the State of Mato Grosso. *Journal of Cleaner Production*, 112, 2593–2600.

Cherubini, F., Raugei, M., & Ulgiati, S. (2008). Lca of magnesium production: Technological overview and worldwide estimation of environmental burdens. *Resources, Conservation and Recycling*, 52, 1093–1100.

Clune, S., Crossin, E., & Verghese, K. (2017). Systematic review of greenhouse gas emissions for different fresh food categories. *Journal of Cleaner Production*, 140(2), 766–783.

Colla, V., Matino, I., Branca, T. A., Fornai, B., Romaniello, L., & Rosito, F. (2017). Efficient use of water resources in the steel industry. *Water*, 9(11), 874.

Coqueret, G. (2022). *Perspectives in sustainable equity investing*. CRC Press.

Cornell, B. (2021). Esg preferences, risk and return. *European Financial Management*, 27(1), 12–19.

Cornell, B., & Shapiro, A. C. (2021). Corporate stakeholders, corporate valuation and esg. *European Financial Management*, 27(2), 196–207.

Daskalaki, C., & Skiadopoulos, G. (2011). Should investors include commodities in their portfolios after all? new evidence. *Journal of Banking Finance*, 35(10), 2606–2626.

Davidson, A., Steve, B., & Gediga, J. (2016). Lead industry life cycles studies: Environmental impact and life cycle assessment of lead battery and architectural sheet production. *International Journal of Life Cycle Assessment*, 21, 1624–1636.

De Jong, M., & Nguyen, A. (2016). Weathered for climate risk: A bond investment proposition. *Financial Analysts Journal*, 72(3), 34–39.

Ekeland, I., Lautier, D., & Villeneuve, B. (2018). Hedging pressure and speculation in commodity markets. *Economic Theory*, 68(1), 83–123. https://doi.org/10.1007/s00199-018-1115-y

Erb, C. B., & Harvey, C. R. (2016). Conquering misperceptions about commodity futures investing. *Financial Analysts Journal*, 72(4), 26–35.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy*, 81(3), 607–636.

Farjana, S. H., Nazmul, H., & MA Parvez, M. (2019). Life cycle assessment of cobalt extraction process. *Journal of Sustainable Mining*, 18(3), 150–161.

Fernandez-Perez, A., Frijns, B., Fuertes, A.-M., & Miffre, J. (2018). The skewness of commodity futures returns. *Journal of Banking & Finance*, 86, 143–158. https://doi.org/10.1016/j.jbankfin.2017.06.015

Fernandez-Perez, A., Fuertes, A.-M., Gonzalez-Fernandez, M., & Miffre, J. (2020). Fear of hazards in commodity futures markets. *Journal of Banking & Finance*, 119, 105902. https://doi.org/10.1016/j.jbankfin.2020.105902

Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics*, 142(2), 499–516.

Frankel, J. A., & Rose, A. K. (2010). *Determinants of agricultural and mineral commodity prices* (Working Paper No. RWP10-038). Harvard Kennedy School of Government.

Gan, Y., & Griffin, W. M. (2018). Analysis of life-cycle GHG emissions for iron ore mining and processing in China — Uncertainty and trends. *Resources Policy*, 58, 90–96.

Geman, H., & Nguyen, V.-N. (2005). Soybean inventory and forward curve dynamics. *Management Science*, 51(7), 1076–1091. https://doi.org/10.1287/mnsc.1050.0361

Glaister, B. J., & Mudd, G. M. (2010). The environmental costs of platinum–PGM mining and sustainability: Is the glass half-full or half-empty? *Minerals Engineering*, 23(5), 438–450.

Gonzalez, M. N. G., & Björnsson, L. (2022). Life cycle assessment of the production of beet sugar and its by-products. *Journal of Cleaner Production*, 346, 131211.

Gorton, G., & Rouwenhorst, K. G. (2006). Facts and fantasies about commodity futures. *Financial Analysts Journal*, 62(2), 47–68.

