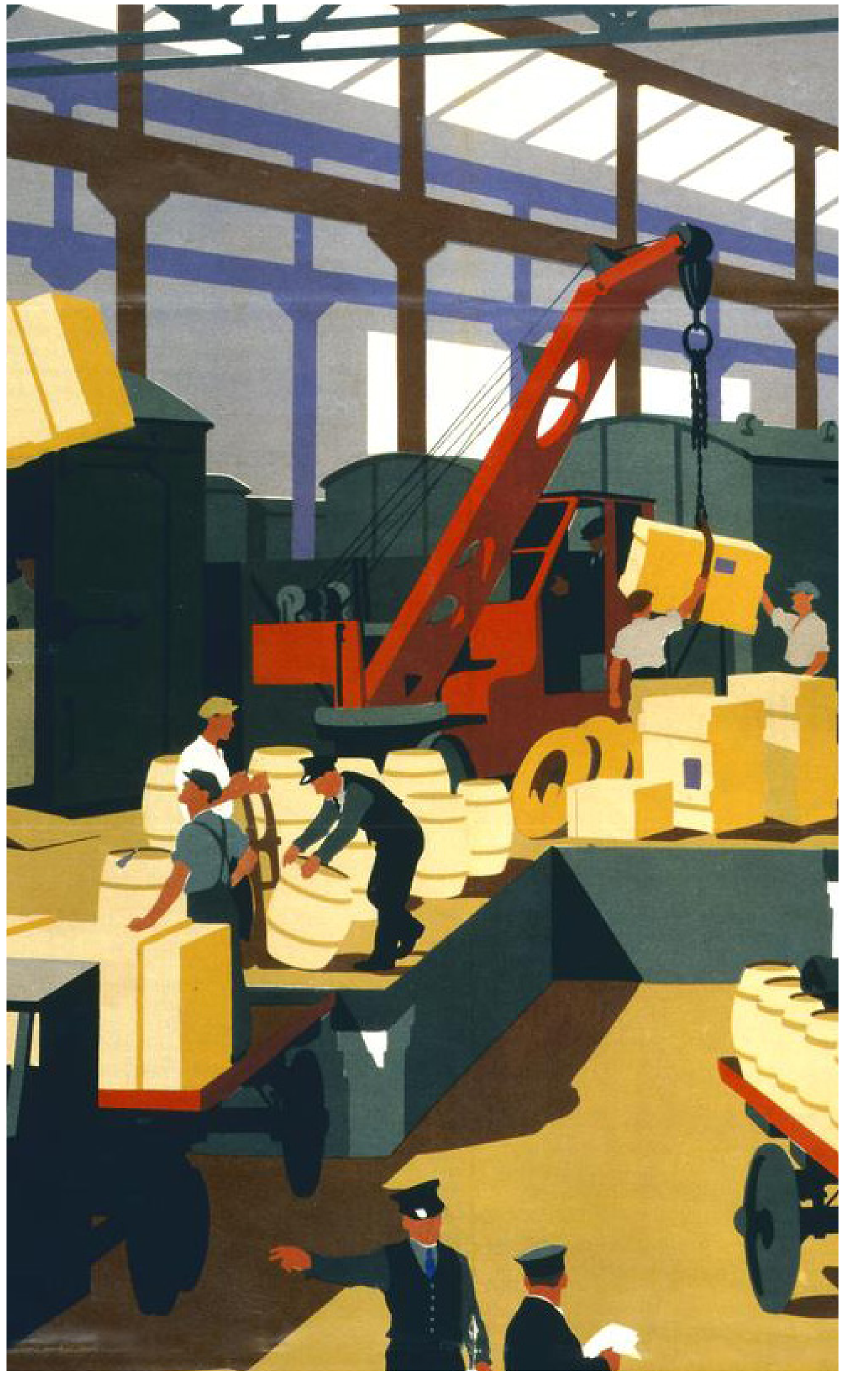
J.P. MORGAN CENTER FOR COMMODITIES
UNIVERSITY OF COLORADO DENVER BUSINESS SCHOOL

GLOBAL COMMODITIES
APPLIED RESEARCH DIGEST

SUMMER 2021



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GLOBAL COMMODITIES APPLIED RESEARCH DIGEST
Vol. 6, No. 1: Summer 2021
Index of Articles

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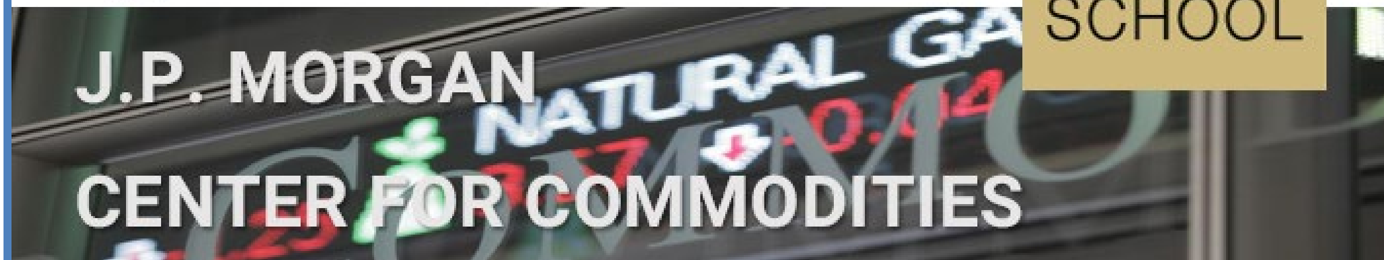


The JPMCC is positioned as a collaboration between business and academia across the broad agriculture, metals, and energy commodity sectors. Our focuses include Commodity Business Education, Applied Commodity Research, and Commodity-Related Public Forums & Discourse.

Undergraduate & Graduate Specializations in Commodities

Our commodity classes cover the dynamics of the physical commodity markets, supply chains, data analytics & forecasting, risk management and trading.

4 Courses – 12 Credit Hours – Evening Courses

Professional Education Opportunities

We are offering 2, four-week online data analytics courses for commodity professionals.

Next Sessions begin in June

Energy & Commodity Analytics for Analysts | Energy Analytics & Big Data for Managers

Masterclass in Commodity Trading & Hedging

Commodity Research

In addition to the *GCARD*, the JPMCC sponsors an annual Commodities Research Symposium where global commodity thought leaders and prominent stakeholders from both academia and industry convene to discuss critical thinking and new research related to commodities.

Upcoming Webinars & Recorded Sessions

Follow us on LinkedIn and our Website for information.

Contact Erica Hyman for more information or to schedule a visit to the Business School.

Erica.Hyman@ucdenver.edu; 303-315-8019

Professional Education

A Collaboration of CU Denver Business School's Global Energy Management (GEM) program and the J.P. Morgan Center for Commodities (JPMCC)

Energy Analytics and Big Data for Managers

This 4-week, online course for managers and new data professionals offers a broad-based, but gentle, introduction to the rapidly expanding disciplines of analytics and Big Data in the energy and commodity industries. The course focuses on developing quantitative data literacy and establishing the foundation of analytics, algorithms, and models. You will be able to comfortably discuss the issues, impacts, and tools of energy analytics.

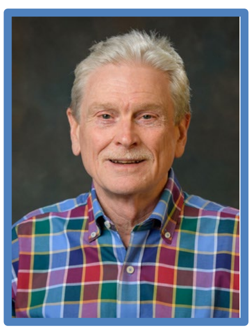
Schedule and Curriculum

The next course offerings are in June through July 2021.

This program will offer an overview of Big Data and energy analytics, including the roles of management, and demonstrate the link to corporate performance indicators and operational efficiency.

Course topics include:

- Introduction to Big Data
- Data is the new currency
- Prediction and predictive analytics
- Industry case studies in energy and commodities



About the Instructor

Tim Coburn, Ph.D., has a career that intersects various aspects of the energy industry, including oil and gas, renewables, coal, transportation, electricity, infrastructure, and human factors. In addition to his extensive research in energy analytics, Dr. Coburn has worked for Phillips Petroleum, Marathon Oil Company, and the National Renewable Energy Laboratory. Dr. Coburn has held professorship roles at numerous universities and is an instructor for CU Denver's Masters in Global Energy Management.

How to Apply

Admission is open to all applicants, with no prerequisites to register. A fundamental knowledge of business statistics and strong quantitative skills are highly recommended.

For any questions about registration, please contact Sarah Derdowski, Executive Director for the Global Energy Management Program, at sarah.derdowski@ucdenver.edu or 303-315-8065.

For more information, please visit: business.ucdenver.edu/managers-energy-analytics

The *Global Commodities Applied Research Digest* (*GCARD*) is produced by the J.P. Morgan Center for Commodities (JPMCC) at the University of Colorado Denver Business School.

The JPMCC's leadership team is as follows. Thomas Brady, Ph.D., is the JPMCC's Executive Director. The JPMCC's Research Director is Jian Yang, Ph.D., CFA, who is also the J.P. Morgan Endowed Research Chair, and Discipline Director and Professor of Finance and Risk Management at the University of Colorado Denver Business School. The JPMCC's Program Director is Yosef Bonaparte, Ph.D., who is also an Associate Professor of Finance at the University of Colorado Denver Business School. The JPMCC's Program Manager, in turn, is Erica Hyman. Periodic updates on the JPMCC's activities can be found at https://www.linkedin.com/school/cu-denver-center-for-commodities/.

In addition, the Chairman of the JPMCC's Industry Advisory Council is Chris Calger, Managing Director, Global Commodities, J.P. Morgan.

The aim of the *GCARD* is to serve the JPMCC's applied research mission by informing commodity industry practitioners on innovative research that will either directly impact their businesses or will impact public policy in the near future. The digest covers topical issues in the agricultural, metals and mining, and energy markets as well as in commodity finance.

The *GCARD* was seeded by a generous grant from the CME Group Foundation and is published twice per year. The *GCARD* is currently supported by funding from Integrated Portfolio Intelligence LLC; FourPoint Energy; and the CME Group.

Complimentary subscriptions to the *GCARD* are available at: http://www.jpmcc-gcard.com/subscribe. Periodic updates on *GCARD*-related activities can be found at:
https://www.linkedin.com/company/jpmcc-gcard/.

Since the Spring of 2016, the *GCARD*'s editorial and project management staff has been as follows. The *GCARD's* Contributing Editor is Ms. Hilary Till, M.Sc. (Statistics), Solich Scholar at the JPMCC and Member of both the JPMCC's Advisory Council and Research Council. In addition, Ms. Till is a Principal of Premia Research LLC. The *GCARD's* Editorial Assistant is Ms. Katherine Farren, CAIA, whom, in turn, is also a Research Associate at Premia Research LLC.

The *GCARD* benefits from the involvement of its distinguished Editorial Advisory Board. This international advisory board consists of experts from across all commodity segments. The board is composed of academics, researchers, educators, policy advisors, and practitioners, all of whom have an interest in disseminating thoughtful research on commodities to a wider audience. Board members provide the Contributing Editor with recommendations on articles that would be of particular relevance to commodity industry participants as well as author articles in their particular areas of commodity expertise.

The *GCARD* also benefits from its academic and professional society partnerships in furthering the international recognition of the digest. These partners have included ECOMFIN, the IAQF, and CAIA. Specifically, the Director of the Energy and Commodity Finance Research Center (ECOMFIN) at the ESSEC Business School (France, Singapore) serves on the *GCARD*'s Editorial Advisory Board while the *GCARD*'s professional society partners, in turn, have included the International Association for Quantitative Finance (IAQF) and the Chartered Alternative Investment Analyst (CAIA) Association.

The *GCARD*'s logo and cover designs were produced by Jell Creative, and its website was created by PS.Design. The *GCARD*'s layout was conceived by Ms. Barbara Mack, MPA, of Pingry Hill Enterprises.

TABLE OF CONTENTS
Vol. 6, No. 1: Summer 2021

J.P. Morgan Center for Commodities (JPMCC)

Introduction

Updates from the JPMCC

Research Director Report

Advisory Council

Research Council

Editorial Advisory Board

Research Council Corner

Research Digest Articles

(Continued on the next page)

Research Digest Articles
(Continued)

Advisory Council Analyses

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. In this article, the authors (a) highlight the unique interpretation issues for commodities investors with regard to ESG investing; (b) provide a summary of the factors that need to be considered when estimating GHG emissions for metals production; (c) outline a rules-based approach for estimating GHG emissions per metal; and (d) construct sample portfolios incorporating GHG-based scores.

The reemergence of the commodity super-cycle discussion has important implications for the global economy and capital markets. Mineral producers, policymakers, and investment managers are all trying to better understand commodity prices to make more informed, long-term decisions. The author proposes a statistical methodology that could help support this decision-making process and provide a framework to discuss super cycles in commodities as well as other macroeconomic and financial questions.

Editorial Advisory Board Analysis

There are several commonly held beliefs in the investment community regarding the relationship between gold and other variables: namely, the U.S. dollar, the 10-year Treasury yield, the oil price, inflation and market volatility or risk. At the same time, we know that central banks have adopted widespread large-scale asset purchase programs during and since the period that began with the Global Financial Crisis (GFC) in 2008/09, over which time monetary authority balance sheets expanded at a dramatic rate. This paper explores the nature of the relationships between gold and the other variables before and after the GFC in this context. The paper shows that the relationships have indeed changed since the GFC in terms of both significance and direction of causality.

Industry Analyses

Industry Analyses
(Continued)

Commodity prices are subject to extreme price volatility and are a prominent source of risk for treasurers. The current geopolitical uncertainty is one of the main causes behind the recent uptick in volatility in many markets, complicating the ability of a treasurer to manage risk. Inevitably, the dairy sector is also affected by these developments and is on the lookout for more advanced market risk management tools. One promising tool is volatility modeling. This paper focuses on how volatility modeling can benefit commodity traders by dynamically managing price risk in the European Union (EU) dairy market with time series models.

This article expands on research into commodity portfolio management that was published in the Winter 2019 edition of the *Global Commodities Applied Research Digest*. Commodity markets are often used to diversify portfolio risk and as a hedge against inflation but, in order to maximize returns and hedging effectiveness, it is necessary to develop an approach that examines each commodity market separately. Accordingly, this article analyzes individual commodity returns and provides guidance on how extreme returns can impact commodity portfolio strategies.

Interview

In this issue of the *GCARD*, we have the pleasure of interviewing Jodie Gunzberg, CFA. Gunzberg is Managing Director and Chief Institutional Investment Strategist for Morgan Stanley Wealth Management. Previously Gunzberg was the Managing Director and Head of U.S. Equities at S&P Dow Jones Indices (S&P DJI). She had originally joined S&P DJI as the Director of Commodities product management. In addition to her impressive track record of professional achievement, Gunzberg has retained a strong passion for education, whether it concerns early-childhood tutoring, university-level mentoring, or professional development for young finance professionals. In this interview, we ask Gunzberg about advice regarding career development, and we also explore both commodity- and education-based themes with her as well.

CU Denver Business School Global Energy Management (GEM) Program

CU Denver Business School's commodity expertise includes not only the J.P. Morgan Center for Commodities, but also its Global Energy Management (GEM) program. The Business School's Master of Science in Global Energy Management program is a business and leadership degree, offered in a hybrid format that turns today's energy professionals into tomorrow's leaders. This degree prepares students to advance in their current field or to shift into a new role or sector.

Updates from the J.P. Morgan Center for Commodities' Leadership Team

We are delighted to welcome you to the eleventh issue of the *GCARD*! We are grateful that so many of the commodity-focused academics and practitioners, who have affiliations with the JPMCC, continue to support this publication. In particular, members of the JPMCC's Research Council, Advisory Council, and the *GCARD*'s Editorial Advisory Board are represented in the current issue along with past presenters at the JPMCC's international commodity symposia.

In this brief article, we will provide updates on both the *GCARD* and the JPMCC's broader activities.

Sponsorship of the *GCARD*

We are proud to announce that Integrated Portfolio Intelligence, LLC (IPI) has become a Silver sponsor of the (*GCARD*). IPI LLC joins the CME Group and FourPoint Energy, LLC as sponsors of the digest. IPI is an alternative investment management firm, which applies quantitative and fundamental methods to investing in global financial markets. IPI's investment process combines extensive markets experience with cutting-edge research and advanced technology. The firm's objective is to produce compelling positive returns across the entire spectrum of market regimes.

For information on becoming a corporate *GCARD* sponsor, one may contact Erica Hyman, the JPMCC's Program Manager, at commodities.center@ucdenver.edu.

Industry Advisory Council

The JPMCC's Advisory Council consists of leading members of the business community who provide guidance and financial support for the activities of the JPMCC, including unique opportunities for students. Advisory Council members specifically provide advice to Dr. Thomas Brady, the JPMCC's Executive Director, on the Center's overall strategy, educational offerings, and applied research efforts.

We are happy to welcome a new member to the JPMCC's prestigious Advisory Council: Sharon Weintraub, who is the Senior Vice President for Gas and Power Trading - International within BP's Trading and Shipping arm in London. Weintraub's career spans commodity derivatives trading, risk management, and chief financial officer duties in positions across the globe, including in Chicago, Houston, London, and Singapore. We look forward to Weintraub's counsel in navigating the new currents in the energy markets for the benefit of our students.

GCARD Editorial Advisory Board

We are also happy to announce the appointment of two additional members to the *GCARD*'s Editorial Advisory Board: Dr. Ilia Bouchouev and Dr. David Jacks. Bouchouev is the former president of Koch Global Partners where he managed the firm's global derivatives trading business for over twenty years until his retirement in 2019. He is currently the managing partner for Pentathlon Investments and is an Adjunct Faculty at New York University and a Research Associate at the Oxford Institute for Energy Studies (U.K.). Bouchouev uniquely combines theoretical and market-microstructure expertise, enabling his articles to be quite relevant for commodity-focused practitioners, academics, and policymakers. He recently co-authored an article on "Oil Risk Premia under Changing Regimes" for the Winter 2020 edition of the *GCARD*.

Jacks' affiliations across academic and policy research institutions include serving as the J.Y. Pillay Professor of Social Sciences at Yale-NUS College (Singapore); Professor, Simon Fraser University (Canada); Research Associate, National Bureau of Economic Research; and Research Fellow, Centre for Economic Policy Research (U.K.). Jacks is one of the top researchers on commodity price cycles and maintains a time series of the real prices for 40 commodities as well as composite indices on his website: http://www.sfu.ca/~djacks/data/boombust/index.html. In addition, he co-authored an article on "Dry Bulk Shipping and the Evolution of Maritime Transport Costs," using data since 1850, for the current edition of the *GCARD*.

Academic Classes

During this Spring, the JPMCC offered the following academic classes at the University of Colorado Denver Business School:

Introduction to Commodities: This entry-level course was designed for freshmen and sophomore students and provided a review of how commodities are produced, supplied and traded across the agriculture, metals and minerals and energy sectors. This course was taught by Dr. Thomas Brady, the JPMCC's Executive Director.

Commodity & Equity Trading: Students gained hands-on experience in commodities and equities trading with a focus on using prevalent industry software. This course was taught by the JPMCC's Program Director, Dr. Yosef Bonaparte.

Commodity Valuation & Investment: Students learned how commodities are managed in the global markets from a hedger, speculator, and arbitrageur point-of-view. This course was taught by Dominick Paoloni, CIMA.

Commodity Data Analysis: Students learned how to analyze commodity prices using quantitative techniques. They were introduced to forecasting and the use of statistical software like EViews and the programming languages, Python and R. This course was taught by Dr. Daniel Jerrett, who also lectures for the JPMCC's Professional Education program, as noted in the next section.

Professional Education Classes

Jointly with CU Denver's Global Energy Management program, the JPMCC hosts the following two professional education classes, which cover energy analytics.

E*nergy Analytics and Big Data for Analysts*: This course is taught by Dr. Daniel Jerrett and takes a deep dive into energy and commodities analytics. Designed for those who want to learn best practices in commodity data analytics, visualization, and forecasting, the course offers hands-on projects with real-world data. Students learn about commodity data analysis utilizing EViews, an industry-leading data management and analysis software package.

Dr. Jerrett has more than 15 years of experience developing and implementing forecasting models, spanning both the private and public sectors. He has spent time in the investment management industry, state, and local governments as well as consulting with Fortune 500 companies. Dr. Jerrett is currently the Chief Investment Officer for Stategy Capital LP and serves on the JPMCC's Advisory Council. In addition, he generously shared his expertise on the measurement of commodity super cycles in the current issue of the *GCARD*.

Energy Analytics and Big Data for Managers: This course is taught by Dr. Tim Coburn and offers a broad-based, but gentle, introduction to the rapidly expanding disciplines of analytics and Big Data in the energy and commodity industries. The course focuses on developing quantitative data literacy and establishing the foundation of analytics, algorithms, and models.

Dr. Coburn's career has spanned the various aspects of the energy industry, including oil and gas, renewables, coal, transportation, electricity, and infrastructure. In addition to his extensive research in energy analytics, Dr. Coburn has worked for Phillips Petroleum, Marathon Oil Company, and the National Renewable Energy Laboratory.

The next offering of this course will occur in June and July of 2021. Additional details can be found on the CU Denver Professional Development website. For questions about registration, please contact Sarah Derdowski, Executive Director for the Global Energy Management Program, at sarah.derdowski@ucdenver.edu.

Annual International Commodities Symposium

This year's annual Research Symposium is confirmed for August 16-17, 2021. Due to ongoing uncertainties with COVID-19, we will be hosting a fully virtual symposium this year. As noted in this issue's Research Director Report by Dr. Jian Yang, the *Journal of Futures Markets* will continue to sponsor a special issue for the 2021 JPMCC symposium. Updates on the conference will be provided at the research section of the JPMCC's website, and we very much look forward to resuming an in-person conference in 2022.

Dr. Thomas Brady, Ph.D., queries a panelist during a JPMCC Research Council meeting. Dr. Brady is the JPMCC's Executive Director at the University of Colorado Denver Business School and is also a Managing Director at Capitalight Research in Canada. (To Dr. Brady's left is Robert Greer, who serves as the JPMCC's Scholar in Residence.)

Executive Director's Concluding Note

I welcome *GCARD* readers staying up-to-date on the JPMCC's numerous activities by visiting the Center's website or by following the Center on LinkedIn, and I hope you have a safe and productive summer!

