ESG Comes to Town

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In recent years, environmental, social and governance (ESG) themes have rapidly risen to prominence within equities and fixed income. In commodities however, this discussion is still in its infancy. While there is now a vast body of literature on incorporating aspects of ESG in stock and bond portfolios, there has been relatively little guidance for commodities investors. In order to develop an investment framework to incorporate ESG into commodities portfolios, we need to identify the key metrics, understand whether these can be standardized across sectors, and construct investible portfolios that reflect these metrics.

Using Bloomberg corporate ESG data and the Bloomberg Industry Classification Standard (BICS), we construct greenhouse gas (GHG) estimates for each metal that is a constituent of the Bloomberg Commodity Index (BCOM) benchmark. The estimation procedure is regression-based and incorporates an error measure for full transparency. As an alternative to a carbon offset-based approach, we identify three possible routes by which commodities investors can control for the different aspects of ESG within their portfolios.

This research is intended to be the first in a series of papers aimed at generalizing our approach across the five commodities sectors and main ESG themes — in much the same way cross-asset risk premia investing has been covered over the past decade. In this article we:

- *Highlight the unique interpretation issues for commodities investors with regard to ESG investing;*
- *Provide a summary of the factors that need to be considered when estimating GHG emissions for metals production;*
- *Propose a transparent, rules-based approach for estimating GHG emissions per metal using primary data available to all Bloomberg users; and*
- *Construct systematic portfolios incorporating GHG-based scores.*

Introduction

The past few years has seen a rapid rise in the popularity of ESG investing. On the back of regulation and evolving investment principles, equity and fixed income investors have integrated environmental, social and governance pillars into their core portfolios. As this has become increasingly commonplace, attention has turned to commodities portfolios. While tempting, it is not a straightforward step to extend the framework used for equities and fixed income to commodities.

Equity and fixed income investors are often motivated by the potential to alter corporate behavior through ownership stakes and providing project financing. For commodities, we make a more modest claim. Commodities are typically included in wider investment portfolios as a source of returns diversification and a hedge against inflation. The aim of investors is to maintain these investment characteristics while reducing portfolio exposure to sources of pollution, social injustice and bad governance. In other words, given ESG characteristics displayed by individual commodities and/or sectors, how can investors optimize exposure?

This approach assumes commodities investors are passive participants in the ESG movement which can be illustrated by way of a stylized example. Equity investors might take a stake in different mining companies to actively seek a reduction in GHG emissions during the extraction processes. With limited ability to affect corporate behavior or spot demand, commodities investors likely need to assume the level of GHG emissions are given (exogenous), and might choose a different investment mix (via futures contracts) to reflect the differences in emissions levels.

Introducing the concept of ESG to commodities is further complicated for a variety of reasons — ranging from the claim that commodities themselves might be contra to the philosophy of ESG investing, to the lack of a clear causal relationship between futures and physical production to investor objectives. This article is the first in a series of papers in which we address these issues and in doing so hope to provide readers with different lenses with which to view ESG investing in commodities.

Establishing a Framework

In order to construct a coherent investment framework, one needs to identify (1) the underlying investment universe and (2) the key issues within the environmental, social and governance pillars (which are often referred to as a 'materiality map'). Our firm is currently launching corporate ESG scores on a rolling basis. These scores are based on a comprehensive database of publicly disclosed company-level data. As part of this effort, materiality maps are created per sector (as defined by Bloomberg's industry classifications), following which company-level sector scores are constructed based on the relevant metrics.

The Bloomberg Commodities Index (BCOM) is a leading commodities benchmark; as of September 2020, it contained 23 commodities covering the five major sectors. Benchmark replication is carried out using U.S. dollar denominated futures. Many investors allocate to either the flagship BCOM index or the sector indices with the aim of being able to diversify portfolio returns, hedge inflation risk and, increasingly, to provide exposure to alternative risk premia.

Given its prominence both in sustainability policy discourse and amongst investors, we begin with GHG emissions. In subsequent articles, we will extend this analysis to match other issues found in the materiality map. Since the BICS framework allows for an easy mapping between metals and mining producers and the metals included in the BCOM benchmark, we start our analysis by focusing on the industrial and precious metals sectors.

Given the investible instruments are futures contracts, we need to measure GHG exposure per contract or per U.S. dollar. In line with standard asset allocation decisions, we use the U.S. dollar as the unit of measurement. Calculating the GHG per U.S. dollar for each metal is a two-step process: identify a suitable data source and transform the raw data to a U.S. dollar metric.