Gorton, G. B., Hayashi, F., & Rouwenhorst, K. G. (2012). The fundamentals of commodity futures returns. *Review of Finance*, 17(1), 35–105.

Gunathilaka, L. F. D. Z., & Gunawardana, K. D. (2015). Carbon footprint calculation from cradle to grave: A case study of rubber manufacturing process in sri lanka. *International Journal of Business and Social Science*, 6(10), 82–94.

Gunson, A. J. (2013). *Quantifying, reducing and improving mine water use* [Doctoral dissertation, University of British Columbia].

Haque, N. (2022). Life cycle assessment of iron ore mining and processing. In *Iron ore* (pp. 691–710). Elsevier.

Haque, N., Hughes, A., Lim, S., & Vernon, C. (2014). Rare earth elements: Overview of mining, mineralogy, uses, sustainability and environmental impact. *Resources*, 3(4), 614–635.

Hasan, M. M., Wong, J. B., & Al Mamun, M. A. (2022). Oil shocks and corporate social responsibility. *Energy Economics*, 107, 105881.

Hedayati, M., Brock, P. M., Nachimuthu, G., & Schwenke, G. (2019). Farm-level strategies to reduce the life cycle greenhouse gas emissions of cotton production: An Australian perspective. *Journal of Cleaner Production*, 212, 974–985.

Hertwich, E. G. (2021). Increased carbon footprint of materials production driven by rise in investments. *Nature Geoscience*, 14(3), 151–155.

Hollstein, F., Prokopczuk, M., & Tharann, B. (2021). Anomalies in commodity futures markets. *Quarterly Journal of Finance*, 11(04), 2150017. https://doi.org/10.1142/s2010139221500178

Hong, H., & Yogo, M. (2012). What does futures market interest tell us about the macroeconomy and asset prices? *Journal of Financial Economics*, 105(3), 473–490.

Hsu, P.-H., Li, K., & Tsou, C.-Y. (2023). The pollution premium. *The Journal of Finance*, 23(3), 1343–1392.

Huang, T.-Y., Perez-Cardona, J. R., Zhao, F., Sutherland, J. W., & Paranthaman, M. P. (2021). Life cycle assessment and techno-economic assessment of lithium recovery from geothermal brine. *ACS Sustainable Chemistry & Engineering*, 9(19), 6551–6560.

Idoine, N., Raycraft, E., Price, S., F. Hobbs, Deady, E., Everett, P., Shaw, R., Evans, E., & Mills, A. (2023). *World mineral production 2017-2021*. British Geological Survey (UK Research; Innovation).

Jekayinfa, S., Olaniran, J., & Sasanya, B. (2013). Life cycle assessment of soybeans production and processing system into soy oil using solvent extraction process. *International Journal of Product Lifecycle Management*, 6(4), 311–321.

Kim, D., Thoma, G., Nutter, D., Milani, F., Ulrich, R., & Norris, G. (2013). Life cycle assessment of cheese and whey production in the USA. *The International Journal of Life Cycle Assessment*, 18, 1019–1035.

Kuang, W. (2021). Are clean energy assets a safe haven for international equity markets? *Journal of Cleaner Production*, 302, 127006.

Lam, W. Y., Kulak, M., Sim, S., King, H., Huijbregts, M. A., Chaplin-Kramer & Rebecca. (2019). Greenhouse gas footprints of palm oil production in Indonesia over space and time. *Science of the Total Environment*, 688, 827–837.

Le Pen, Y., & Sévi, B. (2018). Futures trading and the excess co-movement of commodity prices. *Review of Finance*, 22(1), 381–418.

Lei, H., Xue, M., Liu, H., & Ye, J. (2023). Precious metal as a safe haven for global ESG stocks: Portfolio implications for socially responsible investing. *Resources Policy*, 80, 103170.

Lins, K., Servaes, H., & Tamayo, A. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *The Journal of Finance*, 72(4), 1785–1824.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1), 77–91.

Maus, V., & Werner, T. T. (2024). Impacts for half of the world's mining areas are undocumented. *Nature*, 625(7993), 26–29.