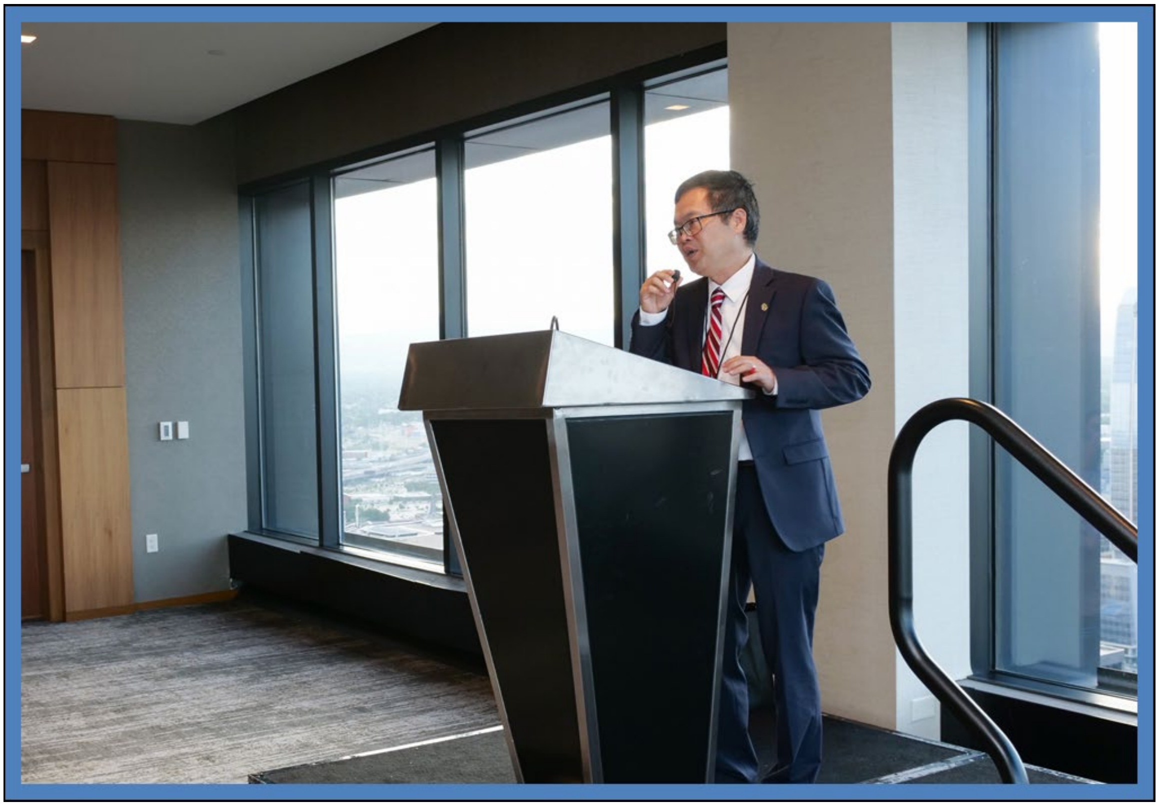
Best Regards,

Tom Brady

Tom Brady, Ph.D.
Executive Director, J.P. Morgan Center for Commodities

Update from the Research Director of the J.P. Morgan Center for Commodities

Jian Yang, Ph.D., CFA
J.P. Morgan Endowed Research Chair, JPMCC Research Director, and Discipline Director and Professor of Finance and Risk Management, University of Colorado Denver Business School



Dr. Jian Yang, Ph.D., CFA, J.P. Morgan Endowed Chair and JPMCC Research Director, introduced the Awards Ceremony at the JPMCC's 3rd Annual International Commodities Symposium. Dr. Yang was the Conference Organizer and Program Chair of the symposium.

In this report, the JPMCC research director will provide updates about recent research activities from October 2020 through February 2021 with the focus on recent academic and applied research in commodities. Due to COVID-19 precautions, other activities requiring in-person gatherings continue to be on hold.

Cover Story Articles in *China Futures* Magazine

During the last several months, we have made intensive efforts and enjoyed much success in sharing applied research insights with business-oriented publications based on recent and past academic research on commodities. This result may be partially prompted by the momentum from our earlier success in publishing cover stories in the October 2020 issue of the *China Futures* magazine of the China Futures Association, as mentioned in the last report. Thanks go to the authors of these articles, including JPMCC Advisory Council members (and their representatives) from J.P. Morgan (Chris Calger and Amar V. Singh), the CME Group (Blu Putnam[1]), and Morgan Stanley (Jodie M. Gunzberg[2]). Thanks also go to the JPMCC Research Council member from the World Bank (John Baffes[3]) for his article. I also want to thank many people in multiple countries (the U.S., China, and Singapore) for their assistance during the publication process, which took place over several months. In particular, Ms. Chunqing Wang (王春卿), the research department head of the China Futures Association, and the JPMCC executive director, Dr. Tom Brady, worked with me tirelessly to bring this project to fruition.

In my opinion, this effort is a good illustration of how to demonstrate the international impact and leadership of JPMCC research during a challenging time, which requires effective collaboration across countries, companies, and disciplines.

Applied Research Insights Cited in the Media

Through additional interactions with the international business media, we have continued to demonstrate the relevance and impact of our research with the global business community and policymakers.

Immediately after the article titled, "Price Discovery in Chinese Agricultural Futures Markets: A Comprehensive Look," was accepted by the *Journal of Futures Markets* (*JFM*) in late November 2020, the JPMCC research director, as lead author, reached out to various media outlets in English and Chinese. On December 22, 2020, the JPMCC was featured by *Reuters* (2020) on research regarding price discovery of the palm oil futures contract in China. The piece was republished in at least 10 media outlets in 8 countries (the U.S., U.K., France, Canada, Malaysia, Singapore, Cyprus, and Namibia). These press outlets include the websites of (a) *Yahoo! Finance*, (b) *Successful Farming* (magazine) in the U.S., (c) *This is Money* (the financial section of *Daily Mail* in the U.K.), (d) *The Star* in Malaysia (the most popular paid English newspaper in the country with a circulation of several hundred thousand), and (e) the *Financial Post* in Canada. Furthermore, as Malaysia currently runs the international benchmark futures contract on palm oil (which is also listed at the CME as a dollar-denominated contract), the Malaysian national news agency, *BERNAMA*, wrote another piece, widely published in the country, as the follow-up to the above *Reuters*' story, further enhancing the visibility of the story featuring the JPMCC. The finding on palm oil futures in China was also featured in a Chinese national news outlet with a somewhat different perspective.

In late December 2020, to share the insights further from the *JFM* paper, the JPMCC research director also provided an exclusive interview for a major newspaper in China, *Farmers' Daily* (农民日报). The interview covered the price discovery performance of all eleven actively traded agricultural futures contracts in China. The piece was published and then posted on the website of the Ministry of Agriculture and Rural Affairs in China, and was also included in the data lab of the Food and Agriculture Organization of the United Nations.

In early January 2021, based on his Ph.D. dissertation covering the live hog and lean hog futures contracts in the U.S., the JPMCC research director also provided comments to *Reuters*, the *Economic Daily* of the State Council of China, and the *China Securities Journal*, regarding the special challenges for the newly launched live hog futures in China, due to non-storability of the underlying asset. In particular, the news story highlighting the research director's comments was published as the #2 headline on the *Economic*

Daily's website. This news story was then widely republished on the officially recognized leading news websites in more than a half of the provinces in China, in addition to the majority of national media websites in the country.

In late January 2021, following the earlier extensive interviews on China's oil futures contracts by the media including *Bloomberg*, the research director was able to share further research and analyses with the *Financial Times*, which was picked up by more than 10 media outlets in 6 countries (namely, in the U.S., U.K., China, France, India, and Indonesia), including on the websites of *Business Insider* and *Yahoo! Finance* in the U.S. and the *China Economic Review* magazine in the U.K. (edited in Hong Kong).

Finally, as a side note, the research director also published his first op-ed in English in the first issue of *Beijing Review* (China's only national news magazine in English) in 2021. Commenting on the prospects for financial sector development outlined in the 14th 5-year plan of China starting in 2021, the article is titled, "Progress Despite Problems," and was published as a cover story. It is closely related to extensive academic research on China's financial system that was conducted by the research director, part of which was also featured by *New York Times*, *Reuters*, and about three dozen international media outlets in 2017.

Planning for the 4th International Commodities Symposium in 2021 and Other Research Updates

The JPMCC is organizing the 4th annual international commodities symposium at the University of Colorado Denver Business School, which will take place virtually via Zoom from August 16 through August 17, 2021. The symposium will have a reduced number of sessions due to the new format. The 4th symposium was originally scheduled in 2020 but was cancelled due to COVID-19. The *Journal of Futures Markets* will continue to sponsor a special issue for the 2021 JPMCC symposium. We will consider paper submissions submitted in 2020 and new submissions in 2021. In 2020, we received paper submissions from researchers in (at least) fifteen countries (the highest number by that time and two more compared with 2019), including Argentina, Australia, Canada, Chile, China, the Czech Republic, France, Germany, India, Italy, Japan, New Zealand, Switzerland, the U.K., and the U.S., in alphabetical order. We have contacted each submitter in 2020 and are pleased to see that the majority of them would still like to have their papers under consideration for presentations in 2021. Nevertheless, some of them withdrew paper submissions, mainly because the papers were accepted for publications or were close to that stage. With additional new submissions by the deadline of early March, we now have the largest number of submissions yet for the symposium, coming from eleven countries (Canada, China, the Czech Republic, France, Germany, India, Italy, Japan, Switzerland, the U.K., and the U.S., in alphabetical order). It is the first time that submissions have been received from Japan and India. We will provide timely updates about the symposium on the website of JPMCC. We also posted a Call for Papers on the Wiley publishing website of the *JFM* with the submission deadline of March 5.

Starting with this symposium, while the research director will remain as *the organizer and program committee chair*, the executive director, Dr. Tom Brady, will serve as the *co-organizer* and *the program committee co-chair* of the symposium and will take the lead in organizing the program of industry panels. Dr. Brady[4] is the former chief economist at Newmont Mining, the world's largest gold mining company. Erica Hyman, our new program manager, will serve as the coordinator for the symposium.

Regarding other research activities, the research director's co-written paper on the price discovery performance of Chinese agricultural futures was submitted (while it was still under a major revision for the *JFM*) and accepted for presentation at the annual NCR134/NCCC-134 conference in April 2021. The NCCC-134 Committee is a U.S. Department of Agriculture (USDA) Cooperative State Research, Education, and Extension Service (CSREES) regional committee that has been in existence for over 25 years. Their emphasis is highly consistent with the applied research mission of the JPMCC.

Conclusion

COVID-19 continues to have a significant impact on the economy, the society, and our own personal lives. But we are optimistic that the worst is behind us, and we hope to meet you virtually this summer at our symposium.

In the meantime, we wish everyone a healthy and safe summer!

Best Regards,

Jian Yang, Ph.D., CFA

Endnotes

We are grateful for the active involvement of the JPMCC's Advisory Council and Research Council in the Center's applied research activities.

1 Blu Putnam, Ph.D., has been a generous contributor to the JPMCC's *GCARD*. His most recent article in the Winter 2020 *GCARD* covered the differential impact of COVID-19 on the various commodity sectors. Dr. Putnam's other articles for the *GCARD* are available at the following link:
http://www.jpmcc-gcard.com/digest-uploads/2021-summer/GCARD%20Index%20of%20Past%20Topics%20Putnam%20032521.pdf.

2 Jodie Gunzberg, CFA, is featured in the "Interview with a Leading Innovator and Thought Leader" section of the current edition of the *GCARD*. She is also a past contributor of the *GCARD* on "Chinese Growth and Commodity Performance."

3 John Baffes, Ph.D., also graciously co-authored an article for the current issue of the *GCARD* on the "Persistence of Commodity Shocks."

4 In addition, Tom Brady, Ph.D., co-authored a paper on "Global Silver Supply Trends" for this issue of the *GCARD*.

Reference

Chow, E. and M.M. Chu, 2020, *Reuters*, "China's Bid to Establish Global Benchmark for Palm Oil Futures Seen an Uphill Battle," December 22. Accessed via website:
https://www.reuters.com/article/china-derivatives-palmoil/chinas-bid-to-establish-global-benchmark-for-palm-oil-futures-seen-an-uphill-battle-idUSL4N2IR19H?edition-redirect=uk on March 23, 2021.

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Persistence of Commodity Shocks

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Almost two-thirds of emerging market and developing economies (EMDEs) and three-quarters of low-income countries rely heavily on commodity extraction and export. This can put their economies at the mercy of global commodity markets, which are prone to shocks. The most recent example is the impact of the COVID-19 pandemic. To the extent such shocks are transitory, commodity-exporting EMDEs can buffer their impact on local economies; to the extent these shocks are permanent, policymakers in these countries need to facilitate a smooth adjustment to a new economic reality. Based on an analysis of 27 commodities during 1970-2019, this paper finds that transitory and permanent shocks contributed almost equally to commodity price variations, although with wide heterogeneity. Permanent shocks accounted for two-thirds of the variability in annual agricultural commodity prices but less than half of the variability in base metals prices. For energy prices, permanent shocks have trended upward, for agricultural prices, downwards, and for metals prices, flat. The volatility triggered in April-October 2020 by the COVID-19 pandemic appears to constitute a series of largely transitory shocks for oil prices.

Introduction

The COVID-19 pandemic delivered an enormous shock to the global economy and led to the deepest global recession since the Second World War, by far surpassing the recession in 2009 that was triggered by the global financial crisis (World Bank, 2020a). The pandemic impacted commodity markets as well, but its effect on prices has been heterogenous (World Bank, 2020b). Between January and April 2020 energy prices dropped nearly 60 percent while metals and food prices declined by 15 and 10 percent, respectively (Figure 1). Metal prices recovered in response to supply shocks and a quicker-than-expected pickup in China's industrial activity, and food prices stabilized as concerns about restrictive policy measures faded. However, the impact of the demand shock on the oil market continues and may become permanent.[1]

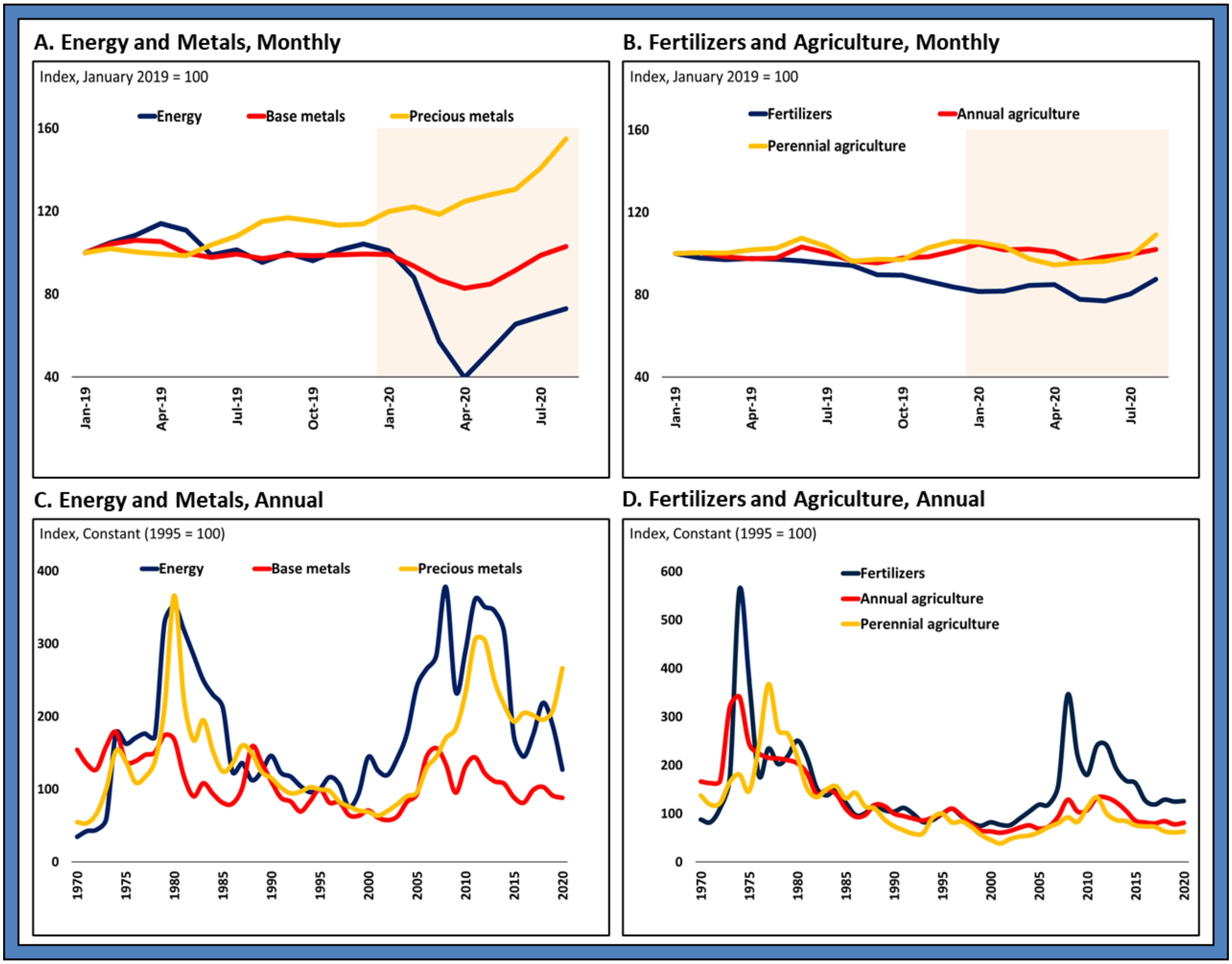
Commodity price movements explain considerable fluctuations in economic activity, particularly in EMDEs (Aguiar and Gopinath, 2007; Kose, 2002). Policymakers can smooth some of these fluctuations with policy stimulus or contraction – provided commodity price movements are temporary. For longer lasting shocks, policymakers need to facilitate their economies' smooth adjustment to a new normal.

Transitory shocks can originate from recessions, such as the 2009 global financial crisis and the 1997 East Asian financial crises (both of which impacted a wide range of commodities), trade tensions (such as in 2018-19 and of special relevance to metals and soybeans) or bans on grain exports during 2007 and 2011 (World Bank, 2019). They can also arise from adverse weather conditions, most common to agriculture, such as El Niño and La Niña episodes or drought-related production shortfalls (such as grains in 1995 and coffee in 1975 and 1985). Transitory shocks can also result from accidents (2019 Vale accident in Brazil which disrupted iron ore supplies), conflicts (the first Gulf War, when Iraq/Kuwait oil production was halted), or terrorist attacks (on the Saudi oil facilities in 2019, which halted oil exports temporarily) (World Bank, 2019).

Figure 1

Commodity Price Indexes

Commodity prices have been impacted differently by COVID-19. Energy prices, which declined more than 60 percent from January to April 2020, were still 32 percent lower in September 2020. Metals and food prices were impacted much less and have returned to pre-pandemic levels. The long-term effects of shocks on prices also varies across commodities.



Source: World Bank.

A.B. Shaded areas denote the pandemic period: January 2020 (when the first human-to-human transmission was confirmed) to September 2020 (last observation of the sample).

C.D. The indexes have been deflated by the U.S. CPI. Last observation is 2019.

Shocks can also exert a permanent impact on commodity markets. For example, the shale technology shock in the natural gas and oil industries rendered the United States a net energy exporter in 2019, for the first time since 1952 (EIA, 2020). The biotechnology shock of the 1990s increased crop productivity by more than 20 percent (Klümper and Qaim, 2014). Policy shocks can also have long-lasting impacts on commodity prices. Examples include government efforts to encourage biofuel production, which caused a 4 percent shift of global land from food to biofuel production (Rulli *et al*., 2016); interventions in agricultural markets by most Organization for Economic Co-operation and Development (OECD) countries, which have been shown to have long-term downward pressures on food prices (Aksoy and Beghin, 2005); and the Organization of the Petroleum Exporting Countries' (OPEC's) decisions to reduce oil supplies (Kaufmann *et al*., 2004).

Shocks, especially those related to energy markets, often propagate succeeding shocks. For example, the COVID-19 oil demand shock, which caused an estimated 10 percent decline in oil consumption during 2020, triggered a policy-driven supply shock of similar magnitude by the OPEC-plus group of a 9.7 mb/d oil production cut in April 2020.[2] The oil price increases of the mid-2000s (driven by EMDE demand, OPEC supply cuts, and geopolitical concerns) rendered shale technology profitable, pushed up the costs of food production, and triggered biofuel policies. Following the oil price collapse of 2014, food production costs declined, but production of shale (through innovation and cost reduction) and biofuels (diverted from food commodities) appear to have a permanent character.

Earlier literature on commodity price movements reached two broad conclusions: prices respond to shocks differently (Cuddington, 1992; Snider, 1924), and price movements are dominated by volatility rather than long-term trends (Cashin and McDermott, 2002; Deaton, 1999). More recent research, however, finds that commodity prices are subject to long-term cyclical patterns, the so-called super cycles (Cuddington and Jerrett, 2008).

This article examines how transitory and permanent shocks impact commodity price movements. Whereas the existing literature analyzes price movements in the context of either super cycles or cyclical versus trend behavior, this analysis allows for business- and medium-term cycles in line with the macroeconomic literature. Specifically, this paper addresses the following questions.

1) How much do transitory and permanent shocks contribute to commodity price variability?
2) How have transitory and permanent shocks compared across commodities?

How Much Do Transitory and Permanent Shocks Contribute to Commodity Price Variability?