An aim of this article is to explore possible avenues by which existing commodities investors can incorporate ESG objectives into their allocations. Presently, the dominant route appears to involve allocating to a commodities benchmark followed by an offset trade (e.g., carbon offsets). Alternatively, some investors have abstained from certain commodities or sectors (e.g., BCOM excluding Agriculture & Livestock). We examine an alternative approach whereby reweighting commodities within a portfolio can reflect investors' ESG preferences and thresholds. We also hope this framework will help re-engage those investors reluctant to allocate to commodities because they believe it is incompatible with ESG investing.

<u>Literature Survey</u>

A review of the literature on the metals' extraction processes highlights several factors which complicate GHG estimation. The main findings are:

1. Metals are jointly extracted (and/or are byproducts);

2. Mining equipment varies by company;

3. Significant geographical variations in soil-type and deposit access;

4. The energy sources for extraction vary by country; and

5. Recycled production of metals is less GHG emissions intensive than primary extraction.

Academic and practitioner studies on estimating GHG scores for metals take one of two approaches, which can be summarized as follows:

1. Macro-based: Combine GHG estimates from supranational agencies with production estimates from industry bodies and

2. Micro-based: Use the data available in public companies' annual and sustainability reports.

The first approach has the benefit of aggregating different production methods and geographical variations, but suffers from a high degree of opacity with respect to estimation methodology and the underlying data sources. The second method is typically based on a limited number of companies and can be biased by region or the companies selected for the study. We use a regression-based method that combines the two approaches above; it aggregates a wide universe of company level data to form a macro-level estimate.

Data

The Bloomberg ESG database contains company-level data, collected annually, on aggregate GHG emissions covering scope 1 and scope 2 (direct and indirect emissions controlled by the company) and revenue breakdowns by business lines. The emissions data is available via sustainability reports. There are not (as yet) universally mandated reporting standards and the data is self-reported. Using the Bloomberg Industry Classification Standard (BICS), we identify metals and mining companies which derive in excess of 85% of total revenue from mining one or more of the following metals – gold, silver, aluminum, copper, zinc and nickel. Companies eligible (for the analysis) are those which disclose GHG emissions. As Figure 1 illustrates, the sample size has grown over the nine-year period spanning 2011 – 2019. Note that as of the writing of this paper, 2019 data was still under collection and some companies were to disclose their metrics in the 2nd half of 2020.

Figure 1
Sample Size (Aggregate Revenue by Metal in U.S. Dollar Millions)

	2011	2012	2013	2014	2015	2016	2017	2018	2019
Aluminum	72,903	62,302	59,981	58,301	41,512	49,922	71,118	84,316	62,661
Copper	27,792	26,354	31,394	24,824	24,287	30,008	33,036	39,797	20,958
Gold	50,865	53,206	51,316	48,109	46,025	48,865	52,966	58,651	42,559
Nickel	1,262	1,464	1,572	1,591	1,230	1,563	1,448	2,020	1,268
Silver	7,958	7,819	5,529	4,682	4,679	4,679	4,809	4,409	1,727
Zinc	2,254	2,065	2,206	2,503	1,703	1,788	2,664	2,992	1,095

Source: Bloomberg.

The coverage ratio provides an indication of the proportion of companies within the database which report GHG emissions (Figure 2).

Figure 2
Coverage Ratio

	2011	2012	2013	2014	2015	2016	2017	2018	2019
Aluminum	55%	66%	64%	62%	53%	60%	71%	67%	55%
Copper	46%	46%	66%	60%	61%	67%	64%	11%	39%
Gold	64%	57%	55%	63%	52%	64%	67%	74%	52%
Nickel	28%	30%	37%	39%	41%	77%	81%	88%	48%
Silver	64%	66%	70%	64%	72%	59%	67%	73%	28%
Zinc	61%	54%	62%	58%	41%	47%	50%	69%	31%

Source: Bloomberg.

It is also important to note there is significant variation in the number of companies that produce each of the metals. There is also an increase in the proportion of companies reporting over time (Figure 2). The count includes companies reporting both revenues and GHG emissions (Figure 3).

Figure 3
Breakdown of Companies per Metal (2011-2019)

	2011	2012	2013	2014	2015	2016	2017	2018	2019
Aluminum	3	3	3	3	3	4	7	8	8
Copper	10	11	13	13	15	16	16	15	10
Gold	22	23	30	34	38	40	45	45	30
Nickel	4	5	6	6	6	7	6	6	4
Silver	5	6	7	10	14	15	15	16	9
Zinc	5	5	7	8	8	9	9	10	4

Source: Bloomberg.