Meißner, S. (2021). The impact of metal mining on global water stress and regional carrying capacities — A GIS-based water impact assessment. *Resources*, 10(12), 120.

Mekonnen, M., & Hoekstra, A. (2010a). *The green, blue and grey water footprint of crops and derived crop products* (tech. rep.). Institute for Water Education.

Mekonnen, M., & Hoekstra, A. (2010b). *Tthe green, blue and grey water footprint of farm animals and animal products* (tech. rep.). UNESCO-IHE Institute for Water Education. URL.

Menla, F., Wu, Y., & Zhang, X. (2023). Esg disclosure, ceo power and incentives and corporate risk-taking. *European Financial Management*.

Mertzanis, C., & Tebourbi, I. (2024). Geopolitical risk and global green bond market growth. *European Financial Management*, eufm.12484.

Miffre, J. (2016). Long-short commodity investing: A review of the literature. *Journal of Commodity Markets*, 1(1), 3–13.

Miffre, J., & Rallis, G. (2007). Momentum strategies in commodity futures markets. *Journal of Banking & Finance*, 31(6), 1863–1886.

Molenaar, R., Senechal, E., Swinkels, L., & Wang, Z. (2023). Empirical evidence on the stock-bond correlation. *SSRN Working Paper*, 4514947.

Naeem, M. A., Nguyen, T. T. H., Nepal, R., Ngo, Q.-T., & Taghizadeh–Hesary, F. (2021). Asymmetric relationship between green bonds and commodities: Evidence from extreme quantile approach. *Finance Research Letters*, 43, 101983.

Naqvi, B., Rizvi, S. K. A., Hasnaoui, A., & Shao, X. (2022). Going beyond sustainability: The diversification benefits of green energy financial products. *Energy Economics*, 111, 106111.

Nguyen, T. T. H., Naeem, M. A., Balli, F., Balli, H. O., & Vo, X. V. (2021). Time-frequency comovement among green bonds, stocks, commodities, clean energy, and conventional bonds. *Finance Research Letters*, 40, 101739.

Northey, S., Nawshad, H., & Mudd, G. (2013). Using sustainability reporting to assess the environmental footprint of copper mining. *Journal of Cleaner Production*, 40, 118–128.

Nuss, P., & Eckelman, M. J. (2014). Life cycle assessment of metals: A scientific synthesis. *PloS one*, 9(7), e101298.

Oestreich, M., & Tsiakas, I. (2015). Carbon emissions and stock returns: Evidence from the eu emissions trading scheme. *Journal of Banking and Finance*, 58, 294–308.

Perks, C., Mudd, G. M., & Currell, M. (2022). Using corporate sustainability reporting to assess the environmental footprint of titanium and zirconium mining. *The Extractive Industries and Society*, 9, 101034.

Petersson, T., Secondi, L., Magnani, A., Antonelli, M., Dembska, K., Valentini, R., Varotto, A., & Castaldi, S. (2021). A multilevel carbon and water footprint dataset of food commodities. *Scientific Data*, 8(1), 127.

Phan, D. H. B., Tran, V. T., Tee, C. M., & Nguyen, N. (2021). Oil price uncertainty, csr and institutional quality: A cross-country evidence. *Energy Economics*, 100, 105339.

Politis, D. N., & White, H. (2004). Automatic block-length selection for the dependent bootstrap. *Econometric Reviews*, 23(1), 53–70.

Qian, Y., Liu, X., & Jiang, Y. (2024). Factor momentum in commodity futures markets. *SSRN Working Paper*, 4678928.

Rad, H., Low, R. K. Y., Miffre, J., & Faff, R. (2020). Does sophistication of the weighting scheme enhance the performance of long-short commodity portfolios? *Journal of Empirical Finance*, 58, 164–180.