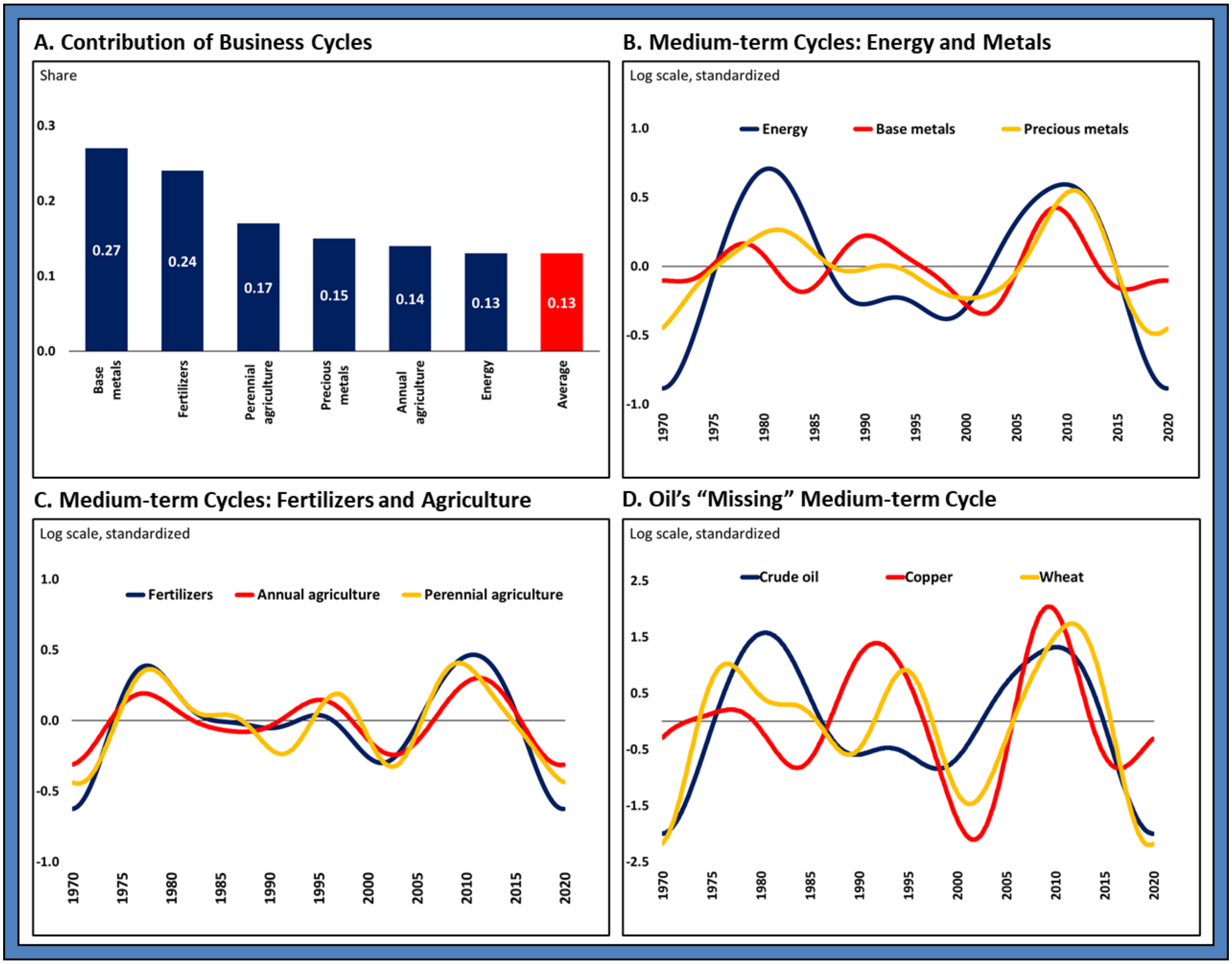
Methodology. To decompose commodity price movements into transitory and permanent components, a novel frequency domain approach is used that has thus far mostly been applied to economic business cycles (Corbae *et al*., 2002; Corbae and Ouliaris, 2006). The analysis rests on monthly data for 27 commodity price series over the period 1970-2019. It includes 3 energy prices, 5 base- and 3 precious-metals prices, 11 agricultural commodity prices (separated into annual and perennial crops) and 4 fertilizer prices.[3] The transitory shocks consist of three components—short-term fluctuations (that unwind in less than 2 years); traditional business cycles with frequency of 2-8 years, as are typically associated with economic activity (Burns and Mitchell, 1946); and medium-term cycles with periodicity of 8-20 years, which are often associated with investment activity (Slade, 1982). The permanent shock component captures movements with periodicity of more than 20 years—consistent with super cycles.

Permanent and transitory shocks account for roughly equal shares. On average across commodities, permanent shocks accounted for 47 percent of price variability. Of the remainder (i.e., transitory shocks), medium-term cycles accounted for 32 percent of price variability and business cycles for 17 percent. Only a small portion (4 percent) of price variability is due to shocks that are unwound in less than two years. The large role of the permanent component is in line with the findings of research into commodity price super cycles (Erten and Ocampo, 2013; Fernández *et al*., 2020). Furthermore, the predominance of the medium-term cycle in the transitory component is in line with recent research that finds a greater role of medium-term cycles than shorter business cycles in output fluctuations or domestic financial cycles (Aldasoro *et al*., 2020; Cao and L'Huillier, 2018).

The composition of transitory shocks differs across commodities. Shocks at medium-term frequency accounted for 55 and 27 percent of price variability in energy and metals, respectively, and only 14 percent for agriculture. In contrast, business cycles accounted for 24 percent of price variability for metals (Figure 2). This greater contribution of business cycle shocks to metal commodity price fluctuations is in line with the strong response of metal consumption to industrial activity.[4] Some of the commodities that exhibited the highest contribution of transitory shocks to price variability are used mainly within the transportation sector. For example, nearly two-thirds of crude oil is used for transportation, three-quarters of natural rubber goes to tire manufacturing, and half of platinum is used in the production of catalytic converters (World Bank, 2020b).

These averages mask heterogeneity across commodities. Transitory shocks were more relevant to the price variation of industrial commodities, while permanent shocks mattered most in agricultural commodity price movements (Figure 3). For agricultural commodities, permanent shocks accounted for two-thirds of price variability, for metals (including base and precious) they accounted for about 45 percent while for energy they accounted for less than 30 percent. Precious metals exhibited the largest heterogeneity as a group, with gold prices driven mostly by permanent shocks, silver driven equally by permanent and transitory shocks, and platinum exhibiting one of the highest shares of medium-term cyclicality.

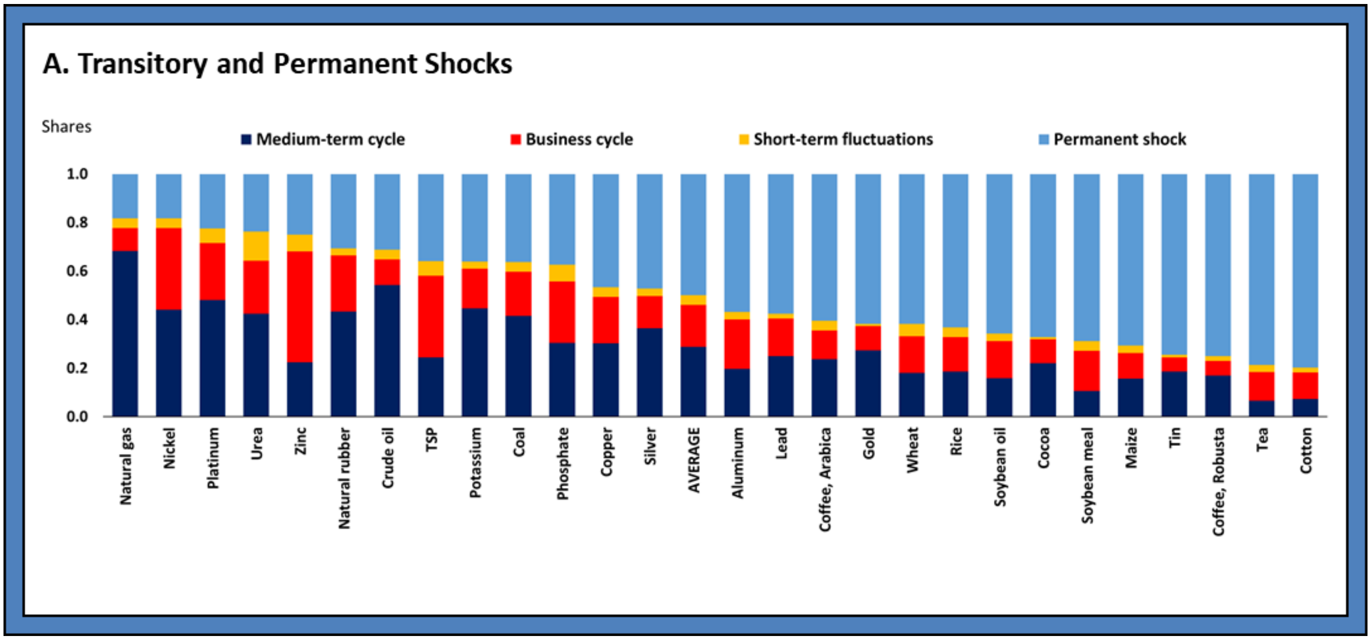
Figure 2
Transitory shocks
The business cycle component of transitory shocks is highest in the metals, consistent with the response of metals demand to industrial activity. There have been three medium-term cycles, peaking in 1978, 1994, and 2020. However, oil was subjected to only two medium-term cycles.



Source: World Bank.

A.-D. Authors' calculations.

Figure 3
Price Variation According to Type of Shock
Transitory and permanent shocks contribute almost equally, on average, to commodity price variation. However, these shares mask large heterogeneity across commodities. Transitory shocks account for most of industrial commodity price variability, while permanent shocks dominate agricultural commodity price movements.



Source: World Bank.

How Have Transitory and Permanent Shocks Evolved?

<u>Transitory Shocks</u>

Almost all commodities have undergone three medium-term cycles since 1970. The first medium-term cycle, which involved all commodities, began in the early 1970s, peaked in 1978, and lasted until the mid-1980s. The second, which peaked in 1994, was most pronounced in base metals and agriculture (with similar duration and amplitude to the first cycle) but did not include energy commodities. The third cycle, which again involved all commodities, began in the early 2000s, peaked in 2010, and for some commodities is still underway as of October 2020.

Crude oil's "missing cycle" reflected offsetting oil-specific shocks. Of the 27 commodities, crude oil and natural gas (whose price is highly correlated with oil) are the only commodities that exhibited two, instead of three, medium-term cycles. During the period spanning the second medium-term cycle, the oil market was subjected to three shocks.

- ***Unconventional and offshore oil.*** New production from unconventional sources of oil came into the market (North Sea, Gulf of Mexico, and Alaska). This was a result of innovation and investment in response to the high prices during the 1970s and early 1980s, partly caused by OPEC supply restrictions (World Bank, 2020b).[5]

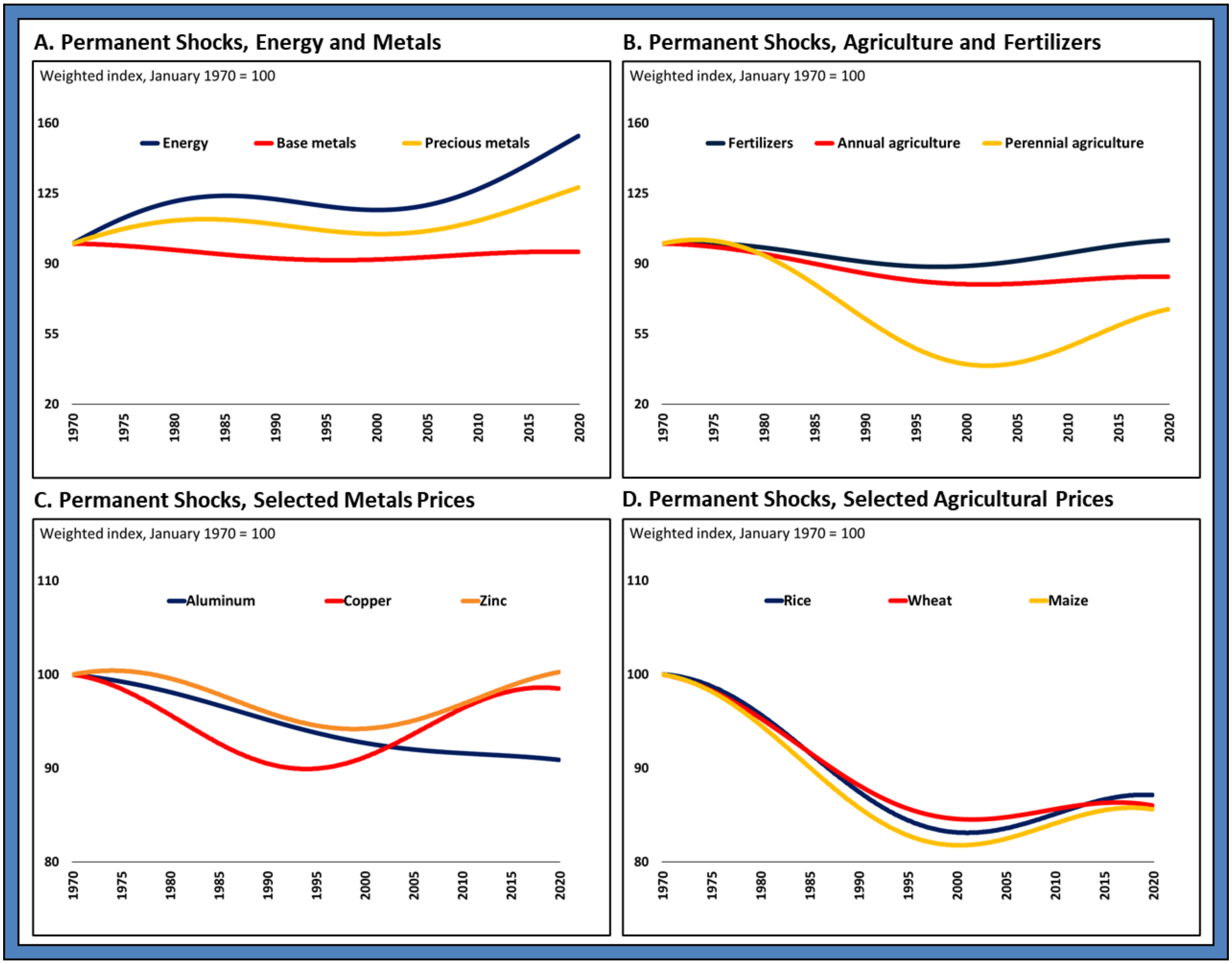
- ***New spare capacity from the former Soviet Union.*** Considerable spare capacity became available in the global oil market following the collapse of the Soviet Union. Prior to its collapse, the Soviet economy featured both inefficient production and energy-intensive consumption (World Bank, 2009).[6]

- ***Substitution and demand contraction.*** High oil prices during the late 1970s and early 1980s led to substitution of oil by other energy sources (especially coal and nuclear energy) in electricity generation. Policy-mandated efficiency standards in many OECD countries lowered global demand for energy (Baffes *et al*., 2020).

Permanent Shocks

The evolution of permanent shocks differed markedly across commodity groups. For energy commodities, the permanent shock component of prices has trended upward, for agricultural and fertilizer prices downward, and for most base metals they have been largely trendless (Figure 4). The upward trend in energy prices may reflect resource depletion and the largely trendless nature of long-term metals price movements may reflect the opposing forces of technological innovation and resource depletion (see discussions in Hamilton (2009) and Marañon and Kumral (2019) on oil and metals, respectively). The downward trend in permanent shocks to agricultural prices is consistent with low-income elasticities of food commodities (Baffes and Etienne, 2016). Commodities with a history of widespread policy interventions (cotton) or subjected to international commodity agreements (cocoa, coffee, crude oil, cotton, natural rubber, and tin) followed a highly non-linear path (see Table 1).[7]

Figure 4
Permanent Shocks
The permanent shock component trends upward for energy and precious metals, is nearly trendless for base metals and fertilizers, and trends downward for agriculture. These trends are homogenous for agriculture but heterogenous for other groups.



Source: World Bank.

A.-D. Authors' calculations.

- **Annual agricultural price trends are highly synchronized and differ from those of other commodity groups.** The contribution of permanent shocks to annual agricultural price variability (68 percent) is the highest among all six commodity groups, and these permanent shocks have evolved in a similar manner across annual agricultural prices (Figure 4).[8] This similarity reflects a diffusion of shocks across commodities due to input substitutability, consumption substitutability, and agricultural policies, which are similar across most crops.

- ***Input substitution.*** Annual agricultural commodities tend to be farmed using the same land, labor, machinery, and other inputs. As a result, reallocation between different annual crops from one year to another prevents large price fluctuations in individual crops. The impact of the restrictions in soybean imports by China from the United States in 2008 was short-lived due to land reallocation and trade diversion. Separately, despite a policy-induced increase in demand for maize, sugarcane, and edible oils over the past two decades, price increases in these three crops were in line with those of other annual crops (e.g., rice and wheat) as land was reallocated (World Bank, 2019).[9]

- ***Consumption substitution.*** Since annual crops have overlapping uses, substitution in consumption can dampen price fluctuations in any one of them. In the example of import restrictions on soybeans discussed earlier, soybean meal was substituted by maize for animal use in China while soybean oil was substituted by palm oil for human consumption (World Bank, 2019).[10]

- ***Policy synchronization.*** Policy interventions for agricultural markets tend to apply to the entire sector and stay in place for several years, even decades, with few or no changes. For example, agricultural policies in the United States and the European Union (EU), the world's largest producers in several agricultural commodity markets, are renewed every few years and apply to the same crops. Indeed, the 1985 Farm Bill reform in the U.S. and the 1992 Common Agricultural Policy reform in the EU applied to all commodities of the respective programs (Baffes and De Gorter, 2005).

Conclusion

This paper finds that commodities are subject to a multitude of different shocks. Permanent shocks account for two-thirds of agricultural price variability but less than half of industrial commodity price variability over the past fifty years. Meanwhile, business cycle shocks play the largest role for base metals, reflecting their heavy use in highly cyclical industries. The COVID-19 pandemic appears to have caused a series of largely temporary shocks for oil prices. Permanent shocks have trended upward for energy and precious metals prices but downward for agricultural prices and have been largely trendless for base metals prices. Annual agricultural commodities were the commodity group with the most homogeneous price trends, reflecting high substitutability in inputs and uses, and similar policies.

The heterogenous behavior of shocks suggests a need for policy flexibility, especially in commodity-exporting countries. Countercyclical macroeconomic policies can help buffer the impact of transitory shocks. Countries that depend on exports of highly "cyclical" commodities that are buffeted by frequent transitory shocks may want to build fiscal buffers during the boom phase and use them during the bust period in order to support economic activity. In contrast, in countries that rely heavily on commodities that are subject to permanent shocks, structural policies may be needed to facilitate adjustments to new economic environments.

Appendix
Model and Data Description
Decomposing Commodity Prices into Cycles and Long-Term Trends

The real price of the commodity, p_t, is expressed as the following sum:

$$p_t \equiv PC_t + TC_t^{[8,20]} + TC_t^{[2,8]} + S_t.$$

PT_t, which represents the permanent component, can be a linear trend, perhaps subjected to structural breaks. $TC_t^{[8,20]}$ denotes the medium-term cycle with a periodicity of 8-20 years as proposed by Blanchard (1997) and popularized by Comin and Gertler (2006). $TC_t^{[2,8]}$ represents the business cycle with a periodicity of 2-8 years, following NBER's traditional definition (Burns and Mitchell, 1946). Lastly, S_t captures fluctuations with periodicity of less than 2 years, which may reflect short-term movements in economic activity or other macroeconomic variables (such as exchange rates and interest rates), seasonality or weather patterns (in the case of agriculture), and *ad hoc* policy shocks. These fluctuations are typically studied within the context of Vector Autoregressive (VAR) models (Baumeister and Hamilton, 2019; Kilian and Murphy, 2014) and Generalized Autoregressive Heteroskedastic (GARCH) models by utilizing high-frequency data, focusing mostly on volatility (Engle 1982). The decomposition is based on the frequency domain methodology developed by Corbae *et al.* (2002) and Corbae and Ouliaris (2006).

The price data were taken from the World Bank's world commodity price data system. The sample covers 50 years: January 1970 through December 2019 (600 observations). The prices, which are reported in nominal U.S. dollar terms, were deflated with the U.S. Consumer Price Index (CPI) (taken from the St. Louis Federal Reserve Bank). Although the World Bank covers more than 70 commodity price series, this paper uses only 27 series. The selection was based on the following criteria:

- **Substitutability**. If commodities are close substitutes, only one was included. For example, because the edible oils are close substitutes, only soybean oil is used in the analysis.

- **Importance**. Commodities whose share in consumption diminished throughout the sample (either because of changes in preferences or substitution to synthetic products) were not included in the sample. Notable exclusions include wool, hides and skins, sisal, and tobacco.

- **Price determination process**. Commodities whose prices are not determined by market-based mechanisms (e.g., commodity exchanges or auctions) are excluded. Notable exclusions are iron ore (its price used to be the outcome of a negotiation process among key players of the steel industry until 2005), bananas (its price reflects quotations from a few large trading companies), sugar (policy interventions reduce the significance of the world price indicator), groundnuts (thinly traded commodity), and timber products (not traded on commodity exchanges).

Following the decomposition analysis, prices were grouped into six broad categories, each of which contained at least three series:

- **Energy**: Coal, crude oil, and natural gas
- **Base metals**: Aluminum, copper, lead, nickel, tin, and zinc
- **Precious metals**: Gold, platinum, and silver
- **Fertilizers**: Phosphate rock, potassium chlorate, TSP, and urea
- **Annual agriculture**: Cotton, maize, rice, soybean meal, soybean oil, and wheat
- **Perennial agriculture**: Cocoa, coffee Arabica, coffee Robusta, natural rubber, and tea

Decomposition results are reported in Table 1. The numbers in the square brackets of the first column represent weights and add to 100 for each commodity group, subject to rounding. The shares of each component add to 100, subject to rounding. For example, coal's shares are: 0.36 + 0.42 + 0.18 + 0.04 = 1. The penultimate column reports the parameter estimate from the regression of T_t on a time trend while the last column reports the Root Mean Square Error (RMSE) – a proxy for nonlinearity.

Table 1
Real Commodity Price Decomposition

	Share of variance explained by				Number of cycles		Trend	
	T_t	$C_t^{[8-20]}$	$C_t^{[2-8]}$	S_t	$C_t^{[8-20]}$	$C_t^{[2-8]}$	β	$RMSE$
ENERGY								
Coal [**4.6**]	0.36	0.42	0.18	0.04	3	11	0.43	5.31
Crude oil [**84.6**]	0.31	0.54	0.11	0.04	2	12	1.02	7.65
Natural gas [**10.8**]	0.19	0.68	0.10	0.03	2	11	0.57	2.50
AVERAGE	**0.29**	**0.55**	**0.13**	**0.04**	**2**	**11**	**0.95**	**6.99**
BASE METALS								
Aluminum [**32.9**]	0.57	0.20	0.20	0.03	4	10	-0.14	0.64
Copper [**47.4**]	0.47	0.30	0.19	0.04	3	9	-0.80	3.31
Lead [**2.2**]	0.57	0.25	0.16	0.02	3	8	-0.54	4.75
Nickel [**9.9**]	0.18	0.44	0.34	0.04	3	11	-0.78	1.63
Tin [**2.6**]	0.74	0.19	0.06	0.01	3	12	0.05	4.38
Zinc [**5.0**]	0.25	0.22	0.46	0.07	3	8	-0.09	2.08
AVERAGE	**0.46**	**0.27**	**0.24**	**0.04**	**3**	**10**	**-0.52**	**2.46**
PRECIOUS METALS								
Gold [**77.8**]	0.62	0.27	0.10	0.01	3	8	1.28	5.38
Platinum [**18.9**]	0.22	0.48	0.23	0.06	3	11	-0.22	1.85
Silver [**3.3**]	0.47	0.36	0.13	0.03	3	11	0.27	13.47
AVERAGE	**0.44**	**0.37**	**0.15**	**0.03**	**3**	**10**	**0.96**	**4.98**
FERTILIZERS								
Phosphate [**16.9**]	0.37	0.30	0.25	0.07	3	9	-0.40	6.48
Potassium [**20.1**]	0.36	0.45	0.16	0.03	3	10	-0.46	3.43
TSP [**21.7**]	0.36	0.24	0.34	0.06	4	9	-0.52	3.91
Urea [**41.3**]	0.24	0.42	0.22	0.12	3	12	-0.02	4.44
AVERAGE	**0.33**	**0.35**	**0.24**	**0.07**	**3**	**10**	**-0.28**	**4.47**
ANNUAL AGRICULTURE								
Cotton [**8.5**]	0.80	0.07	0.11	0.02	3	13	-0.07	9.00
Maize [**20.5**]	0.70	0.16	0.11	0.03	3	10	-0.50	3.55
Rice [**15.2**]	0.63	0.19	0.14	0.04	3	9	-0.43	3.29
Soybean meal [**29.0**]	0.69	0.10	0.17	0.04	3	10	-0.48	3.48
Soybean oil [**14.3**]	0.66	0.16	0.15	0.03	3	11	-0.72	3.15
Wheat [**12.5**]	0.62	0.18	0.15	0.05	3	9	-0.42	2.60
AVERAGE	**0.68**	**0.14**	**0.14**	**0.04**	**3**	**10**	**-0.47**	**3.78**
PERENNIAL AGRICULTURE								
Cocoa [**25.6**]	0.67	0.22	0.10	0.01	3	11	0.03	15.41
Coffee Arabica [**15.7**]	0.61	0.24	0.12	0.04	3	14	0.22	10.38
Coffee Robusta [**15.7**]	0.75	0.17	0.06	0.02	3	13	0.42	15.86
Natural Rubber [**30.6**]	0.31	0.43	0.23	0.03	3	10	-0.36	17.39
Tea [**12.4**]	0.78	0.07	0.12	0.03	3	13	-0.17	9.47
AVERAGE	**0.62**	**0.23**	**0.13**	**0.03**	***3***	***12***	**-0.03**	**14.56**
ALL AVERAGE	***0.47***	***0.32***	***0.17***	***0.04***	***3***	***11***	***0.10***	***6.21***

Notes: Description of terms appears in the text.