In subsequent sections, we also include data for steel, lead, platinum and coal where required, as they assist in estimates. Please note that when included, the estimates for these non-BCOM constituents are calculated in a same manner as the BCOM constituents.

Estimation Methodology

The first step is to estimate the amount of metal produced in metric tons (tonnes). The transformation from U.S. dollar revenue to tonnage is carried out using the spot price of each respective metal. The Bloomberg tickers used as a proxy for the spot price are given in Figure 4. Since the price varies over the course of the year, we use the average spot price per calendar year. In the absence of a more detailed picture of hedging behavior, this assumption is reasonable.

Figure 4
Bloomberg Tickers: Metal Spot Prices

Metal	Gold	Silver	Copper	Aluminum	Nickel	Zinc
Ticker	XAU	XAG	LMCADY	LMAHDY	LMNIDY	LMZSDY

Source: Bloomberg.

Based on the spot prices, we have a corporate dataset containing an estimate for physical production/extraction by metal and the overall GHG emissions. The output varies considerably by firm as does the product mix (Figures 5 and 6). For this analysis, we do not account for possible economies of scale in production (which is typically modeled using a version of the Cobb-Douglas production function) since we want to keep the regression model parsimonious. We might revisit this assumption in later articles.

Companies are divided into production groups, which are defined by the mix of metals each company produces. As seen in Figure 5, we have 23 production groups. A pre-processing step for the regression is to calculate an average emission per metal based on each of the production groups.

Figure 5
Pure-Play Companies versus Mixed-Production Companies

Production type	Production group	Count (2018)
Pure play	Aluminum	6
	Coal	7
	Gold	26
	Iron	6
	Nickel	2
	Platinum	2
Mixed production	Aluminum-Coal-Copper-Iron	1
	Aluminum-Gold-Nickel	1
	Coal-Copper-Iron	1
	Coal-Iron	1
	Coal-Iron-Platinum	1
	Copper-Gold	2
	Copper-Gold-Lead-Nickel-Silver-Zinc	1
	Copper-Gold-Lead-Silver-Zinc	3
	Copper-Gold-Platinum-Zinc	1
	Copper-Gold-Silver	2
	Copper-Gold-Silver-Zinc	3
	Copper-Zinc	1
	Gold-Lead-Silver-Zinc	2
	Gold-Nickel	1
	Gold-Nickel-Platinum	1
	Gold-Platinum	1
	Gold-Silver	6

Source: Bloomberg.

Our research has determined that limiting cross-production produces more credible estimates. Accordingly, we start by focusing on the industrial metals sector (hence excluding companies that produce any precious metals.)

Figure 6
Estimated Metals & GHG Production (Base-Only Groups, 2012-2019)

Group	Aluminum	Coal	Copper	Iron	Nickel	Zinc	GHG
Aluminum (AL)	141,035	0	0	0	0	0	488,506
Coal (CA)	0	485,230	0	0	0	0	98,780
Copper (HG)	0	0	3,493	0	0	0	15,300
Iron (FE)	0	0	0	19,369	0	0	40,140
Nickel (NI)	0	0	0	0	262	0	2,953
AL + CA + HG + FE	45,627	154,262	5,804	26,868	0	0	239,300
AL + HG + FE	5,772	0	858	5,029	0	0	26,800
CA + HG + FE	0	178,403	6,706	11,668	0	0	65,600
CA + FE	0	68,829	0	5,676	0	0	19,009
HG + Zinc	0	0	1,673	0	0	1,367	5,051

Source: Bloomberg.

Calculating Metal Intensities

Given the use of annual data and the steady increase of GHG disclosure, we use the full sample for the analysis. In our study, the estimation of metal intensities is based on a three-step process:

1. Gold intensity is based on pure-players, using a trimmed mean;

2. Industrial metals intensities are calculated using Ordinary Least Squares (OLS) regression on data aggregated to production groups; and

3. A plug-in approach is used to calculate the silver intensity using the gold-silver joint producer group.

Gold Intensity

Since we have a relatively large number of pure-play gold miners, we estimate intensity by using the median of intensities across companies. This accounts for outliers with negligibly small production levels. The (median) gold intensity is calculated to be 20,298 tons of GHG per (metric) tonne of gold extracted.