Rad, H., Low, R. K. Y., Miffre, J., & Faff, R. (2022). The strategic allocation to style-integrated portfolios of commodity futures. *Journal of Commodity Markets*, 28, 100259. https://doi.org/10.1016/j.jcomm.2022.100259

R&M. (2019). *World concentrated orange juice market report 2019: Analysis, forecast, size, trends and insights 2007-2018 and 2019-2025* (tech. rep.). Research and Markets. URL.

Rost, S., Gerten, D., Bondeau, A., Lucht, W., Rohwer, J., & Schaphoff, S. (2008). Agricultural green and blue water consumption and its influence on the global water system. *Water Resources Research*, 44(9).

Ruano, F., & Barros, V. (2022). Commodities and portfolio diversification: Myth or fact? *The Quarterly Review of Economics and Finance*, 86, 281–295.

Sakkas, A., & Tessaromatis, N. (2020). Factor based commodity investing. *Journal of Banking & Finance*, 115, 105807.

Seabra, J. E. A., Macedo, I. C., Chum, H. L., Faroni, C. E., & Sarto, C. A. (2011). Life cycle assessment of Brazilian sugarcane products: GHG emissions and energy use. *Biofuels, Bioproducts and Biorefining*, 5(5), 519–532.

Shrout, P. E., & Bolger, N. (2002). Mediation in experimental and nonexperimental studies: New procedures and recommendations. *Psychological Methods*, 7(4), 422–445.

Shu, R., Cao, X., & Wu, M. (2021). Clarifying regional water scarcity in agriculture based on the theory of blue, green and grey water footprints. *Water Resources Management*, 35(3), 1101–1118.

Spanos, C., Turney, D. E., & Fthenakis, V. (2015). Life-cycle analysis of flow-assisted nickel zinc-, manganese dioxide-, and valve-regulated lead-acid batteries designed for demand-charge reduction. *Renewable and Sustainable Energy Reviews*, 43, 478–494.

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225, 175–199.

Survey, U. G. (2023). *Mineral commodity summary*. Government Printing Office.

Swinkels, L., & Markwat, T. (2024). Corporate carbon emissions data for equity and bond portfolios. *Managerial Finance*, 50, 118–139.

Szymanowska, M., De Roon, F., Nijman, T., & Van den Goorbergh, R. (2014). An anatomy of commodity futures risk premia. *Journal of Finance*, 69(1), 453–482.

Tang, K., & Xiong, W. (2012). Index investment and the financialization of commodities. *Financial Analysts Journal*, 68(6), 54–74.

Ulrich, S., Trench, A., & Hagemann, S. (2020). Greenhouse gas emissions and production cost footprints in australian gold mines. *Journal of Cleaner Production*, 267, 122118.

Vera, M. L., Torres, W. R., Galli, C. I., Chagnes, A., & Flexer, V. (2023). Environmental impact of direct lithium extraction from brines. *Nature Reviews Earth & Environment*, 4(3), 149–165.

Wang, S., & Zhang, T. (2023). Predictability of commodity futures returns with machine learning models. *Journal of Futures Markets*, Forthcoming.

Wang, Y., & Xu, M. (2023). Can esg activities stabilise ipo prices? evidence from the hong kong stock market. *European Financial Management*.

Wilson, C., & Caldecott, B. (2023). Investigating the role of passive funds in carbon-intensive capital markets: Evidence from US bonds. *Ecological Economics*, 209, 107792.

Yang, F. (2013). Investment shocks and the commodity basis spread. *Journal of Financial Economics*, 110(1), 164–184.

Yang, J., Zhou, Y., & Wang, Z. (2009). The stock–bond correlation and macroeconomic conditions: One and a half centuries of evidence. *Journal of Banking & Finance*, 33(4), 670–680.

Yoon, B., Lee, J., & Byun, R. (2018). Does esg performance enhance firm value? evidence from korea. *Sustainability*, 10(10), 3635.

Zerbib, O. D. (2022). A sustainable capital asset pricing model (s-capm): Evidence from environmental integration and sin stock exclusion. *Review of Finance*, 26(6), 1345–1388.

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering baron and kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, 37(2).