Endnotes

This paper is based on the October 2020 Special Focus article in the World Bank's *Commodity Market Outlook*.

Responsibility for the content remains solely with the authors and should not be attributed to the World Bank.

1 According to BP (2020), 2019 may have been the year during which global oil consumption peaked, marking a considerable revision to earlier projections which placed the "peak demand" year in the early 2030s. For example, IEA (2019) projected that global oil consumption would plateau around 2030. Peak demand discussions, which emerged after the 2014 price collapse (Dale and Fattouh, 2018), replaced the "peak oil supply" debate of the early 2010s (Helbling *et al*., 2011; Kumhof and Muir, 2014).

2 The demand plunge and production cuts following COVID-19 were the largest in history.

3 The selection of commodity prices analyzed in this paper was based on unique selection criteria by excluding commodities (a) that are close substitutes (e.g., selecting only one edible oil), (b) that are no longer economically important (e.g., hides and skins), or (c) whose prices are not determined at an exchange (e.g., bananas). Following the decomposition, the individual commodities were combined into six groupings, based on the uses and production characteristics of commodities (see Appendix). A few studies that have used both individual commodity price series and indexes (e.g., Erten and Ocampo, 2013; Jacks, 2019; Ojeda-Joya *et al*., 2019) used data obtained directly from the International Monetary Fund or World Bank commodity price databases without applying selection criteria.

4 The relationship between metals prices and economic activity has been well-established by numerous authors. See, for example, Baffes *et al*. (2020), Davutyan and Roberts (1994), Labys *et al*. (1999), Labys *et al*., (1998), Marañon and Kumral (2019), Roberts (2009), Stuermer (2017), and Tilton (1990).

5 The three unconventional sources of oil – U.S. shale oil, Canadian oil sands, and biofuels – are also associated with the third medium-term cycle (Baffes *et al*., 2015). In the first and third medium-term cycles, these unconventional sources of oil account for about 10 percent of global oil supplies (measured at the end of the cycle).

6 The collapse of the Soviet Union played a similar role in metals and grain commodities. However, the increase in supplies of those commodities was much smaller and gradual.

7 Cotton has been subjected to a high degree of government intervention by most major producers, including subsidies by the United States and the EU, taxation of Sub-Saharan cotton producers, and various types of policy interventions by Central Asian producers. Throughout the 1960s and 1970s the cotton market was also subjected to policy distortions by the Soviet Union (Baffes, 2011).

8 Permanent shocks to agriculture have lasting effects on economic activity in low-income countries through their impact on labor productivity (Dieppe *et al*., 2020).

9 Global demand for maize, a key feedstock for ethanol production in the United States, doubled over the past two decades. This compares with 26-28 percent increases in global demand for rice and wheat, broadly in line with the 27 percent global population growth over this period.

10 The imposition of tariffs by China on U.S. soybean imports resulted in trade diversion. As China's soybean imports from the U.S. declined and increased from Brazil, the EU began importing more from the U.S. and less from Brazil.

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On the Negative Pricing of WTI Crude Oil Futures

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WTI crude oil futures markets experienced the unprecedented phenomenon of negative prices on April 20, 2020. Several energy market pundits attributed the event to the large United States oil exchange-traded fund ("USO") due to the rolling of positions out of the May 2020 contract (CLK20) before the contract's maturity on April 21, 2020. We show empirically that USO flows have not influenced the flat price of WTI futures in general, nor of the CLK20 contract in particular. A blend of macroeconomic/geopolitical conditions, including the sudden demand plunge associated with COVID-19 pandemic-control measures and various supply spikes due to Russia-Saudi Arabia tensions, contributed to a contangoed WTI futures curve that attracted cash-and-carry (C&C) arbitrage, sharply increasing the inventories at Cushing, and feeding into a super-contango, as concerns on storage capacity loomed. That said, a full understanding of the negative WTI price phenomenon of April 20, 2020 requires a formal examination of market microstructure issues on that day, which is a matter for further research.

Introduction

The futures price of the May 2020 delivery futures contract on WTI crude oil (CLK20) swung dramatically from $18.27 (April 17, 2020) to a negative price of -$37.63 (April 20, 2020) – meaning effectively that sellers paid buyers to take crude oil barrels off their hands – and climbed back to $10.01 at maturity (April 21, 2020). This is the first time that a WTI futures contract has experienced negative prices since NYMEX WTI trading began on March 30, 1983. The existence of the United States Oil fund (with ticker symbol USO), one of the main trackers of the WTI crude oil performance, has been controversial and a frequent target of criticism by energy market pundits. In particular, some oil market commentators have implicitly or explicitly stated that the massive USO long futures positions on WTI crude oil and the corresponding rolls as contract maturity approached are to blame for the anomalous negative CLK20 pricing.

This article contributes to the literature on the price behavior of WTI crude oil futures contracts, firstly, by empirically testing the conjecture that USO trading induced the unprecedented negative price. For this purpose, the authors conduct an eclectic set of Granger-causality tests to determine whether USO flows (changes in open interest) have any predictive power for price changes of CLK20. The results indicate that USO flows did not drive the returns of CLK20 which is not surprising upon the recognition that USO had already rolled all of its long positions on CLK20 to more distant contracts as of April 13, 2020 (or seven

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days before the CLK20 price crash) and even at the close of April 12, 2020, only a fourth of its long contracts needed yet to be rolled as the process is spread out over four days. The test results suggest more generally that USO flows do not influence the flat price of any WTI futures contracts it has ever traded.

The second contribution of this article is to examine the plausible contributing causes of the pricing of CLK20 in April. The findings suggest that the pricing of WTI futures in April 2020 was influenced by the rampant cash-and-carry (C&C) arbitrage that was catalyzed by a dramatic oversupply of crude oil. In the early months of 2020, the oversupply of crude oil inherited from the last decade (oil "glut") took an adverse turn due to the shattered worldwide demand because of COVID-19 pandemic control measures, together with spikes in supply associated with geopolitical tensions between Russia and Saudi Arabia. The WTI futures market steered into a contango which acted as a strong catalyst for C&C arbitrage. The latter, in turn, sharply increased the Cushing (Oklahoma) inventories and storage costs and fed into a super-contango that attracted further C&C trades. As the maturity of CLK20 became closer, the spiraling dynamics between arbitrage and inventory triggered fears of an eventual tank tops scenario in Cushing. That said, in order to fully understand the reason why the WTI futures contract price could trade at a negative price on the day before contract maturity, one would also formally need to explore a number of technical, market microstructure factors of that day.

Relevance of the Research Question

The research question is important as it relates to the ongoing commodity markets financialization debate. The findings speak to the literature on the financialization of energy futures markets by showing that index traders and long-only asset managers, such as USO, are unlikely to have driven the flat price of crude oil futures away from its fundamental value and thus, they did not alter the outright price formation process (Fattouh *et al*., 2013; Bessembinder *et al*., 2016; Byun, 2017). This suggests that calls for further regulation of speculative participants might be, at this stage, premature since it could, in fact, be detrimental as it may discourage these providers of risk-absorption and liquidity from trading crude oil futures.

The findings also speak to the empirical literature on the theory of storage by bringing indirect evidence that the law of one price implied by the cost-of-carry model does not hold in the presence of storage constraints. In so doing, it complements the analysis of Ederington *et al.* (2020) by focusing on the anomalous negative pricing of CLK20, and by showing that limits in the availability of storage facilities can hinder the execution of C&C riskless arbitrages, which otherwise could provide a bid for the near-month contract. Practical implications include lessons for C&C traders, who need to exert caution during super-contangoed futures markets as storage constraints effectively imply that the C&C strategy can suddenly become quite challenging and thus, highly risky in incurring substantial margin calls during the period of the trade.[1] Likewise, traders and investors not seeking to take physical delivery need to exert caution in rolling their long positions sufficiently ahead of maturity to avoid being caught in dramatic liquidity freeze outs (Bouchouev, 2020; Bouchouev, 2021). Commodity futures markets can sometimes have "nodal liquidity": before entering a commodity futures position, a market participant should understand what flow would be on the other side of the trade to be able to exit at non-distressed levels (Till, 2008).

Data and Methodology

The paper relies on a wide sample of daily settlement prices and open interest (or total outstanding contracts) for all 446 WTI crude oil futures traded from March 30, 1983 to June 29, 2020. For comparison, we also obtain the settlement prices of front and second-nearest maturity futures contracts on Brent crude oil over the available period December 12, 1988 to June 29, 2020.[2] All prices are from Refinitiv Datastream. The investigation also employs daily long USO open interest data on WTI crude oil from October 24, 2008 to June 29, 2020 (as sourced from United States Commodities Fund (USCF) archives.)

The paper also looks at crude oil storage capacity, supply and demand data. Weekly working storage capacities for the U.S. and different Petroleum Administration for Defense Districts (PADDs) – PADD 1 (East Coast), PADD 2 (Midwest which includes Cushing), PADD 3 (Gulf Coast), PADD 4 (Rocky Mountains) and PADD 5 (West Coast) – are obtained from the Energy Information Administration (EIA) website. We also obtain from the EIA website: monthly worldwide crude oil production, as a measure of supply. Finally, we obtain monthly worldwide (and U.S.) crude oil and liquid fuels consumption data, as a proxy for world (and U.S.) demand, from Refinitiv Datastream. The start date of the different datasets is dictated by data availability, and the end date is June 26, 2020 throughout.

To test the hypothesis that USO flows do not influence the outright price of WTI futures contracts generally, the authors estimate a panel regression of the pooled WTI excess returns on their lagged values as well as on lagged values of the changes in USO's open interest,

$$r_t = \alpha_i + \alpha_{tm} + \sum_{j=1}^{P} \beta_j r_{t-j} + \sum_{j=1}^{P} \gamma_j \Delta OI_{t-j} + \varepsilon_t, i = 1, \dots, 148, \ t = 1, \dots, T \quad (1)$$

where r_t is the WTI excess return from the end of day $t-1$ to the end of day t, ΔOI_t the change in USO's open interest from day $t-1$ end to day t end, α_i are individual fixed effects to account for unobserved heterogeneity across futures contracts, α_{tm} are monthly time effects to account for seasonality in crude oil markets, β_j and $\gamma_j, j = 1, \dots, P$ denote the marginal effects of prior futures returns and USO's flows, respectively, on current returns, P is a maximum lag order to capture any serial dependence in daily returns, and ε_t is an error term.

To test the hypothesis that USO trading from March 6, 2020 to April 13, 2020 (i.e., the short period during which USO held long positions on CLK20) did not influence the outright price of CLK20, the authors respecify the above Granger-causality model Equations (1) by introducing a CLK20 dummy variable, D_t, as follows:

$$r_t = \alpha_i + \alpha_{tm} + \left(\sum_{j=1}^{P} \beta_j + \sum_{j=1}^{P} \beta_{D,j} D_t\right) r_{t-j} + \left(\sum_{j=1}^{P} \gamma_j + \sum_{j=1}^{P} \gamma_{D,j} D_t\right) \Delta OI_{t-j} + \varepsilon_t \quad (2)$$

where D_t is a dummy equal to 1 on days t from March 6, 2020 to April 13, 2020 (when USO held open interest on CLK20) and 0 otherwise; the additional parameters $\beta_{D,j}$ and $\gamma_{D,j}$ in these equations capture the specific effects of USO trading on CLK20 prices, over and above the effect of USO trading on all other WTI contracts (as captured by β_j and γ_j).

Results from Granger-causality Tests

The joint hypothesis $H_0: \gamma_1 = \cdots = \gamma_P = 0$ with reference to Equation (1) is not rejected by the Wald test, which is confirmed by individual ($\gamma_j = 0$) tests using t-statistics. This suggests that nearly since USO's inception, from October 24, 2008 to June 29, 2020, its flows have not caused WTI futures price changes. USO is a price taker, not a price maker.

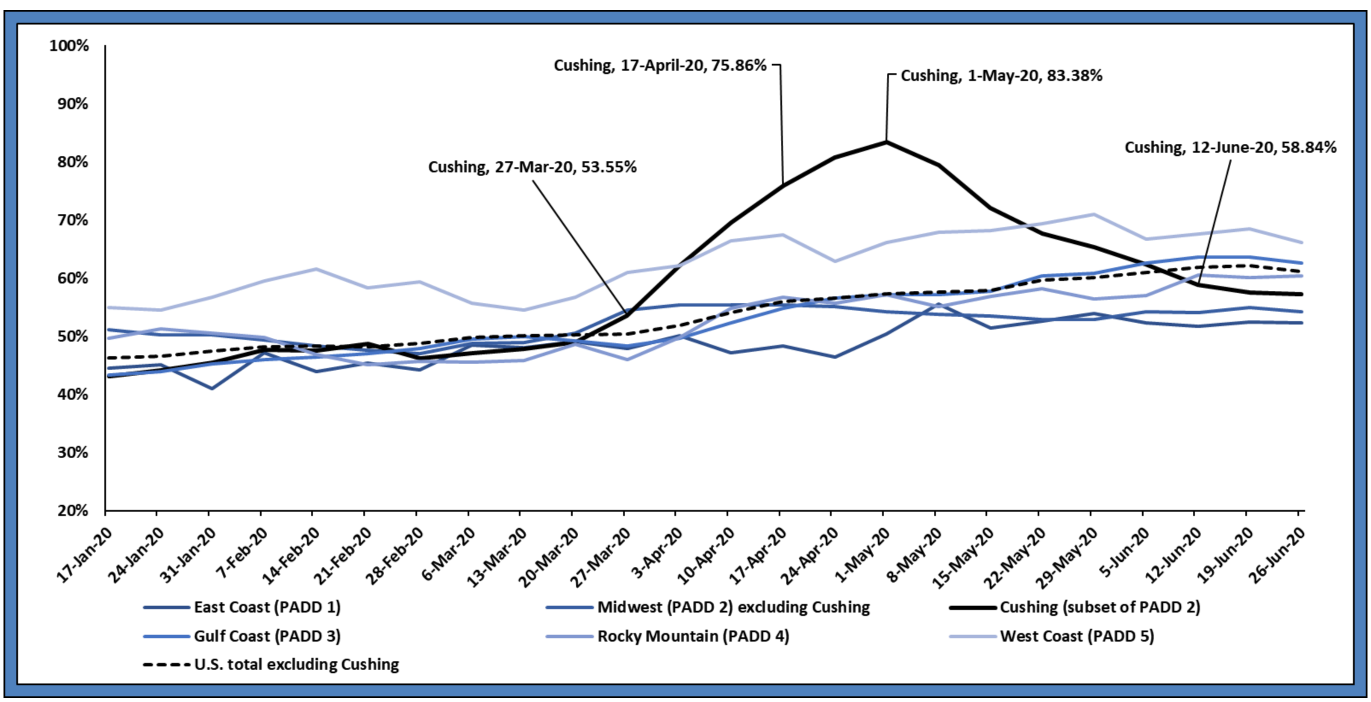
The joint restrictions $H_0: \gamma_{D,1} = \cdots = \gamma_{D,P} = 0$ in Equation (2) are not rejected either by similar tests. These findings in conjunction with those from the prior tests based on Equation (1), and the fact that USO did not hold any CLK20 contracts already 7 business days before its maturity, suggest that overall USO's flows did not drive the anomalous price changes of this contract. Overall, the evidence suggests that USO is unlikely to have induced the negative pricing of CLK20 on April 20, 2020, one day before contract expiry.

Robustness tests as regards the model specification used to conduct the Granger-causality tests (variants of Equations (1) and (2) with different maximum lag orders P, various controls, and considering the lag distributed effect of spreads) do not challenge the above findings.

Other Findings

Through the following graph the authors show that while there is an upward trend in the storage utilization rate in all hubs, there is a dramatic jump in the Cushing utilization rate during April 2020.

Figure 1
Crude Oil Storage Capacity Utilization in Different PADDs



The graph clearly illustrates the fact that unlike the other hubs, Cushing is the physical settlement point for WTI futures and hence, its inventory dynamics reflect more than operational factors.

The sudden slowdown of crude oil demand (driven by COVID-19 control measures) alongside the Russia versus Saudi Arabia tensions that triggered supply spikes are likely to have played a role in turning the early 2020 modest contango in the WTI futures market into a super-contango in late March 2020. This super-contango would have attracted C&C arbitrage in WTI crude oil and would have naturally induced the sharp increase in the Cushing storage utilization rate. Brent futures also entered a super-contango state, but not as much as WTI, and the Brent futures price did not enter negative territory. Even though rampant C&C arbitrage might have also occurred using Brent futures contracts, a key contrast with WTI futures contracts is that they can be cash-settled.

In support of the claim that the contango of the WTI crude oil futures market attracted C&C arbitrage which, in turn, raised inventory levels at Cushing, and induced a super-contango, the authors measure the correlation between the futures spread at week t (measured as the difference between the front and second-nearest futures prices) and the Cushing inventory at $t + 2$. From January 17, 2020 to June 19, 2020, the correlation is a significant -0.86; the more negative the futures spread at time t (deeper contango), the more C&C arbitrage trades, and, consequently, the Cushing inventories rise 2 weeks ahead when the delivery of the expired long position takes place. Similarly, the correlations between spread at t and inventory at $t + j$, $j = \{1,3,4\}$ weeks are significant and negative at -0.77, -0.82 and -0.70, respectively. This is consistent with Cushing inventory levels being strongly linked to arbitrage activity; arbitrageurs contract storage capacity ahead to exploit distortions between futures prices at different maturities. In addition, the authors provide data-based illustrative examples of how the C&C arbitrage might have induced the sharp inventory build-up at Cushing (as Figure 1 shows) during April 2020.

Regarding the typical behavior of market participants, like USO other long-only (or long-short strategy) asset managers are unlikely, in the main, to have held CLK20 on April 20, 2020 since they have no interest in taking or making delivery of the physical asset at maturity and thus, they typically roll their positions to more distant contracts a few weeks before front-end contracts mature. One documented exception, though, is in Bouchouev (2020), who discusses the Bank of China's retail investment product: Yuan You Bao ("Crude Oil Treasure"), which "still held positions for thousands of retail investors" at the start of April 20, 2020.

Hedge funds that engage in pure speculation (*e.g.*, CTAs) are unlikely to have held long CLK20 on April 20, 2020 for two reasons. First, since speculators do not want to take physical delivery which would require additional costs (*e.g.*, storage costs, insurance) they usually roll their contracts a few weeks prior to maturity to avoid exposure to illiquidity-driven price fluctuations. Second, various trading signals in March (roll yield, momentum, basis-momentum, relative basis) hinted towards a poor forthcoming performance of CLK20 and thus, rational speculators ought to have then taken short (as opposed to long) positions in that contract. Finally, long hedgers are also unlikely to have been largely caught in the predicament of holding CLK20 on April 20, 2020 because, first, they typically close their positions weeks before maturity to avoid illiquidity issues and second, as the WTI market entered a phase of deep contango, long hedgers would have had an incentive to decrease their long hedge rather than increase it. The Commodity Futures Trading Commission's (CFTC's) Interim Staff Report (2020) confirms this; traders in the

"Product/Merchant" group held below average long positions on CLK20; namely, only 14.7% of the open interest on April 20, 2020 was associated with long hedgers, which is considerably less than the trailing average of 52.5% on the penultimate day of trading of contracts active in the previous 12-months.

The CFTC's Interim Staff Report (2020) reveals that the share of long open interest held by "non-reportable" (small) traders and "other reportables" as higher than average for the penultimate day of trading. CFTC (2021) defines the "other reportables" category as excluding physical market participants, swap dealers, or managed money. Because the non-reportable and "other reportables" participants would likely not have had access to storage with which to resolve their long futures positions by taking physical delivery of oil, these participants would have been at risk to an "unexpected shortfall in buy orders," as phrased by Pirrong (2020c). The next section provides a discussion on how a liquidity freeze out could have occurred, which is based on considering who would typically be the natural buyers of crude oil futures contracts so close to contract maturity.

Liquidity Freeze Outs

How might have a liquidity freeze out occurred on April 20, 2020? Such a freeze out could occur, for example, due to "strategic behavior" on the part of commercials holding short futures positions (against physical holdings), who could observe the historically high open interest coming into the contract's maturity and could have chosen to delay buying in (short) hedges, an activity which would have normally provided a bid for exiting non-commercial long futures contract holders. Another risk for non-commercial traders holding futures contracts near to a contract's maturity (during a time of limited storage capacity) is that those participants who may still have had access to very limited storage could have delayed putting on new trades, given the amount of open interest remaining at the time, which would enable them to enter into a storage play at exceptional levels and thereby not go long the front-month futures contract except at extremely favorable levels for a C&C trade. Further, other physical traders may not have been "motivated to buy … futures [contracts] and take delivery of physical barrels … [when there was] high uncertainty about the availability of storage capacity," as noted by Bouchouev (2021). An aggravating factor on April 20, 2020 could have been a strategy employed by proprietary trading firms of going long the near-month contract at the Trade-at-Settlement (TAS) price earlier in the day, followed by aggressively closing out these positions with sell orders near the close. And they did so at a time when "buyers [who could or would] take physical delivery of WTI crude had all but disappeared", as discussed in Vaughan *et al.* (2020); such a strategy, it should be noted, would have led to substantial profits for these intraday trading participants. Bouchouev (2021) discusses the further signaling that would have happened when there was an emergence of unfilled TAS orders on April 20, 2020, indicating an imbalance of longs attempting to liquidate positions, putting such participants in quite a vulnerable state. At any rate, as the events of April 20, 2020 arguably showed, liquidity provision is not automatic during the day *before* the futures contract matures, if participants who otherwise have previously provided a bid for crude oil futures contracts near to the contract's maturity do not do so, either due to exerting "market power" or due to limits on effective storage capacity. In addition to the Bouchouev references, the consideration of this collection of factors is informed by the discussions in Pirrong, (2020a), Pirrong (2020), and Pirrong (2020c).[3]

Conclusions

Using a comprehensive dataset of WTI crude oil futures prices and USO open interest, the authors conduct formal empirical tests of the contention that United States Oil fund (USO), the largest WTI crude oil exchange traded fund, induced the catastrophic negative pricing of the WTI crude oil futures contract for May delivery (CLK20). The analysis shows that USO flows do not Granger-cause the outright prices of WTI futures contracts in general, nor of the CLK20 contract in particular.