Industrial Metal Intensity

The regression estimates for industrial metals are given in Figure 7 along with the confidence intervals. As we can see, the estimation is noisy around the mean, leading to intervals that contain negative values in the case of copper, nickel and zinc.

Figure 7
Base Metal Intensities

	Intensity	Standard error	Confidence interval (5%)	Confidence interval (95%)
Copper	1.8	1.1	-1.2	4.7
Aluminum	3.5	0.1	3.3	3.6
Nickel	11.3	26.7	-62.9	85.4
Zinc	1.6	5.3	-13.1	16.2

Source: Bloomberg.

Naturally, the floor on estimates are 0 and we show the negative values simply to highlight the uncertainty bounds around the estimation. We believe these are a reflection of the variation due to disparate geographies in which the metals are mined, differences in infrastructure and the difficulty in attributing emissions to individual metals in cases of co-production.

Silver Intensity

Due to the fact silver is often extracted as a byproduct of zinc, nickel and copper mining, it is difficult to estimate the intensity using the standard regression-based approach. Instead, silver intensity is estimated as a residual using the emissions data from the joint gold-and-silver producer group. The gold estimate (from above) is plugged-in to provide the gold contribution to GHG emissions. The residual amount of emissions is attributed to silver extraction. Based on this method, the median value of the silver intensity is 63.9 tons of GHG per metric ton of silver.

How Do the Estimates Compare to the Literature?

By highlighting the emissions over the lifecycle of the extraction process, the body of academic literature illustrates the different considerations that lead to estimation variability. These include (in no particular order) the location of mines (soil/rock composition), method of extraction and refining, the equipment used for extraction, energy sources and the percentage of recycling. This is reflected in the confidence intervals (Figure 8).

Figure 8
Literature Estimates

	Nickel	Copper	Lead	Zinc	Aluminum	Silver	Gold
Mean	11.3	4.5	2.1	3.8	13.9	76.3	23,949
Standard deviation	4.8	2.5	0.8	0.7	7.5	68	8,515

Sources: Bloomberg, The Silver Institute, The World Gold Council, and academic citations listed in References section.

Some common examples include the dominance of renewable energy versus coal in Scandinavia and Australia respectively, the use of different purification processes for refining zinc and the lower emissions levels of using recycled scrap metals versus primary mining.

Aggregating over different geographies and companies creates an average value that might not fit many companies individually, but is the best representation of the group. This should be consistent with a commodities investor's needs in that the reference (deliverable) entity for a commodities futures contract is not linked to a particular company; and hence can treated as a (hypothetical) 'average producer'.

Portfolio Applications

The estimate for GHG emissions outlined above is on a per tonne basis. How can benchmark investors incorporate this into their portfolios? One approach is to convert the intensities into a U.S. dollar metric. The conversion per tonne to U.S. dollars can be handled by dividing the intensity per tonne by the spot metal price per tonne. For metal *i* at time *t*, we have:

$$GHG\ per\ US\ dollar_t^i = \frac{GHG\ per\ tonne_t^i}{US\ dollar\ per\ tonne_t^i}$$

Since the numerator is estimated using a long history while the denominator is a spot measure, the time variation in the measure is from the denominator, which is similar to a dividend yield measure for equities (Figure 9).

Figure 9
GHG per U.S. Dollar

	Gold	Silver	Copper	Aluminum	Nickel	Zinc
2014	5.07	1.09	2.48	18.57	6.78	7.47
2015	5.54	1.32	3.11	20.87	9.85	8.49
2016	5.15	1.22	3.51	21.56	11.91	7.91
2017	5.1	1.21	2.77	17.6	10.96	5.62
2018	5.06	1.32	2.61	16.43	8.7	5.6
2019	4.62	1.28	2.83	19.24	8.29	6.36
Jan – Jun 2020	3.9	1.25	3.11	21.73	9.09	7.91

Source: Bloomberg.

Changes in GHG per U.S. dollar (GHGD) is implicitly an inverse function of price trends: a negative trend in a metal's price translates to an increase in the GHGD. This can be explained in the following terms: a cheapening of an asset (in this case the commodity future) translates to a greater number of futures purchased — indirectly resulting in holding more physical assets. Given this relationship, tilting exposures based on GHGD will introduce trend-based tilts.

In this study, portfolios are rebalanced on a monthly frequency; weights are calculated at each month-end and applied in the upcoming month. It is important to note that for all three models presented, the results are not point-in-time since the GHG estimate encompasses the full sample. From September 2020 onwards, results will contain no forward-looking data.