Further analysis suggests that the contango associated with a disastrous blend of macroeconomic and geopolitical conditions, such as a rising surplus triggered by geopolitical tensions and a demand obliterated by the COVID-19 lockdowns, attracted a splurge of cash-and-carry (C&C) arbitrage trades that increased the Cushing inventories with a negative feedback effect on the intensity of the contango and C&C arbitrage opportunities.

In uncovering exactly why crude oil prices could have become negative on April 20, 2020, one needs to understand the precise interplay of the technical factors on that day, some of which we have touched upon, but which is a topic for future formal research.

Endnotes

1 Hecht (2015) describes how cash-and-carry trades work in the commodity markets, including how these trades have "virtually no risk other than margin flow via mark-to-market risk for the period" of the trade.

2 Unlike the WTI crude oil futures contract that can only be physically settled, the Brent crude oil futures is a deliverable contract based on an Exchange of Futures for Physical delivery with an option to cash settle (ICE Futures Europe, 2021).

3 For completeness, we should note that the Pirrong references include additional insights on the kinds of market manipulations that can potentially occur, especially during times of limited storage, based on past historical examples.

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Keywords

WTI crude oil, negative price, theory of storage, contango, cash and carry arbitrage.

The New Benchmark for Forecasts of the Real Price of Crude Oil

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How can we assess the quality of a forecast? We propose a new benchmark to evaluate forecasts of averaged series and show that the real price of oil is more difficult to predict than we previously thought.

Is the Real Price of Crude Oil Predictable?

The payoff to investments in new oil production, oil-intensive goods purchases, and oil-related research all hinge critically on the quality of oil-price forecasts. Forecasts can be derived from a variety of approaches, including expert knowledge, economic or statistical models, or the prices of financial assets. But how should a forecaster assess the quality of a specific forecast?

A common way to address this question is to compare the accuracy of a forecast to that of a benchmark forecast. For forecasts of the real price of crude oil, this benchmark has typically been the no-change benchmark – a naïve forecast that simply takes the last observed value of the series of interest to predict future values. Indeed, an increasing number of studies document that model-based forecasts of the real price of crude oil outperform the simple no-change benchmark (Baumeister and Kilian, 2012; Alquist *et al*., 2013; Baumeister *et al*., 2014; Baumeister and Kilian, 2014, 2015; Snudden, 2018; Funk, 2018; Garratt *et al*., 2019). This evidence has been used to conclude that the real price of oil is predictable in general, and that econometrics models are more useful to forecast prices than a naïve approach.

Our paper challenges this conclusion by observing that the real price of crude oil is typically constructed as an average monthly price of daily data. We show that this seemingly innocent transformation invalidates the conventional interpretation of forecast comparisons with the no-change benchmark. Instead, we propose an alternative no-change benchmark that is based on monthly closing prices. The new benchmark re-establishes meaningful forecast comparisons and has large effects on the evaluation of different oil-price forecasts.

Why We Need a Different Benchmark to Evaluate Forecasts of the Real Price of Crude Oil

The appeal of the no-change benchmark originates from its relationship with the random walk model. The random walk model has been used to approximate the behavior of many economic and financial series. It assumes that any future observation of a series is given by its last observed value plus a random innovation. Under the random walk hypothesis, any future changes in the series are unpredictable, and the no-change forecast is the optimal forecast for all future observations. Consequently, forecast-improvements over the no-change benchmark allow forecasters to reject the random walk hypothesis and to claim that the series of interest is predictable.

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However, this general logic fails when the series of interest is constructed by averaging higher-frequency data. This is the case for many macroeconomic variables such as real interest rates and real commodity prices, which are often expressed as deflated monthly or quarterly averages of daily observations. It can be shown that under the random walk hypothesis, the averaged data do not follow a random walk, but rather a cumulative sum of a moving-average process (Working, 1960). This implies that averaged series have a predictable pattern by design, even when all future changes in the daily data are completely random. For such series, improvements over the conventional no-change forecast are not informative about the predictability of the underlying series or the practical usefulness of a specific forecasting approach.

Our paper shows that the original interpretation of forecast comparisons can be restored by introducing an alternative no-change benchmark. This benchmark is not the last value of the averaged monthly or quarterly series that we want to predict, but rather the last value of the underlying high-frequency observation. Under the random walk null hypothesis, the new no-change benchmark is the optimal forecast for all future observations, including the averaged series.

The difference in the forecast accuracy between these two no-change benchmarks can be sizeable. When the underlying series follows a random walk, the theoretical improvements in the one-step-ahead mean squared prediction error (MSPE) are larger than 45 percent when using the last observed daily value instead of the last observed monthly or quarterly average value. A simple change of the benchmark can thus have large effects on assessments of different oil-price forecasting models.

Closing Prices Drastically Improve Model-Based Forecasts of the Real Price of Crude Oil, But the New Benchmark is Difficult to Beat

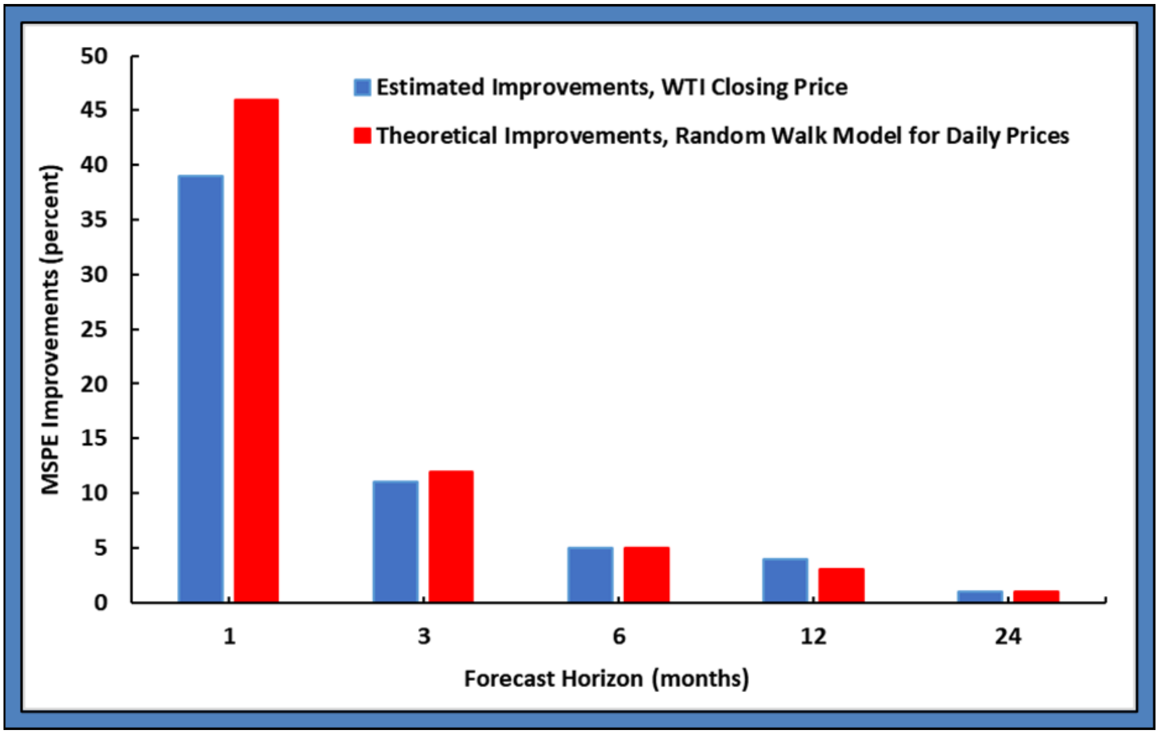
We study the importance of these effects in the case of the real price of crude oil. The focus of the empirical application is real-time forecasts of monthly averages of oil prices, which is the standard approach in the literature. For this purpose, we update a real-time dataset for oil-market and other economic variables created by Baumeister and Kilian (2012).

As in the typical setup of existing studies, it is assumed that the forecaster uses the available information at the end of each month to form their prediction for the following months. Based on our theoretical insights, we construct a new benchmark from real monthly closing prices and revisit the claim that these models can predict the real price of crude oil. We also investigate the extent to which the use of closing prices can improve model-based forecasts more generally.

The main empirical result from these exercises is that replacing average prices with closing prices considerably improves traditional forecasting approaches for the real price of oil. A simple no-change forecast based on the last closing price reduces the MSPE of the conventional no-change forecast computed from average monthly prices by 40 percent for one-month-ahead forecasts. The directional accuracy for the one-month-ahead forecasts is higher than 70 percent. The gains decrease with the forecast horizon but are still apparent up to the 12-months-ahead forecast.

The magnitude and the pattern in the forecast-improvements are roughly consistent with the theoretical predictions of a random walk model for daily oil prices. For example, the theoretical improvements from using the new benchmark instead of the conventional, average-price benchmark for the 1-, 3- and 12-month horizons are 46, 12 and 3 percent, respectively; see Figure 1 on the next page. The empirical counterparts for the real price of WTI (West Texas Intermediate) crude oil are 39, 11 and 4 percent, respectively. We show that this pattern arises because all forecasting gains from using closing prices are realized at the one-step-ahead prediction and become relatively less important for longer-horizon forecasts.

Figure 1
Accuracy-Improvements for Forecasts of the Real Price of WTI Crude Oil



Another major result is that forecasting models of the price of oil should be estimated with the monthly closing price, even if the goal is to predict average prices. Traditionally, models of the real price of crude oil have been estimated with the same series the forecaster wants to predict: the monthly average price of oil. We show that the forecasts derived from several popular forecasting models – including univariate time-series models, vector-autoregressive models, a futures-based forecast and a simple forecast combination – improve considerably when these models are estimated with closing prices instead.

At the one-month horizon, forecasts from models that are estimated with closing prices produce large improvements of about 40 percent over the average no-change forecast. As for the new no-change forecast, accuracy-gains are especially significant for shorter forecast horizons and become less pronounced for longer-horizons forecasts. We document that these gains are remarkably robust to the choice of the crude oil benchmark and the sample period. By contrast, most of the forecasts that are derived from the same models are unable to beat the conventional no-change forecast when models are estimated with closing prices. This suggests that closing prices should be used to estimate these models even if the forecaster's goal is to predict average prices.

How do models that are estimated with closing prices fare against the new benchmark? Although the model-based forecasts in some cases show lower MSPE ratios and better directional accuracy than the new no-change benchmark, these improvements are rarely statistically significant and consistent across both criteria. Only the futures-based forecasts for 1 and 2 years are both economically and statistically more accurate than the new benchmark. This shows that the choice of the benchmark matters and that improvements over the conventional benchmark are not necessarily indicative that oil prices are predictable.

Implications for Forecasts of the Real Price of Crude Oil and of Other Commodity Prices

Our findings have two broader implications. First, the introduction of a new benchmark can raise the bar for model-based forecasts to claim improvements over the no-change forecast. We show that this is indeed the case for the real price of crude oil. Forecasts that are generated from several popular models often outperform the conventional no-change benchmark, especially when these models are estimated using closing prices instead of average prices. However, they generally do not improve upon the new benchmark. Only the futures-based forecast provides better forecasts than the monthly closing-price benchmark and only for horizons of one year and beyond.

These results suggest that real oil prices are more difficult to predict and, in this sense, closer to asset prices than implied by the previous literature. They also suggest that closing prices provide better measures of oil price expectations than many models that rely on average prices. As such, the use of closing prices could shed new light on the transmission of oil price shocks and on the predictive power of oil prices for other macroeconomic variables.

The second implication concerns policymakers and applied forecasters who forecast averaged data. Our results highlight that incorporating information from high-frequency observations can yield large gains even in the context of the simple models many practitioners prefer. Such gains are likely to occur in any setting where forecasters work with averaged data and the underlying series are very persistent. This includes the prices of other primary commodities. In this environment, one would expect forecasts from econometric models to beat the conventional no-change forecasts that are based on averaged data, even if the underlying data used to obtain the averaged series is entirely or approximately unpredictable. For policymakers and applied forecasters, the easiest way to improve traditional forecasts for such series – particularly for short- and medium-term horizons – is to rely on the last higher-frequency observation rather than on lower-frequency averages.

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Dry Bulk Shipping and the Evolution of Maritime Transport Costs, 1850-2020

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This paper evaluates the dynamic effects of fuel price shocks, shipping demand shocks, and shipping supply shocks on real maritime transport costs in the long run. We first analyze a new and large dataset on dry bulk freight rates for the period from 1850 to 2020, finding that they followed a downward but undulating path with a cumulative decline of 79%. Next, we turn to understanding the drivers of booms and busts in the dry bulk shipping industry around this trend, finding that shipping demand shocks strongly dominate all others as drivers of real dry bulk freight rates. Furthermore, while shipping demand shocks have increased in importance over time, shipping supply shocks in particular have become less relevant.

Introduction

Events in the past year have amply demonstrated that volatility in shipping markets not only never went away but also that it is back … big time. Thus, the Baltic Exchange Dry Index nearly quadrupled in value in the short period of time from the end-of-January to the end-of-June 2020 as the aftershocks of COVID-19 first ravaged, then spurred international trade in bulk commodities.

Alongside such considerations of dramatic intra-annual movements in freight rates, professional sentiment has long argued for the existence of alternating booms and busts in the maritime shipping industry which can take years to complete (Metaxas, 1971; Cufley, 1972; Stopford, 2009). What is more, a burgeoning academic literature in behavioral finance and industrial organization has taken these claims to heart, finding that such boom/bust activity goes a long way in understanding the dynamics of ship building, ship earnings, and ship prices in the dry bulk sector.

The key underlying mechanism in these papers is the role of unanticipated positive shipping demand shocks and their propagation over time. In the wake of such shocks, the attendant booms in maritime freight rates generate over-investment in shipping supply either due to time-to-build constraints as in Kalouptsidi (2014) or firms being simultaneously too optimistic in their projections of future freight rates and too pessimistic in their projections of their competitors' responses as in Greenwood and Hansen (2015).

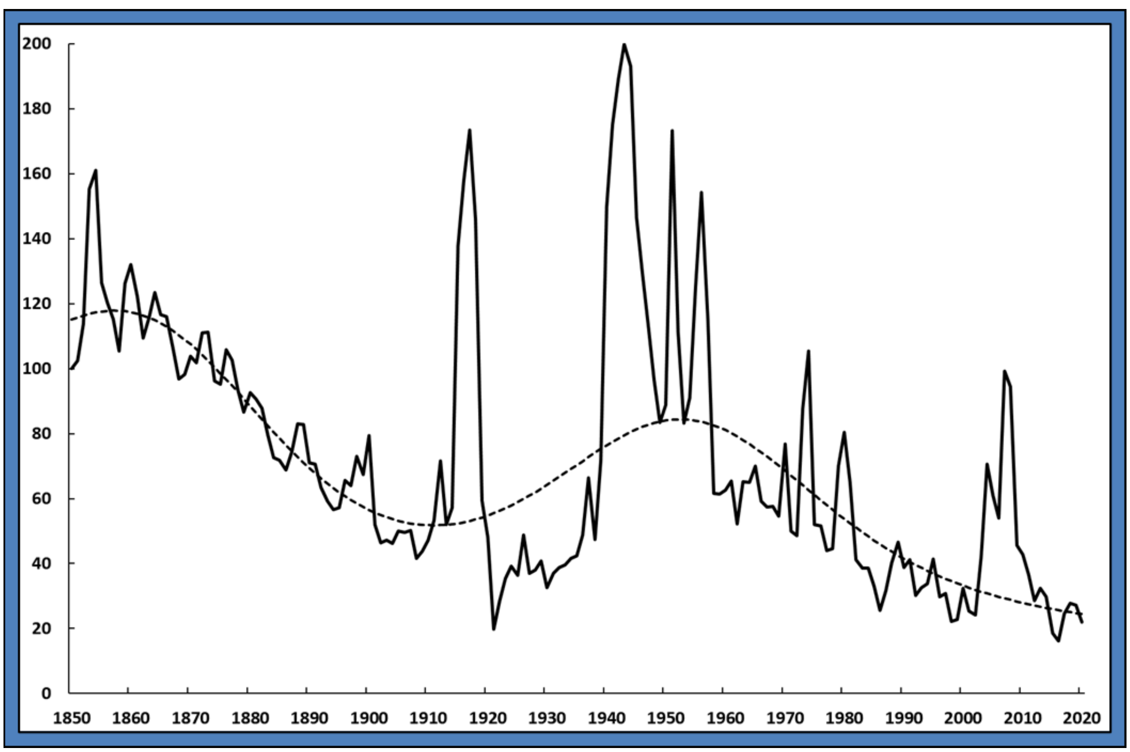
A New Series of Dry Bulk Freight Rates

One of the chief outputs of this paper comes in the form of a new and comprehensive dataset on global dry bulk freight rates from 1850 to 2020. We narrow our attention to activity in the dry bulk sector — that is, commodity cargo like coal, grains, and ore which is shipped in large, unpackaged parcels — for two principal reasons. For one, this sector represents roughly 50% of world trade by volume in the present day (UNCTAD, 2015). Historically, this share would have been even higher, given that the composition of trade by value only began to favor manufactured goods from the late 1950s (Jacks and Tang, 2018). Thus, developments in the dry bulk sector loom large in our understanding of the global economy, shipping markets, and their co-evolution.

For another, dry bulk markets are decentralized spot markets whereby parties must engage in a search process in order to hire a ship for a specific itinerary. Thus, their hire rates — that is, dry bulk freight rates — reflect real-time conditions in the supply of and demand for their services. This is in contrast to other means of maritime transport like containerships or liners which operate in between fixed ports on fixed schedules and which sometimes can be bound to long-term contracts.

All told, there are 10,448 observations on maritime freight rates underlying the real dry bulk index presented below. Our method of aggregating these data into a single real dry bulk index comes in applying the "repeat-sailings" methodology first proposed in Klovland (2009). This procedure has strong intuitive appeal in that it roughly amounts to calculating an unweighted average of changes in real freight rates in any given year. The final series is depicted in Figure 1 below. To our knowledge, this is the longest consistently-measured and continuous series on the costs of shipping goods in the literature.

Figure 1
Real Dry Bulk Index, 1850-2020 (1850=100)



Notes: The solid black line represents the real dry bulk freight rate index, constructed as described in the full paper. The dotted black line is an estimate of the long-run trend derived from the Christiano-Fitzgerald band pass filter which assumes a cyclical component of 70 years duration in the real dry bulk freight rate index.

Figure 1 allows us to document the following important facts:

(1) real dry bulk freight rates are estimated to have followed a downward but undulating path over time: thus, they fell by 55% from 1850 to 1910, rose by 62% from 1910 to 1950, and fell – once again – by 71% from 1950 with a cumulative decline of 79% between 1850 and 2020.

(2) behind these slowly evolving trends, there were also often abrupt movements with real dry bulk freight rates in some instances nearly tripling on a year-to-year basis.

We relate this secular decline to a historical literature which documents significant productivity growth as radical changes in goods handling and storage in ports, naval architecture, and propulsion took place (Harley, 1988; Mohammed and Williamson, 2004; Tenold, 2019). Abstracting away from this long-run trend and its potential productivity-related determinants, we then narrow our focus to understanding the drivers of booms and busts in the dry bulk shipping industry which occur at a higher frequency.

That is, is it possible to rationalize the often extreme inter-annual changes we observe in dry bulk freight rates by considering fundamentals in the sector?

Methodology

We build on a canonical structural vector autoregressive (VAR) model with sign restrictions to set-identify shocks in the dry bulk freight market. Faust (1998), Canova and De Nicolo (2002), and Uhlig (2005) pioneered this model which has become a go-to in empirical macroeconomics. The same methodology makes it possible to set-identify the various shocks that drive dry bulk freight rates at any one moment that might have offsetting impacts. Based on assumptions related to basic supply-and-demand analysis, we specify four orthogonal shocks to real maritime freight rates which we interpret as a shipping demand shock, a shipping supply shock, a fuel price shock, and a residual shock.

In particular, we assume that a positive aggregate demand shock represents an unexpected expansion in global economic activity as in periods of rapid industrialization and urbanization. This, in turn, leads to not only higher global Gross Domestic Product (GDP), but also higher global shipping tonnage, higher real fuel prices, and higher real freight rates. One key mechanism at work here is that an increase in dry bulk freight rates due to an increase in shipping demand triggers not only investment in new shipping capacity but also technological change in the wider industry.

In contrast, a shipping supply shock represents an unexpected inward shift of the shipping supply curve. We associate such shocks with declines in world gross tonnage and assume that they negatively affect global GDP and real fuel prices but positively affect real maritime freight rates. Likewise, we assume that positive fuel price shocks negatively affect global GDP and the supply of shipping services but an increase in real maritime freight rates.

Finally, the residual term captures all remaining uncorrelated shocks, including changes in expectation and potential measurement error. For our purposes, it can also – at least partially – be interpreted as a utilization shock (see Kilian, Nomikos, and Zhou, 2020). For example, the International Maritime

Organization introduced regulation in 2020 imposing a reduction in the sulfur content of fuels used by ships. One means of compliance is through the use of scrubbers for filtration purposes, but this comes with additional monetary and time costs of installation, additional weight for non-shipping purposes, and additional fuel costs as a scrubber-equipped ship consumes roughly 5% more fuel per tonne of cargo (Kerriou, 2020). Here, we assume that residual shocks negatively affect global real GDP, positively affect world gross tonnage, and lead to higher real freight rates. However, we leave the effect of such a residual shock on real fuel prices unrestricted.

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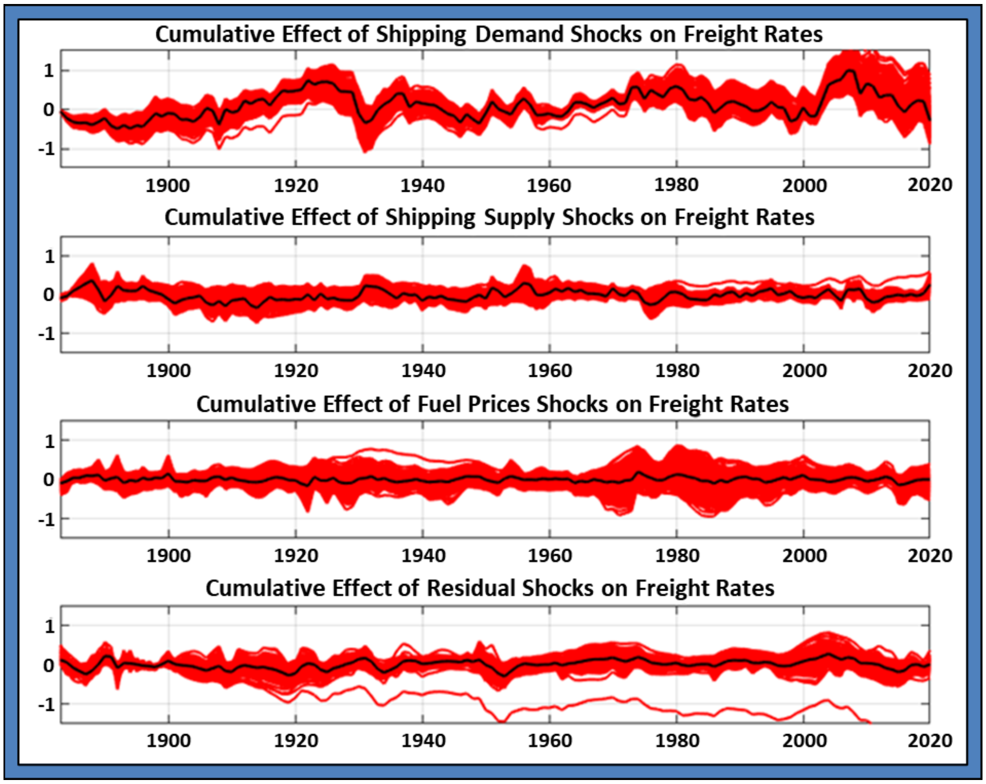
Results

Based on the sign-restricted VAR model, we compute structural impulse response functions and historical decompositions for real dry bulk freight rates. The historical decompositions depicted in Figure 2 on the next page are of particular interest: they show the cumulative contribution at each point in time of each of the four structural shocks in driving booms and busts in real dry bulk freight rates. Thus, they serve to quantify the independent contribution of the four shocks to the deviation of our new series from its base projection after accounting for long-run trends in real dry bulk freight rates.

Figure 2 also allows us to visually discern the historical drivers of booms and busts in the dry bulk shipping industry. The vertical scales are identical across the four sub-panels so that the figures clearly illustrate the relative importance of a given shock. Another way of intuitively thinking about these historical decompositions is that each of the sub-panels represents a counterfactual simulation of what real dry bulk freight rates would have been if it had only been driven by one particular shock.

Figure 2
Historical Decompositions of Real Freight Rates



Notes: The chart shows the historical decompositions from the 68% joint highest posterior density sets obtained from the posterior distribution of the structural models. The cumulative effects implied by the most likely structural model (modal model) are depicted in black. The results shown are based on 5,000 draws from the reduced-form posterior distribution with 20,000 draws of the rotation matrix each, as extensively explained in the full paper.

Table 1 more precisely quantifies these impressions by numerically summarizing the contribution of each shock by period. Our results indicate that shipping demand shocks strongly dominate all others as drivers of real dry bulk freight rates over the long run. For the full period from 1880 to 2020, shipping demand shocks explain 49% of the variation in real dry bulk freight rates while shipping supply shocks explain 22%. These two fundamental shocks which are related to simple supply and demand conditions, thus, explain a significant majority (71%) of the medium- and long-run variation in real dry bulk freight rates. Fuel price shocks and residual shocks respectively explain 11% and 18% of the same.

Table 1
Shares of Shocks in Explaining Booms and Busts in Freight Rates by Period

	Shipping demand shock	Shipping supply shock	Fuel price shock	Residual shock
Full sample: 1880-2020	49%	22%	11%	18%
Pre-World War I: 1880-1913	44%	29%	11%	16%
Interwar: 1919-1939	56%	17%	8%	19%
Post-World War II: 1949-2020	50%	20%	11%	19%

Notes: Table 1 reports the share of variation in the real dry bulk index explained by the four structural shocks for the period from 1880 to 2020 and three sub-periods.

It is also possible to replicate this decomposition for shorter spans of time by using the parameter estimates derived from the full sample in combination with the respective size of shocks for various sub-periods. Table 1 shows that the contribution of shipping demand shocks to variation in real dry bulk freight rates increased substantially in the interwar years and remained elevated in the post-World War II era. Likewise, the contribution of shipping supply shocks decreased substantially in the interwar years and remained suppressed in the post-World War II era. Finally, the contribution of both fuel price shocks and residual shocks remained roughly constant through the three sub-periods.

Tasks for Future Research

What remains as tasks for the future comes in developing disaggregated measures of maritime transport costs across commodity classifications and destination/origin pairings. That is, it would be useful to have a characterization of the respective shares of shocks for particular commodity-destination-origin combinations which could then be matched with known features of commodity and industrial production and their geographical determinants.

An additional way forward would also come in developing a much more refined measure of shipping supply, specifically as it relates to the dry bulk sector. Here, we have had to abstract away from the implications of increasing specialization by ship type, technological change in propulsion, and time-varying utilization rates which may vitally affect any measure of the effective – as opposed to the observed – supply of dry bulk shipping services. Thus, in any final reckoning of the respective role of fundamentals in the dry bulk shipping market, shipping supply may yet reemerge as a more dominant force if our current measure of mercantile gross tonnage diverges too far from actual supply conditions on the ground.

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Keywords

Dry bulk, maritime freight rates, structural VAR.

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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.

Literature Survey

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.

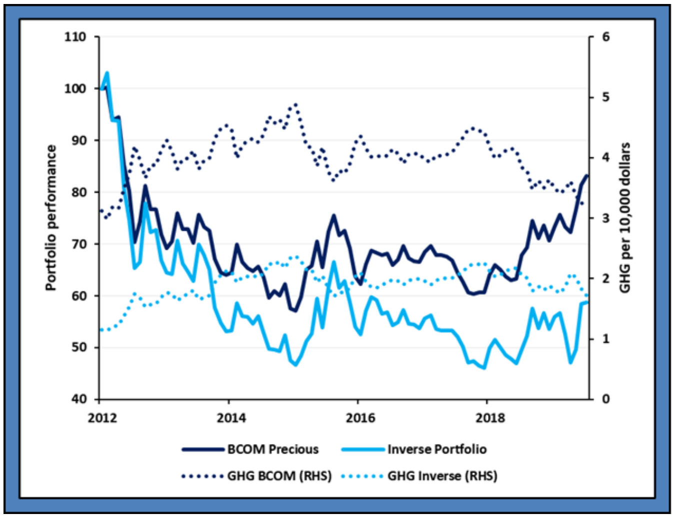
Inverse GHGD Weights

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:

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

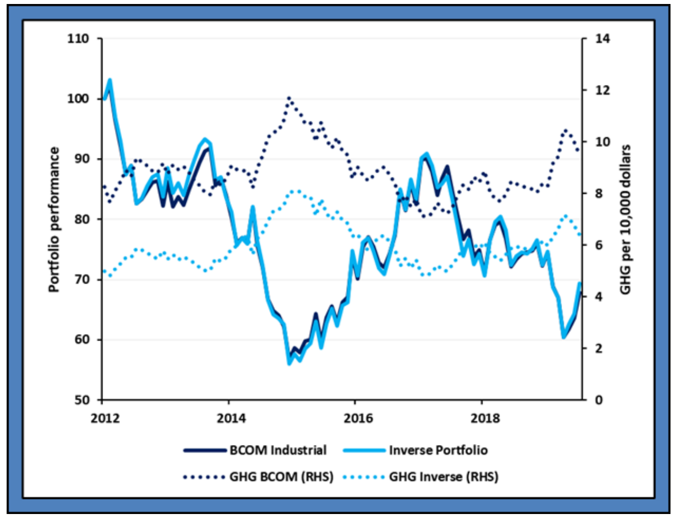
$$\omega_t^i = \frac{\varphi_t^i}{\sum_{i=1}^{N} \varphi_t^i}$$

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.

Rules-based Tilting

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.

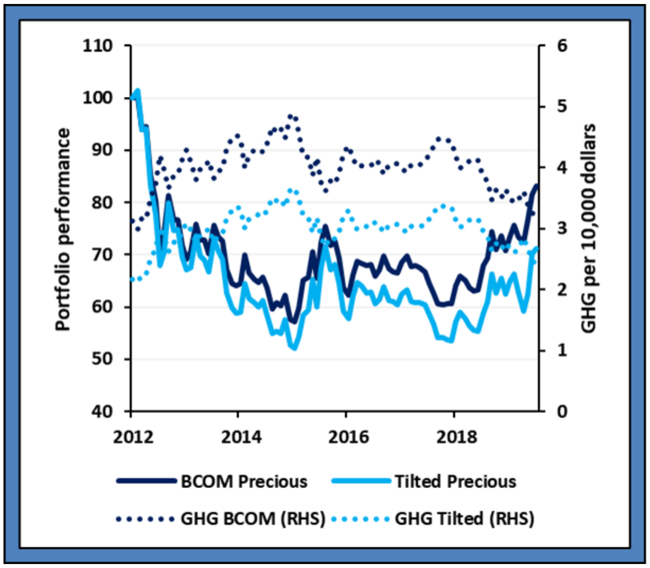
The final weight is given by:

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

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).

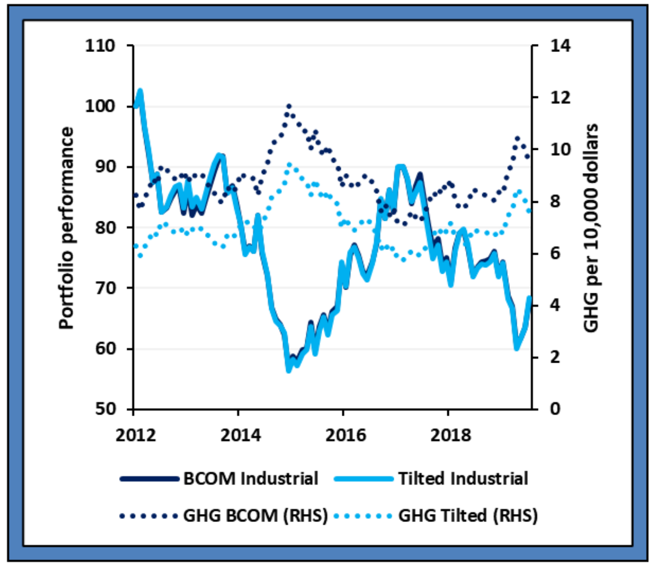
In the case of industrial metals, the results are similar to that of the inverse GHGD portfolio. There is little-to-no impact on portfolio performance by introducing GHG-based tilts. However, the reduction in GHG per 10,000 dollars is smaller (but still meaningful) given the objective function is not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

Figure 14
Precious Metals



Source: Bloomberg.

Figure 15
Industrial Metals



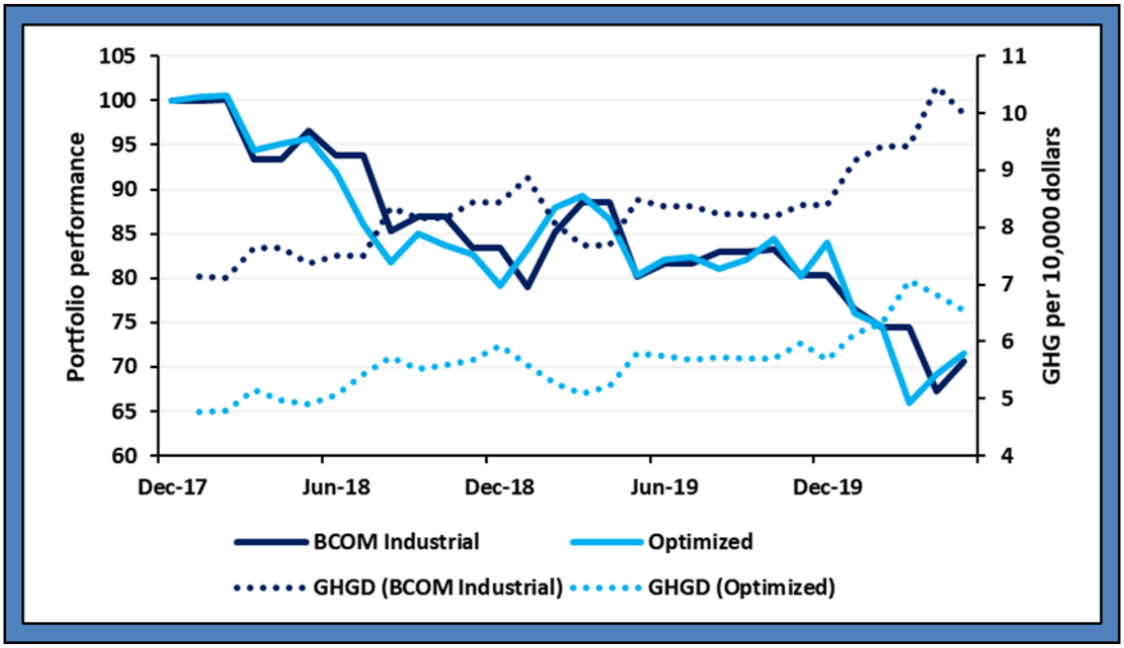
Source: Bloomberg.

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).

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How Super is the Commodity Cycle?

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Introduction

To borrow a phrase once used about business cycles, it can be said that "*the study of [super] cycles necessarily begins with the measurement of [super] cycles*" (adapted from Baxter and King, 1999). This was the lead quote in a 2008 International Monetary Fund journal article introducing the concept of statistically measuring super cycles. Dr. John Cuddington[1] and Dr. Daniel Jerrett utilized band-pass filters to isolate cycles in commodity prices at varying frequencies. With the current re-emergence of the super-cycle discussion, it seems timely to revisit and update the analysis to help inform the current conversation.

Defining Super Cycles

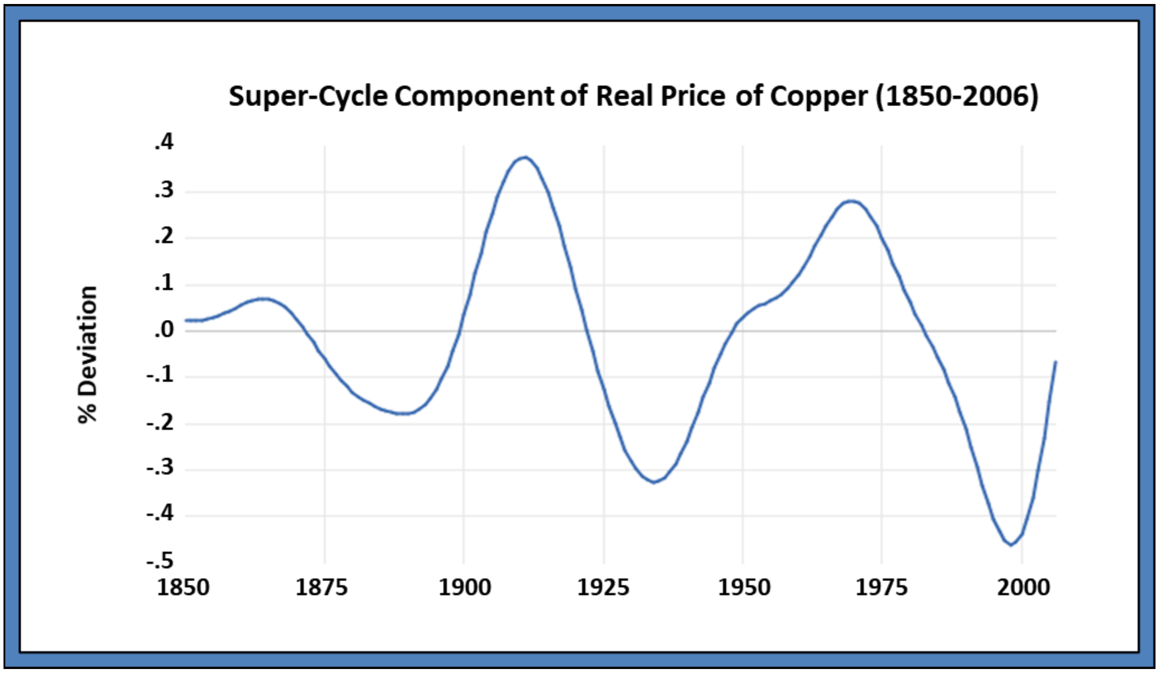
In early 2005, former Citigroup Director, Alan Heap, declared that "a super cycle is underway, driven by material intensive economic growth in China" (Heap, 2005). Heap's analysis suggested that super cycles have two unique features: 1. Prolonged cycles with expansions of roughly 10-35 years (suggesting full cycles of 20-70 years) and 2. Broad-based, affecting a wide range of commodities. Heap said that there had been three super cycles since the late 1800s occurring during the U.S. industrialization, post-war reconstruction in Europe followed by Japan, and the industrialization and urbanization of China beginning in the early 2000s. All were demand driven.

It is well known that short-to-medium run supply conditions in commodity markets can be quite constrained due to capacity and time to bring new deposits online. Therefore, it should be evident that a large demand shock such as above-trend economic growth in China could create a supply-demand imbalance that results in large, sustained price increases as seen in the early 2000s.

Measuring Super Cycles

Cuddington and Jerrett (2008) took an agnostic view of super cycles and used a series of statistical techniques to document facts around commodity price behavior. The super cycle, as defined by Heap, had a complete cyclical frequency of 20-70 years. Band-pass filters were used to extract cyclical components as well as the long-run trend from a 150-year dataset of real metals prices. The filtering technique found evidence supporting the hypothesis that three super cycles had occurred over the past 150 years and the amplitude of the super cycles was large with variations of 20 to 40 percent above and below the long-run trends. Figure 1 shows the super-cycle component for the real price of copper from the original 2008 analysis.

Figure 1



In addition to extracting the super-cycle component of copper, the analysis was performed on a broader group of metals. Simple correlations of the super-cycle components were large and statistically significant in most cases. Principal component analysis (PCA) was used to measure the amount of co-movement in the group of metals. If a super cycle is being driven by broad-based economic growth, one would expect to see commodity prices moving together. PCA can be used to measure the importance of unobservable common factors affecting the super-cycle components. The first principal component explained 66 percent of the overall joint co-variation in the six metal super-cycle components. It is left to the analyst to then correlate the unobserved factor with something that could be driving prices. In this case, it was assumed that the first principal component was highly correlated with global real GDP, supporting Heap's hypothesis that super-cycles are driven, in part, by periods of above-trend economic growth and industrialization and urbanization.

The analysis was extended to look at iron ore, steel, and molybdenum (Jerrett and Cuddington, 2008) and to oil prices (Zellou and Cuddington, 2012). Super cycles were found to occur during similarly defined time periods in both studies, further supporting the super-cycle hypothesis.

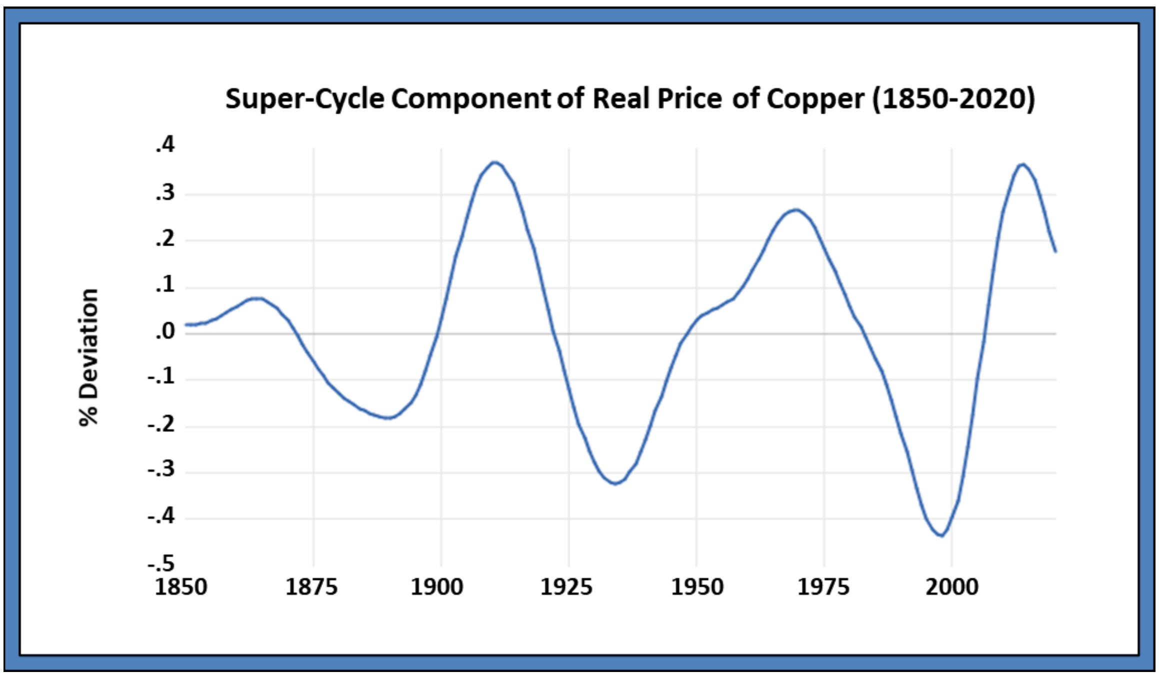
Are All Cycles Super?

There have been discussions in the past few months regarding commodity prices and the possibility of entering a new super cycle driven, in part, by the ongoing move to green technology as well as supply constraints from a decade of underinvestment in exploration and production. In addition, many commodities have seen recent price increases which could be a combination of economic recovery from the Coronavirus pandemic, current, low inventories in many commodities, and a weak U.S. dollar. The question is, are these current market forces transitory and more importantly, is the forthcoming technological change a large enough structural driver to affect commodity markets in a similar way to prior super cycles?

No two super cycles are alike, and one could assume that with declining commodity intensity in many countries, the continued energy transition, and demographics becoming a headwind for many parts of the world, the look and feel of super cycles and the associated amplitude may be quite different both across the entire commodity complex and within individual commodities.

The original statistical analysis was updated through 2020 to determine where the current super cycle is relative to long-run trends. This can help inform the current discussion of whether a new super cycle is emerging. Figure 2 shows the super-cycle component of the real price of copper through the end of 2020. The super-cycle component peaked in 2014 but remains above its long-run trend suggesting we may still be in the tail end of the super cycle that began in the early 2000s or possibly a new cycle is emerging without the decline in amplitude seen in past super cycles.