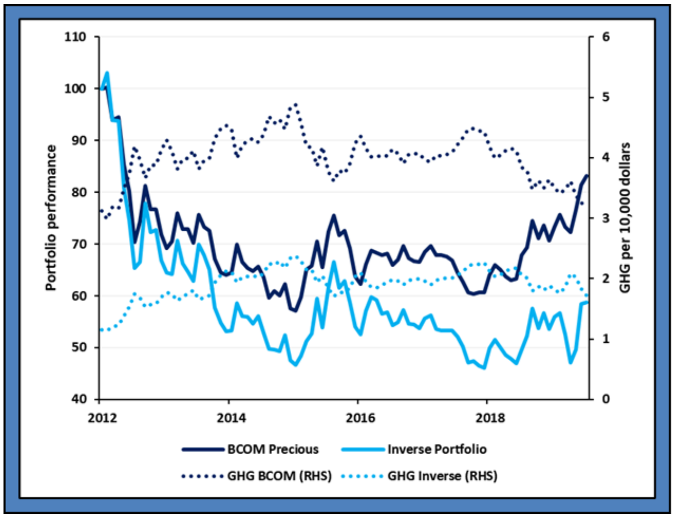
Inverse GHGD Weights

Weights are allocated to commodities inversely proportional to the GHGD value. This approach seeks to equalize the marginal contributions to GHG emissions per commodity. The methodology is identical to an inverse volatility portfolio and is a 2-step process. For commodity *i* at time *t*, the weight allocated (ω) is given by:

$$\varphi_t^i = \frac{1}{GHGD_t^i}$$

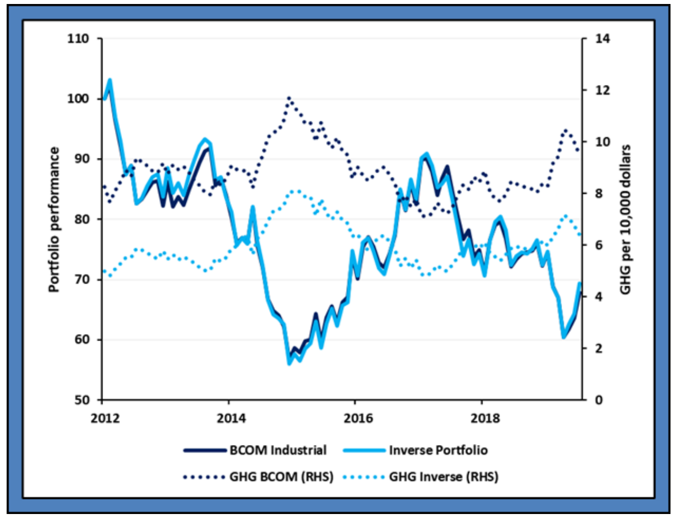
$$\omega_t^i = \frac{\varphi_t^i}{\sum_{i=1}^{N} \varphi_t^i}$$

Figure 10
Precious Metals



Source: Bloomberg.

Figure 11
Industrial Metals



Source: Bloomberg.

The results for precious metals and industrial metals are strikingly different. With precious metals, there is a trade-off between the GHGD of the portfolio and the annualized portfolio return (Figure 10). In the case of industrial metals, a lower GHGD is not accompanied by any performance degradation (Figure 11). This can be explained by (1) the number of constituents per portfolio and (2) the relationship between metal prices.

Figure 12
Industrial Metals: Similar Pairwise Correlations

	Nickel	Copper	Aluminum	Zinc
Nickel		0.51	0.56	0.52
Copper			0.57	0.69
Aluminum				0.61
Zinc				

Source Bloomberg.

Figure 13
Annualized Volatility of Returns

	Annualized volatility
Nickel	28.5%
Copper	18.9%
Aluminum	17.1%
Zinc	20.3%
Gold	14.3%
Silver	26.9%

Source Bloomberg.

While the correlation between gold and silver is high (0.8 over the period 2012 – June 2020), silver volatility is approximately twice that of gold (Figure 13). An increase in the weight of silver leads to higher portfolio volatility. Furthermore, during the recent past the correlation between gold and silver has fallen (0.6 over the period 2018 – 2020) with inflationary concerns and the use of gold as a store-of-value asset. From Figure 9, we see the GHGD for silver is approximately 1/5th that of gold. As a result, the precious metals portfolio consists of 70-80% silver and 20-30% gold, which is a reversal of the weights in the BCOM precious metals index. The average reduction is 2.1 tonnes of GHG per 10,000 dollars in exchange for a reduction in returns of 4.4% per annum.

The similar performance of the inverse GHGD weight industrial metals portfolio and the BCOM Industrial Metals benchmark can be attributed to the similar correlations (Figure 12) and volatilities (Figure 13) between the four industrial metals. In the portfolio context, the impact of the relatively high volatility of nickel is mitigated by the modest pairwise correlations. In effect, this makes the constituents of the industrial metals portfolio interchangeable, leading to the result of lower GHGD with little impact on portfolio returns.

The inverse GHGD weighting provides a route to lower the value of GHG associated with a commodities portfolio. However, it does not control — either implicitly or explicitly — the degree to which the ESG portfolio deviates from the BCOM benchmark. This unconstrained portfolio might not suit those seeking to incorporate elements of ESG investing while continuing to track the broad benchmark. To account for this, we modify the model above in two ways: the first is by applying a rules-based tilt on BCOM weights and the second is to use an optimization-based approach.

<u>Rules-based Tilting</u>

We combine the GHGD scores and the BCOM benchmark weights. Once again, we maintain a monthly rebalancing frequency. At a given time *t*, the modified score for commodity *i* is given by τ:

$$\tau_t^i = \left(1 + \beta_t^i\right) * \left(1 + \omega_t^i\right)^\gamma$$

Here β and ω refer to the BCOM benchmark weight and inverse GHGD weight, respectively. The degree to which weights are tilted based on GHG scores is controlled by γ (tilt factor). For illustration purposes, we set γ = 1 for the remainder of this section.

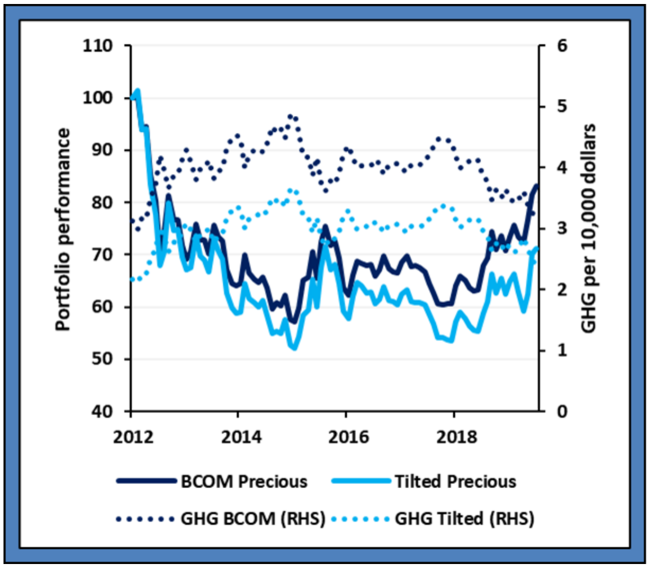
The final weight is given by:

$$\theta_t^i = \frac{\tau_t^i}{\sum_{i=1}^N \tau_t^i}$$

The results over the period 2012 – June 2020 are shown in Figures 14 and 15. With respect to the precious metals portfolio, lowering the impact of the GHGD score relative to the inverse GHGD approach moderates the underweight in gold (relative to the BCOM benchmark). Over the sample period, the average allocation to gold was 48%. Relative to the BCOM Precious Metals benchmark, a reduction in 1 tonne of GHG (per 10,000 dollar) is accompanied by a corresponding decline in portfolio returns of 2% per annum (Figure 14).

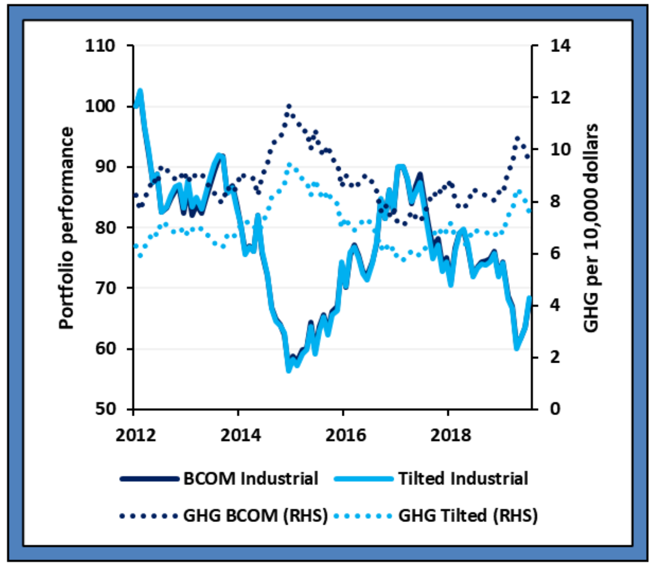
In the case of industrial metals, the results are similar to that of the inverse GHGD portfolio. There is little-to-no impact on portfolio performance by introducing GHG-based tilts. However, the reduction in GHG per 10,000 dollars is smaller (but still meaningful) given the objective function is not solely GHG reduction (Figure 15).