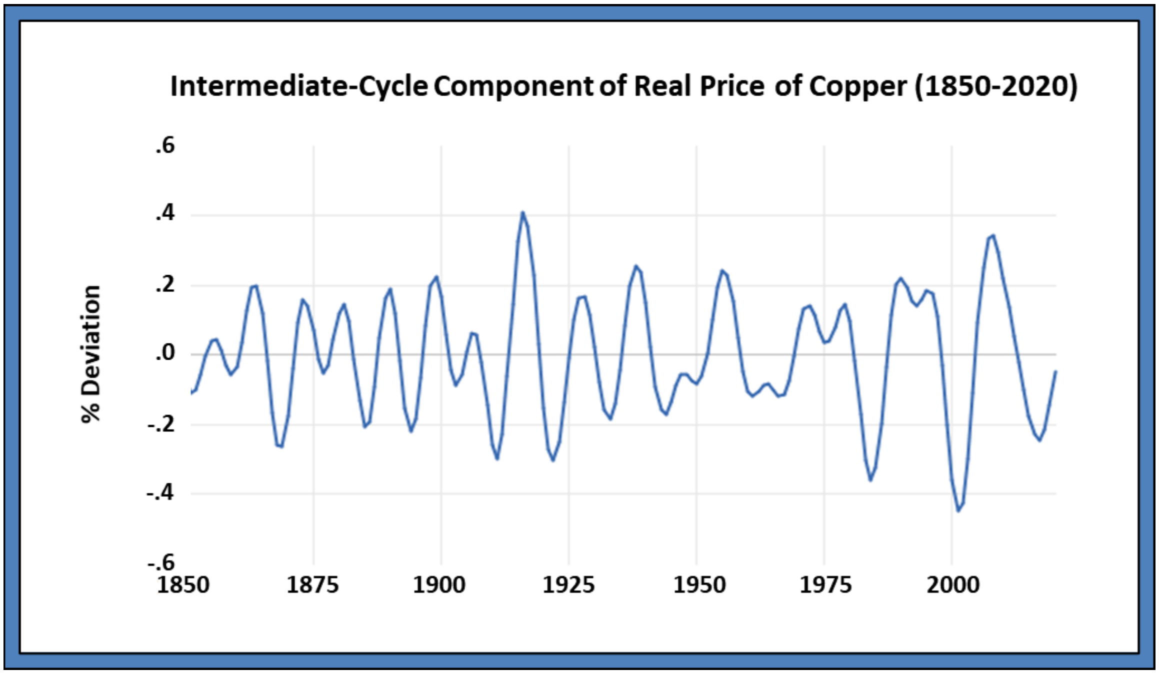
Figure 2



The statistical methodology offers the flexibility to isolate any cyclical frequency from a time series.[2] In addition to isolating the super-cycle component, both the intermediate component (8-20 years) and the business-cycle (2-8 years) component can be extracted using band-pass filters.

The intermediate cycle of 8-20 years correlates well with the investment cycle that many commodities producers experience. The timing of this cycle can have impacts on the super-cycle discussion. Using copper as an example, the super-cycle component is still above trend, albeit declining. The intermediate cycle reached a trough in 2017 after a decade of declining, and subsequently, a decade of little to no investment in production and exploration. Figure 3 shows the intermediate cycle for the real price of copper.

Figure 3



LME copper inventories in late 2020 were the lowest since 2007.[3] This corresponds to the timing of significant price increases in the fourth quarter of 2020. With China experiencing early signs of an economic recovery, the supply shortage could keep upward pressure on copper prices in the intermediate term. The question is does this represent the emergence of a new super cycle or is this the result of under investment in the industry that will correct in the coming years?

2021 and Beyond

The current discussion of the ongoing transition to green technology does represent a source of continued demand for decades to come. The commitment by many nations to be carbon neutral and less energy intensive by 2050-2060 requires significant infrastructure investment which will be commodity intensive. Structural models of commodity prices have shown that at major stages of economic development including agricultural and industrial, the intensity of use in commodities increases, increasing the likelihood of a super cycle. This is followed by a transition to a period of less-material intensive growth as economies transition to a service-driven economy. The current discussion around green technology raises an interesting question: is the global economy entering a new phase of economic development and technological change unlike any we have seen before that will be material intensive?

Cuddington and Jerrett did not set out to prove or disprove the existence of super cycles in their original 2008 paper. Rather, they wanted to introduce a framework that could inform a broader discussion about long-run price movements and develop a peer-reviewed, statistical methodology to support it. Before one can conjecture about the existence of any economic phenomenon, one must be able to measure it.

The reemergence of the super-cycle discussion has important implications for the global economy and capital markets. Mineral producers, policymakers, and investment managers are all trying to better understand commodity prices to make more informed, long-term decisions. This statistical methodology is one of many possible tools that could help support the decision-making process and provide a framework to discuss super cycles in commodities and lend itself to other macroeconomic and financial questions.

Endnotes

Of note, this article was cited in Wallace (2021).

1 John T. Cuddington is the former William J. Coulter Professor of Mineral Economics at the Colorado School of Mines.

2 As Christiano and Fitzgerald (2003, p. 1) argue: The theory of the spectral analysis of time series provides a rigorous foundation for the notion that there are different frequency components of the data. An advantage of this theory, relative to other perspectives on decomposing time series, is that it does not require a commitment to any statistical model of the data. Instead, it relies on the Spectral Representation Theorem, according to which any time series within a broad class can be decomposed into different frequency components. The theory also supplies a tool for extracting those components. That tool is the ideal band pass filter.

3 Source of data: https://www.lme.com/en-GB/Market-Data/Reports-and-data/Warehouse-and-stocks-reports.

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Disclaimer

Gold Price Relationships Before and After the Global Financial Crisis

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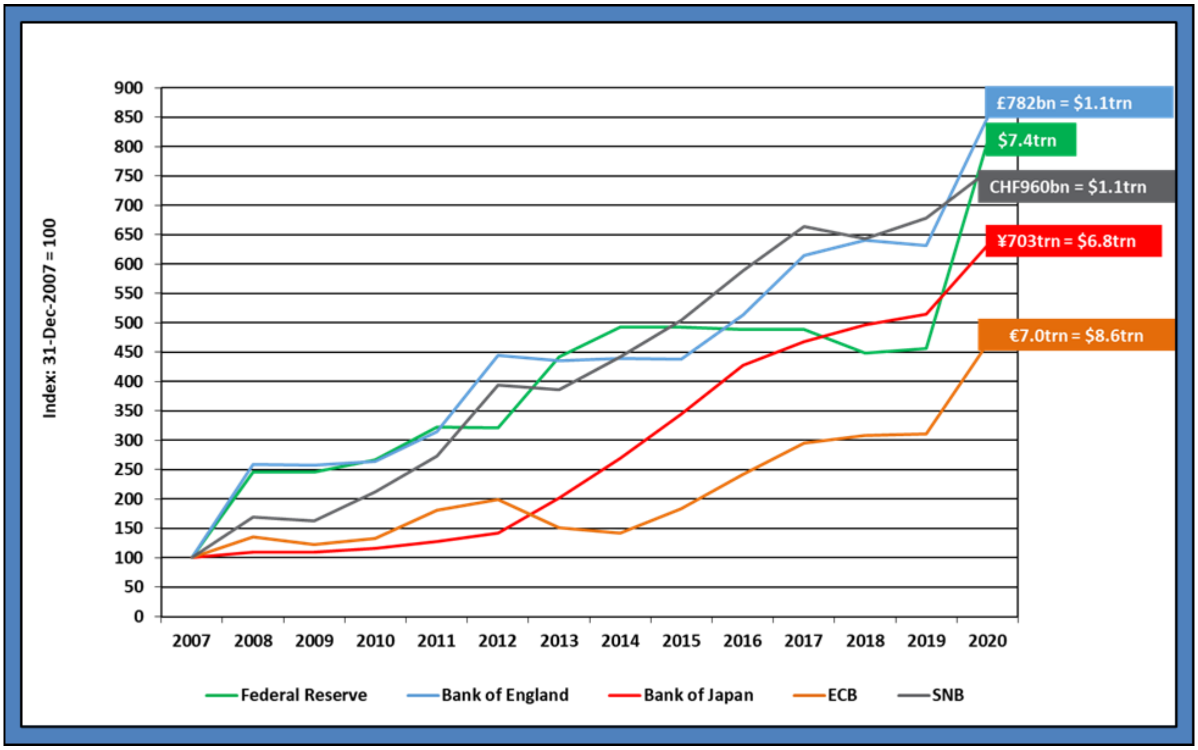
Dr. Daniel Murray, Ph.D., Deputy Chief Investment Officer and Global Head of Research at EFG Asset Management (U.K.), presenting at the EFG Knowledge Exchange Investment Summit held in London in January 2020. Dr. Murray is also a member of the *GCARD*'s Editorial Advisory Board.

Introduction

A feature of financial markets over the past 12 years is that central banks around the world have engaged in a series of large-scale asset purchase programs. Policies that once would have been viewed as nothing more than theoretical textbook anomalies are now firmly established as a core part of central bankers' toolkits. The Federal Reserve's balance sheet has grown by about 8x since the onset of the Global Financial Crisis, as have the balance sheets of the Bank of England and the Swiss National Bank (SNB); the Bank of Japan's balance sheet has expanded over sixfold while the European Central Banks's (ECB's) has increased by a factor of nearly five. A natural question to ask is: what impact has this unusual central bank activity had on the market for gold?

Figure 1
Central Bank Balance Sheets Since the Global Financial Crisis



Sources: National Central Banks, EFG calculations.

What Drives the Gold Price?

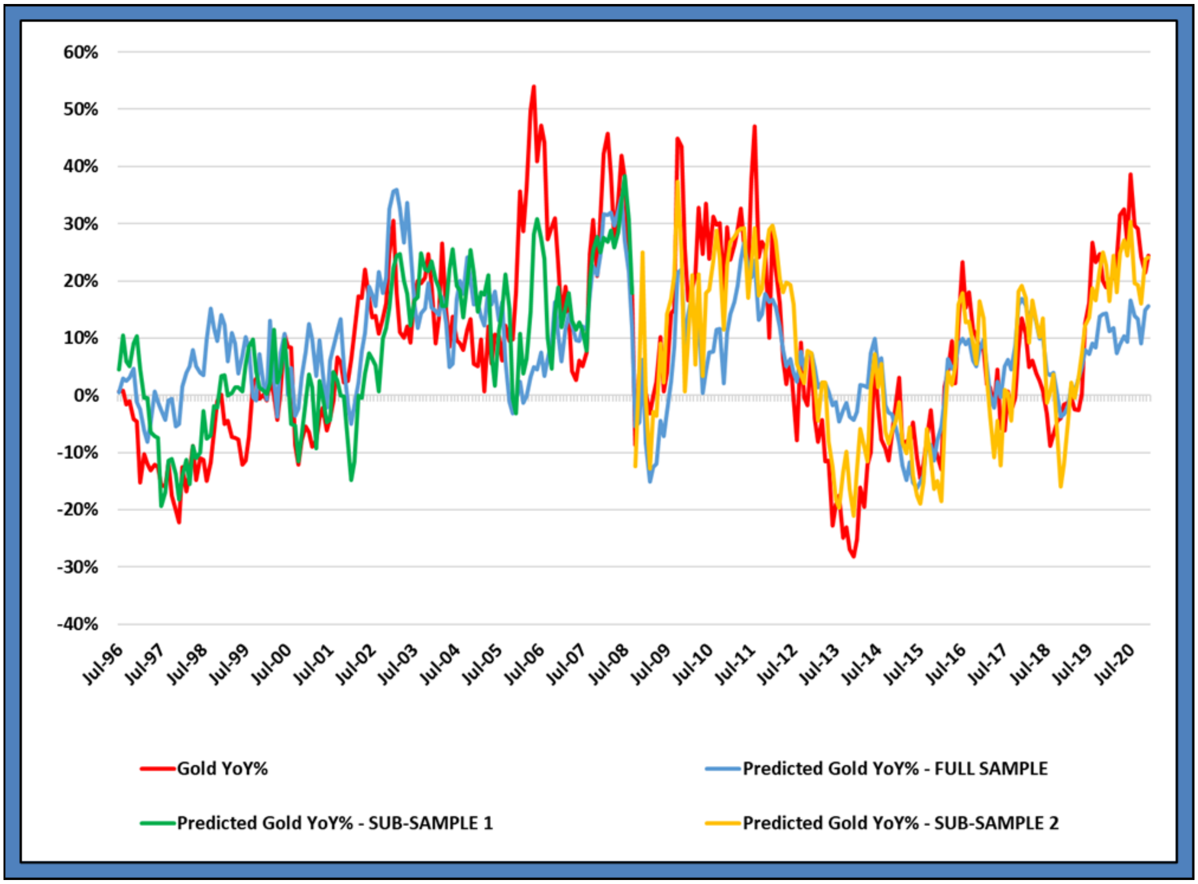
Unlike most metals, gold is unusual in that it has relatively few practical uses. The majority of gold demand has historically been for jewelry and investment purposes. On average over the 10 years to end 2019, 51.3% of gold demand was for jewelry, 29.3% was for investment purposes and a further 11.3% originated from central banks and other institutions. Only 8.2% of gold demand was attributed to technological uses, comprised of electronics (6.3%), other industrial (1.3%) and dentistry (0.5%). Over the first three quarters of 2020, the investment share of total demand increased sharply to 55% as the shares attributable to demand for jewelry and from central banks dropped.

These different demand groups roughly coincide with the four factor groups the World Gold Council identifies as driving the gold market:

- (i) Wealth and economic expansion
- (ii) Market risk and uncertainty
- (iii) Opportunity cost
- (iv) Momentum and positioning.

On their website the World Gold Council shows the results of a model that seeks to explain movements in the gold price according to these four factor groups. Whilst details of the model are not provided, it is possible to perform a simple linear regression analysis that appears to broadly replicate the World Gold Council's model using monthly data from July 1996 to December 2020. For reference, the dependent variable is year-over-year percent changes in the gold price and the explanatory variables are year-over-year changes in the VIX index of implied volatility and the 10-year Treasury yield and year-over-year percent changes in the oil price, the trade weighted U.S. dollar and the U.S. Consumer Price Index (CPI inflation). Figure 2 shows how the model does a reasonable job at explaining changes in the gold price. For reference, the R^2 of the model is 36.8%.

Figure 2
YoY% Changes in the Gold Price: Predicted and Actual



Sources: Bloomberg, EViews, EFG calculations.

Figure 2 also shows the predicted values for two sub-sample models using the same dependent and explanatory variables. The first sub-sample runs from July 1996 to September 2008 and the second sub-sample starts in October 2008 and ends in December 2020. October 2008 was chosen because that was the month in which the U.S. Federal Reserve began its first quantitative easing program. July 1996 was chosen as the start date so that there are an equal number of observations before and after the suspected break point (which increases the power of the breakpoint test).

Several points are worth noting. First, the R^2 for the first sub-sample regression is 58.7%, a decent improvement over the whole sample regression. The second sub-sample R^2 jumps even more impressively to 75.4%. Furthermore, there are meaningful changes in the parameter estimates.

In the whole sample regression, the coefficients on CPI inflation and on changes in the VIX are not significant whereas the CPI inflation coefficient is significant in both sub-samples and the VIX coefficient is significant only in the second sub-sample. However, the coefficient on CPI inflation changes sign from positive in the first sub-sample to negative in the second sub-sample as does the coefficient on changes in the 10-year Treasury yield. And in the first sub-sample, the constant and the coefficient on percent changes in the oil price are insignificant whereas they are highly significant in the second sub-sample. Only the coefficient on the trade weighted dollar was significant with an unchanged sign in both sub-sample regressions. See Table A1 in the Appendix for more detail. So the relationship appears to have changed meaningfully before and after the Global Financial Crisis (GFC). A simple Chow test confirms that a structural break is present from October 2008 onwards (F statistic = 43.1).

A VAR Approach to Causality

Whilst a simple single equation linear approach to modeling the gold price is informative and intuitive in some respects, it assumes that the left-hand side variable is determined by the right-hand side variables. In reality the relationships between these variables are more complex with a high degree of interaction between them. For example, a commonly held market view is that the gold price is negatively correlated with the U.S. dollar. Whilst the simple linear approach does indeed seem to confirm that view, it says nothing about the direction of causality. Does the gold price lead the dollar or vice versa? Is the relationship two-way? What about interactions between and with the other variables? Using a simple linear approach may lead to erroneous conclusions being drawn.

One way to investigate the relationships between these variables is to use a Vector Autoregressive or VAR model. Following a similar approach to the simple linear model described above, VAR analysis was performed both on the full sample and the two sub-sample periods.

A convenient feature of VAR models is that they allow straightforward investigation of Granger causality. Table 1 shows the results for year-over-year percent changes in the gold price. The analysis illustrates how in the full sample it is only changes in the 10-year Treasury yield that weakly Granger cause percent changes in the gold price and in the first sub-sample there is no evidence of Granger causality from any of the variables to the gold price. However, there is evidence in the second sub-sample that percent changes in the gold price are Granger caused by the 10-year Treasury yield, the trade weighted dollar and inflation. This apparent shift in causal relationships supports the view that the behavior of the gold price and its relationship with other variables has changed meaningfully since the GFC.

Table 1
What Granger Causes YoY% Changes in the Gold Price?

		Dependent Variable: Gold Price YoY%		
		Full	Sub Sample 1	Sub Sample 2
Lagged Variables	Brent Oil Price YoY%	X	X	X
	10-Year Treasury yield Change over 12m	(✓)	X	✓
	Trade Weighted Dollar YoY%	X	X	(✓)
	CPI YoY%	X	X	✓
	VIX Change over 12m	X	X	X

✓ = statistically significant at 5%, (✓) = statistically significant at 10%, X = not statistically significant

Sources: EViews, EFG calculations.

It's also interesting to look at other relationships to see if percent changes in the gold price Granger cause any of the other variables. This information is summarized in Table 2.

Table 2
What is Granger Caused by YoY% Changes in the Gold Price?

		Dependent Variable				
Lagged Variable: Gold Price YoY%		Brent Oil Price YoY%	10-Year Treasury Yield Change over 12m	Trade Weighted Dollar YoY%	CPI YoY%	VIX Change over 12m
	Full Sample	X	X	X	(✓)	X
	Sub-sample 1	(✓)	X	✓	X	X
	Sub-sample 2	X	✓	X	(✓)	X

✓ = statistically significant at 5%, (✓) = statistically significant at 10%, X = not statistically significant

Sources: EViews, EFG calculations.

The results here are also revealing and supportive of the view that the relationships have changed since the GFC. In the full sample analysis percent changes in the gold price weakly Granger cause inflation whereas in the first sub-sample percent changes in the gold price Granger cause only percent changes in the price of Brent oil and the trade weighted dollar. In the second sub-sample the results change yet again: percent changes in the gold price Granger cause only changes in the 10-year Treasury yield and inflation.

If we consider the second sub-sample relationship as the one that best describes the current environment, it suggests that there is bi-directional Granger causality between percent changes in the gold price and changes in the 10-year Treasury yield and inflation, whilst there is weaker evidence that percent changes in the gold price are Granger caused by percent changes in the trade weighted dollar.

Impulse Responses

A separate feature of VAR models is that they allow investigation of what would happen to the system if a variable were to experience an unexpected shock. As with the Granger causality analysis, the focus will remain on the behavior of gold and for the sake of brevity results are discussed solely for the second sub-sample. A full set of charts showing the impulse response functions for both sub-samples is provided in the Appendix.

Of the five impulse response functions related to the impact on gold of an unexpected change in one of the other variables, only two are significant. These are shown in Figures 3a and 3b. For the other variables – percent changes in the price of Brent oil, inflation and the change in the VIX index – the responses are not meaningful.

Figure 3a

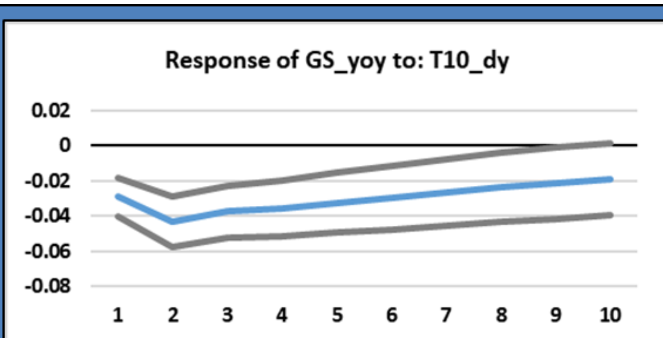
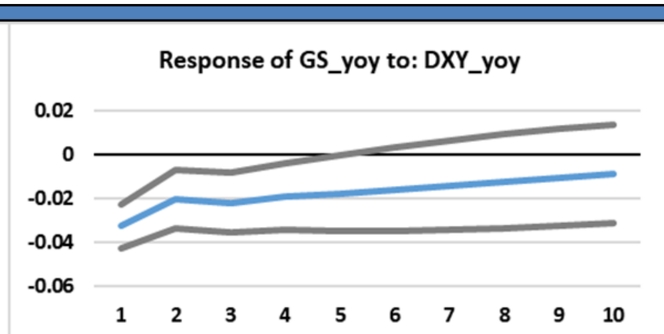


Figure 3b



Sources: EViews, EFG calculations.

Note: GS_yoy = YoY% change in the gold price, T10_dy = YoY change in the 10-year Treasury yield, DXY_yoy = YoY% change in the trade weighted dollar.

Figure 3a illustrates how a sudden move (one standard deviation) higher (lower) in the 10-year Treasury yield would be expected to result in an immediate decline (increase) in the year-over-year percent change in the gold price, the effect of which peaks one month after the initial shock. Figure 3b illustrates how a sudden move higher (lower) in the trade weighted dollar would also be expected to result in an immediate decline (increase) in the year-over-year percent change in the gold price, the effect of which declines immediately after the initial shock.[1] These results are perhaps not surprising given the Granger causality discussed above. For reference, the impulse response functions of gold to the other variables in the first sub-sample are all statistically insignificant from 0 apart from the trade weighted dollar for which the response is similar to but weaker than in the second sub-sample.

Conclusions

The purpose of this article was to investigate the behavior of the gold price to see if its relationships with other variables have changed in the post-GFC environment. A standard linear regression approach suggests that a structural break occurred during the GFC - perhaps as a result of semi-permanent changes in the operation of monetary policies around the world - following which the relationship between gold and the other variables appears to have changed meaningfully. However, such a modeling approach may not be appropriate.

Further insights are provided by a VAR analysis that allows for more sophisticated interactions between the variables. The results of this analysis are also consistent with a structural break having occurred during the GFC, as evidenced by significant changes in Granger causality test results. Those tests and the accompanying impulse response functions indicate that year-over-year percent changes in the gold price respond negatively to unexpected changes in the 10-year Treasury yield and percent changes in the trade weighted dollar. However, these relationships are bi-directional: it is inappropriate to assume that causality runs in one direction only, as is the case with the linear model. What is perhaps more surprising and contrary to widely held market wisdom is that no statistical relationship has been found between percent changes in the gold price and changes in the VIX index.