Figure 14
Precious Metals



Source: Bloomberg.

Figure 15
Industrial Metals



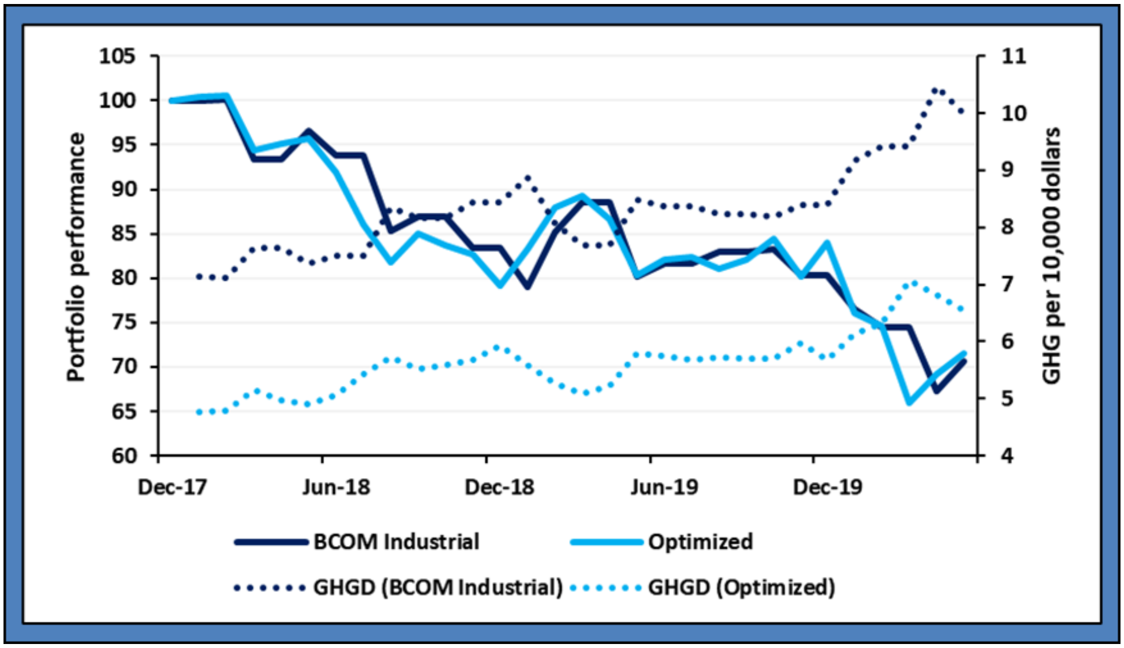
Source: Bloomberg.

Portfolio Optimization

Finally, we turn to an optimization-based approach to assign weights. The objective function is the minimization of (portfolio) GHGD while controlling for deviations in returns and constituent weights from the benchmark. The weight constraints can be viewed as an additional layer of security in the event of a sudden change in the correlation structure. Weights are floored at 0.5x those in the BCOM sector benchmark.

For consistency purposes, we maintain the identical lookback window over which volatility and correlations are calculated. To ensure a sufficient window length for estimation stability, we use 36-monthly returns. In this example, we use a Tracking Error Volatility (TEV) constraint of 100 bps per month. Relative to the rules-based tilted portfolio, optimization offers a more significant reduction in GHG per dollar invested (Figure 16).

Figure 16
Performance Versus GHGD: Optimization Versus Tilting



Source: Bloomberg.

Extensions

Our portfolio analysis is predicated on metal scores based on GHG emissions during extractive processes – i.e., mining/new production. Assessing the linkage between spot rates (physical demand) and inventory could potentially allow for more accurate estimation of GHG emissions per metal. We examine the constituents of precious metals portfolios as an example.

Newly mined gold comprises 75% of annual gold supply; the residual 25% comes from recycling, of which 90% is attributed to jewelry and 10% to technology hardware (World Gold Council, 2020). The processes involved in recycled gold purification are dependent on the degree of purity, the scale of the production/refining process and which particular impurities need removing. This makes it difficult to estimate GHG emissions for recycling processes. Similarly, over the 2011-2020 period, 82% of annual demand for silver was sourced through mining — with 18% recycled (The Silver Institute, 2020.) Once again, there are various techniques to refine silver.

If a reliable source of GHG estimates for recycled metals were available, a more comprehensive measure could be constructed via the weighted average GHG of primary and recycled estimates. In the case of gold and silver, mining-only data captures the bulk of physical demand and the mining-to-recycling ratios for these metals are approximately the same. This suggests that unless recycling emissions differ significantly, the portfolio weights using the weighted average measure should not differ meaningfully. An analogous study for industrial metals is a more intensive task. While the covariance-driven substitutability would be unchanged, it may lead to results that produce different GHGD estimates.

Conclusion

Using a novel approach based on corporate data from the Bloomberg ESG library, we estimate GHG intensities for industrial and precious metals constituents in the BCOM benchmark index. Aggregating company-level data to provide macro estimates allows us to account for variations in emissions by geography, extraction processes and operation size along with providing a degree of transparency regarding the underlying source data. This article, which focuses on the metals sectors and GHG emissions, is an initial step in providing coverage spanning the BCOM universe across a range of environmental, social and governance factors.

We also discuss how several common approaches to portfolio construction can be used to incorporate these ESG scores into commodities benchmarks. The three approaches discussed — inverse weighting, rules-based tilting and optimization — provide a range of choices that trade-off between complexity and control in managing deviations from the benchmark. Depending on requirements, readers can modify each of these to construct custom ESG-tilted benchmarks.

In future research, we intend to expand our analysis to cover the remaining sectors using the Bloomberg ESG materiality map as a guide. By identifying the key issues for each of the three pillars, commodities portfolios can reflect investors' ESG objectives while displaying the diversification and inflation-hedging properties of this asset class.

Endnote

A link to the full publication — which includes the technical appendix — can be found via the link: ESG comes to town (https://www.bloomberg.com/professional/bloomberg-index-research-downloads/?dyn=indexreportcommodities).

References

Carbon Disclosure Project. Accessed via website: https://www.cdp.net/en on January 6, 2021.

The World Gold Council, 2020, "Gold Supply." Accessed via website: https://www.gold.org/about-gold/gold-supply on January 6, 2021.

Haque, N. and T. Norgate, 2010, "Energy and Greenhouse Gas Impacts of Mining and Mineral Processing Operations," *Journal of Cleaner Production*, Vol. 18, No. 3, February, pp. 266-274.

Haque, N. and T. Norgate, 2012, "Using Life Cycle Assessment to Evaluate Some Environmental Impacts of Gold Production," *Journal of Cleaner Production*, Vol. 29-30, July, pp. 53-63.

Haque, N. and T. Norgate, 2013, "Estimation of GHG Emissions for Ferroalloy Production Using Life Cycle Assessment with Particular Reference to Australia," *Journal of Cleaner Production*, Vol. 39, January, pp. 220-230.

Lindeman, A.J., 2020, "Benefits and Challenges in Extracting Signals from ESG Data," Bloomberg LP, February. Accessed via website: Benefits and Challenges in Extracting Signals (https://data.bloomberglp.com/professional/sites/10/ESG-Investment-Insights_Benefits-Challenges-in-Extracting-Signals-from-ESG-Data.pdf?bbgsum-page=DG-WS-PROF-BLOG-POST-90575&mpam-page=27675&tactic-page=tactic-blog-post) on January 6, 2021.

Norgate, T., Jahanshahi, S. and W.J. Rankin, 2007, "Assessing the Environmental Impact of Metal Production Processes," *Journal of Cleaner Production*, Vol. 15, No. 8-9, pp. 838-848.

Nuss, P. and M. Eckelman, 2014, "Life Cycle Assessment of Metals: A Scientific Synthesis," PLoS ONE, Vol. 9, No. 7, July.

The Silver Institute, 2020, "Silver Supply and Demand." Accessed via website: https://www.silverinstitute.org/silver-supply-demand/ on January 6, 2021.

Usapein, P. and C. Tongcumpou, 2016, "Greenhouse Gas Emissions in Jewelry Industry: A Case Study of Silver Flat Ring," *Applied Environmental Research*, Vol. 38, No. 1, February, pp. 11-18.

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