More generally, market participants often make assertions about the relationship between the gold price and the variables used in the analysis presented in this report. This article seeks to deepen and formalize our understanding of those relationships, taking into consideration the dramatic shift in monetary policy operation that has taken place since the GFC.

Appendix

Table A1
Ordinary Least Squares (OLS) Regression Results

	FULL SAMPLE		SUB-SAMPLE 1		SUB-SAMPLE 2	
	Coefficient	t statistic	Coefficient	t statistic	Coefficient	t statistic
BRENT_YOY	0.125	3.748	-0.034	-1.055	0.410	9.256
T10_DY	-0.074	-6.015	0.042	2.743	-0.195	-17.693
DXY_YOY	-0.866	-8.239	-1.289	-11.403	-0.917	-7.852
CPIYOY	0.001	0.067	0.080	6.792	-0.064	-6.025
VIX_DY	0.000	-0.208	-0.001	-0.424	0.002	2.642
C	0.053	2.695	-0.130	-4.312	0.149	8.186

Table A2
Granger Causality Results: Full Sample
Null: lagged coefficients do not Granger cause the dependent variable
Values in cells are probabilities of not rejecting the Null based on Chi-sq test statistics

		FULL SAMPLE Dependent Variable					
		GS_YOY	BRENT_YOY	T10_DY	DXY_YOY	CPIYOY	VIX_DY
Lagged Variables	GS_YOY		0.484	0.565	0.433	0.094	0.697
	BRENT_YOY	0.468		0.250	0.154	0.000	0.134
	T10_DY	0.072	0.017		0.204	0.053	0.817
	DXY_YOY	0.391	0.041	0.717		0.123	0.535
	CPIYOY	0.353	0.111	0.155	0.142		0.002
	VIX_DY	0.515	0.054	0.039	0.457	0.003	

Table A3
Granger Causality Results: Sub-sample 1
Null: lagged coefficients do not Granger cause the dependent variable
Values in cells are probabilities of not rejecting the Null based on Chi-sq test statistics

		SUB SAMPLE 1 Dependent Variable					
		GS_YOY	BRENT_YOY	T10_DY	DXY_YOY	CPIYOY	VIX_DY
Lagged Variables	GS_YOY		0.059	0.351	0.002	0.271	0.569
	BRENT_YOY	0.159		0.306	0.491	0.000	0.023
	T10_DY	0.945	0.002		0.439	0.055	0.773
	DXY_YOY	0.456	0.045	0.136		0.474	0.266
	CPIYOY	0.128	0.000	0.285	0.001		0.045
	VIX_DY	0.605	0.097	0.255	0.739	0.704	

Table A4
Granger Causality Results: Sub-sample 2
Null: lagged coefficients do not Granger cause the dependent variable
Values in cells are probabilities of not rejecting the Null based on Chi-sq test statistics

		SUB SAMPLE 2 Dependent Variable					
		GS_YOY	BRENT_YOY	T10_DY	DXY_YOY	CPIYOY	VIX_DY
Lagged Variables	GS_YOY		0.716	0.034	0.495	0.072	0.182
	BRENT_YOY	0.620		0.102	0.735	0.000	0.117
	T10_DY	0.005	0.967		0.414	0.049	0.363
	DXY_YOY	0.056	0.021	0.041		0.004	0.641
	CPIYOY	0.025	0.068	0.035	0.195		0.040
	VIX_DY	0.985	0.004	0.601	0.436	0.087	

Charts A1-10
Impulse Response Functions for Year-over-Year Percent Changes in the Gold Price

Sub-sample 1

Chart A-1

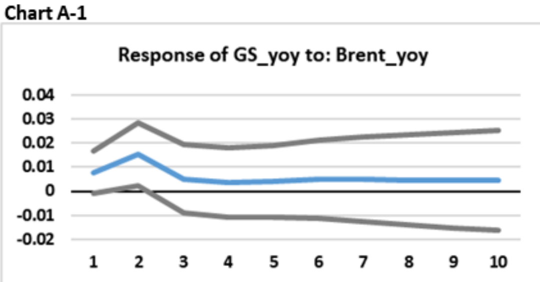


Chart A-2

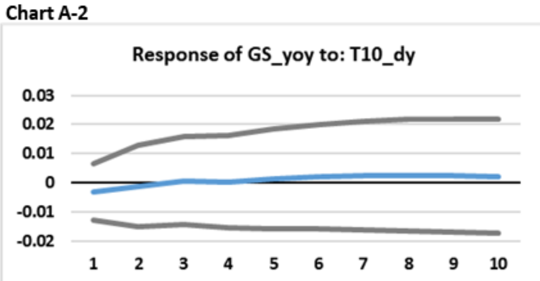


Chart A-3

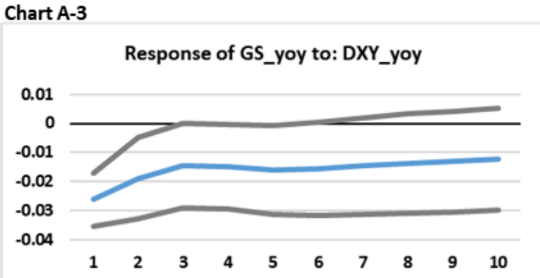


Chart A-4

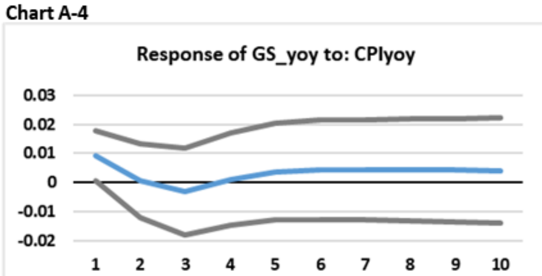
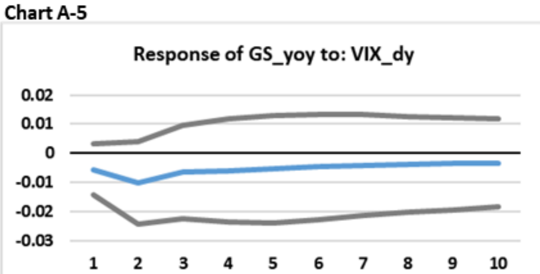


Chart A-5



Sub-sample 2

Chart A-6

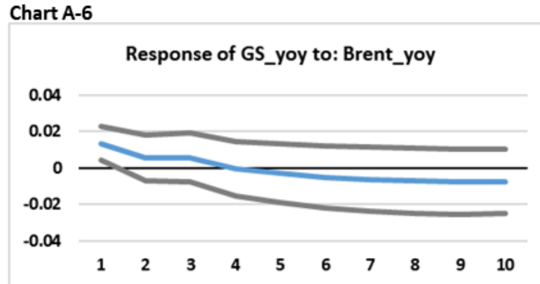


Chart A-7

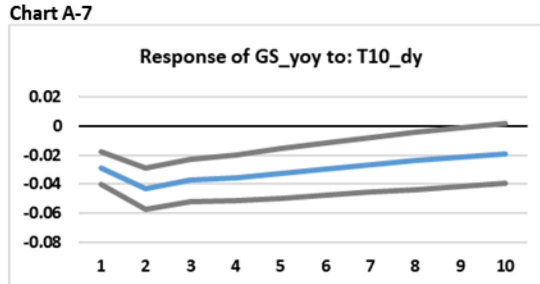


Chart A-8

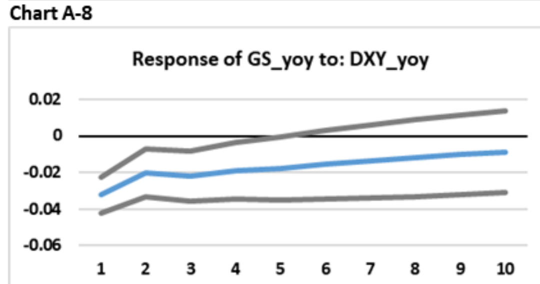


Chart A-9

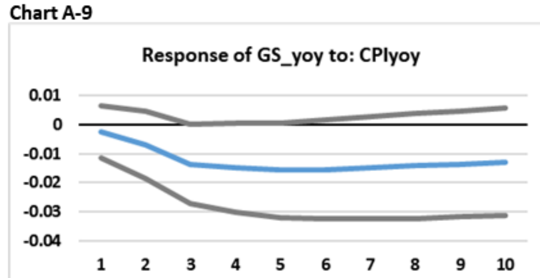
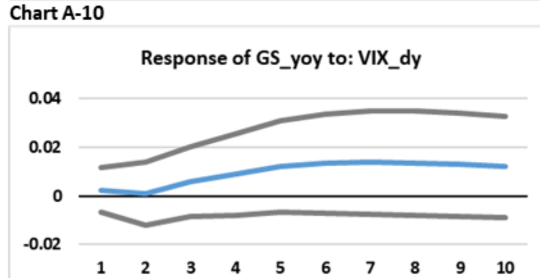


Chart A-10



Endnote

1 Intuitively, these two responses may be connected since a stronger dollar is supported by a wider yield spread of U.S. government bonds over those issued by other countries. Analysis shows that while changes in the trade weighted dollar Granger cause changes in the 10-year Treasury yield the opposite is not true.

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A Review of Global Silver Supply Trends

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Chantelle Schieven
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This article provides a broad sweep review of both the long-term trends in global silver mining supply and in global silver supply concentration. The authors anticipate mine supply growth to remain challenged and for industry consolidation to marginally increase.

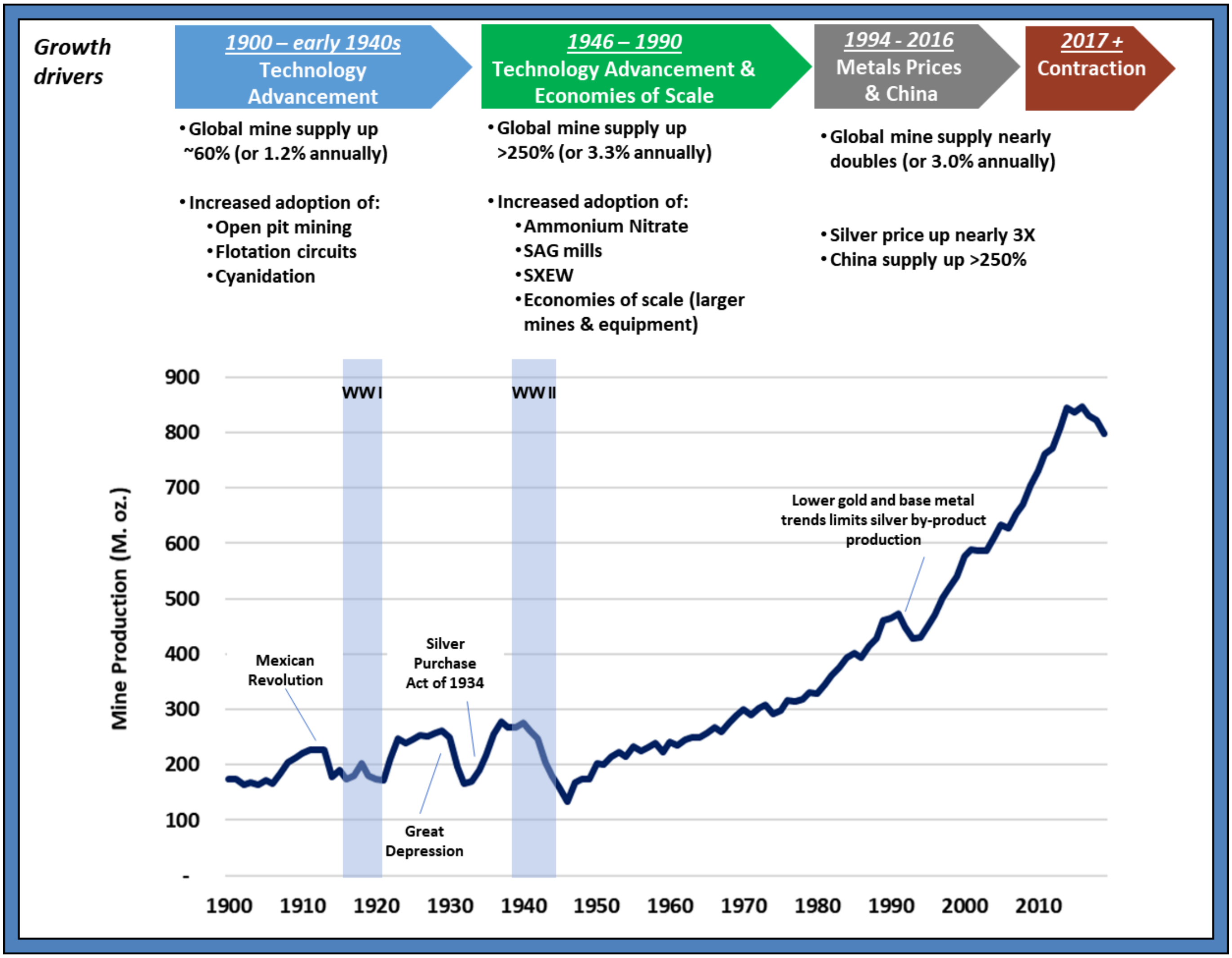
Long-Term Global Silver Mine Supply Trends

In this section, we review global silver mine supply trends. Figure 1 displays global silver mine supply since 1900 and the various drivers that buoyed growth including technology advancements, economies of scale and relatively new sources of supply (namely from China). As shown, global silver mine supply totaled slightly under 175M ounces in 1900. Aside from declines resulting from the Mexican Revolution that began in 1910, the First World War and the Great Depression, by 1940 global mine supply increased by approximately 60 percent to 275M ounces (or 1.2 percent annually). Silver mine production, along with that of other metals, benefited from increased adoption of open pit mining methods, improved ore separation techniques (such as froth flotation) as well as cyanidation processing. In the midst of the Great Depression, global mine supply declined by 35 percent, and the value of silver was nearly cut in half to average $0.28 per ounce in 1933. To stabilize the value of silver, in 1934 Congress enacted the Silver Purchase Act whereby all U.S. mined silver was sold to the U.S. Mint for either storage or to be made into coins. By 1936, global production levels climbed back to pre-Depression levels.

Following the Second World War, during which global silver mine supply declined by over 50 percent, the years from 1946 through 1990 realized fairly steady increases in global production. Over this 45-year period, global supply climbed by over 250 percent to nearly 475M ounces (or by 3.3 percent annually). Widespread use of ammonium nitrate for blasting, heap leaching, semi-autogenous grinding (SAG) mills, Solvent Extraction/Electrowinning (SX-EW) processing and others contributed to increased production across precious and base metal operations, allowing mining companies to profitably extract gold from lower-grade and more complex ore types. Accompanying the implementation of new technologies during the 1980s and 1990s, silver mine supply growth is also being driven by large gains in economies of scale with mining and other equipment. For example, Caterpillar haul truck capacities climbed from approximately 35 tonnes in 1950 to 150 tonnes with the CAT 785 in 1984 to over 360 tonnes in 1998.[1]

The early 1990s saw a sharp pullback with global mine supply declining by approximately 45M ounces to 420M ounces by 1994. Supplies declined from primary silver mining operations as well as from by-product sources. Over this period, prices dropped by over 30 percent for copper, approximately 14 percent for gold and by nearly 20 percent for silver.

Figure 1
Silver Mine Supply (in Million Ounces) and Significant Growth Drivers



Sources: United States Geological Survey (USGS), Silver Institute, CPM Group, Bloomberg, and Capitalight Research.

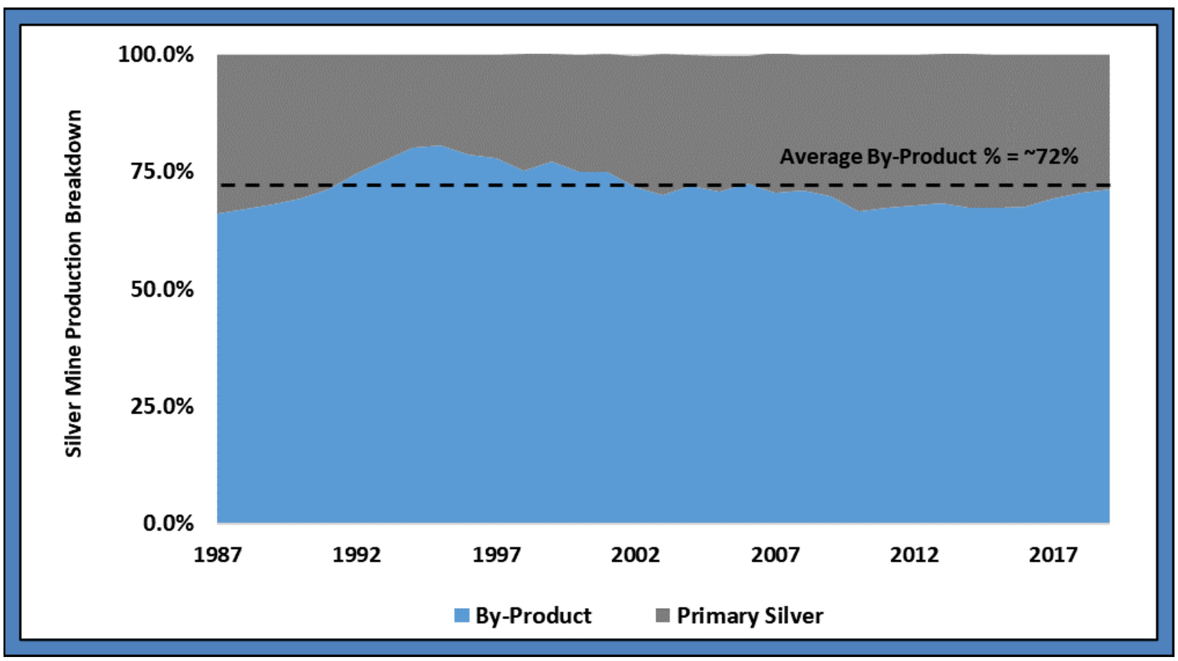
Reverting back to Figure 1, the most recent period of significant growth in mine supply commenced in 1994 through 2016, resulting from a period of prolonged increases in silver prices, as well as the prices for gold and copper and most mineral commodities, with the progression of the Metals Super Cycle. Average annual silver prices climbed from $4.30 per ounce in 1993 to over $35/ounce in 2011, prior to retreating to over $17 in 2016. Over this period global silver mine supply almost doubled to nearly 850M ounces. Growth in Chinese mine supply was a key driver as output from the country increased from under 34M ounces in 1993 to over 120M ounces in 2016 (up nearly 260 percent).

From 2016 through 2019, global supply contracted by over 55M ounces, driven by large declines in Peru (nearly 11M ounces) and China (approximately 10M ounces). The suspension of the mining license at the Escobal mine in Guatemala in 2017 (which continues to be on care and maintenance) has contributed to an over 20M ounce decline over this period. Overall, the majority of the drop resulted from lower production from primary silver mines (which includes Escobal) with only marginal declines from by-product sources.

By-Product and Primary Silver Mine Supply

In contrast to gold, the majority of silver mine supply has been and continues as a by-product with production and investment decisions generally driven by either gold, copper, lead and/or zinc prices and outlook.[2] Figure 2 displays the breakdown of annual silver mine production between primary and by-product operations since the late 1980s. As shown, on average over 70 percent of annual silver mine supply results from by-product sources. As such, global silver mine supply is less responsive to sustained increases and decreases in silver prices, influenced more by market trends in lead and zinc, followed by copper and gold.

Figure 2
Breakdown of Annual Silver Mine Supply

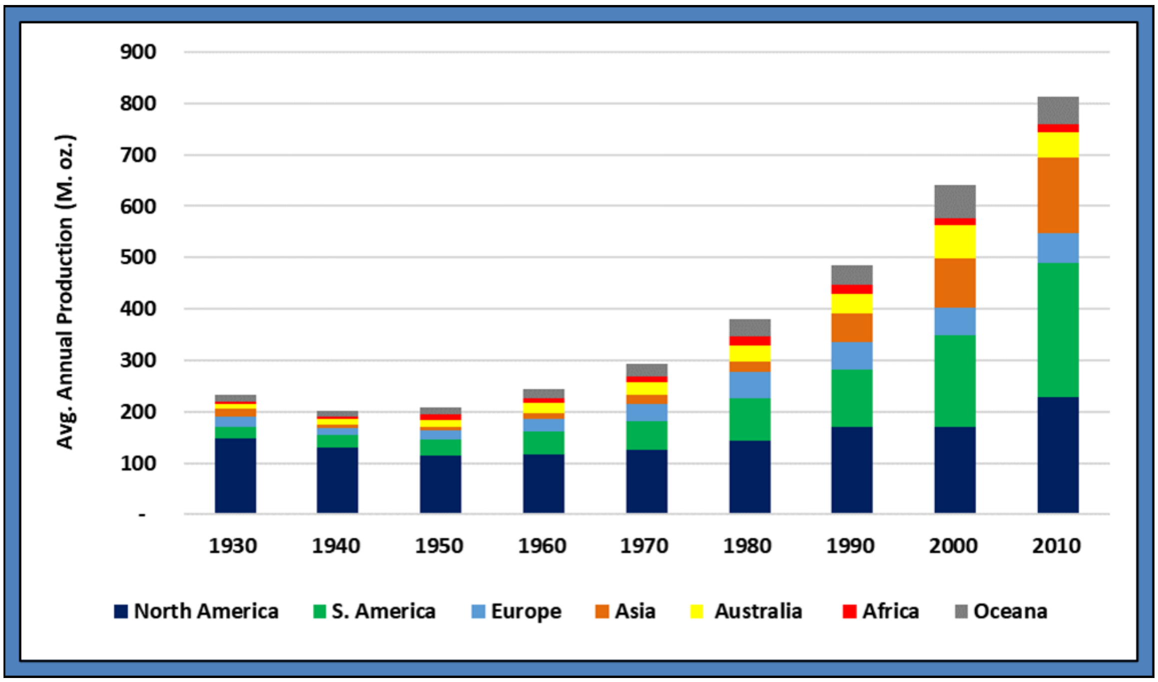


Sources: USGS, Silver Institute, CPM Group, Bloomberg, and Capitalight Research.

Figure 3 provides an overview of average annual silver mine production by key geographies by decade since the 1930s. As shown, during the 1930s, '40s and '50s, well over 60 percent of the annual global total was from North America (which includes the U.S., Canada and Mexico).[3] Production from South American countries has grown steadily, from average annual production of 30M ounces during the 1950s to over 260M ounces during each of the last 10 years. Also recording significant increases has been Asia which generated less than 10M ounces annually during the 1950s to nearly 150M ounces during each of the last 10 years.

Figure 3

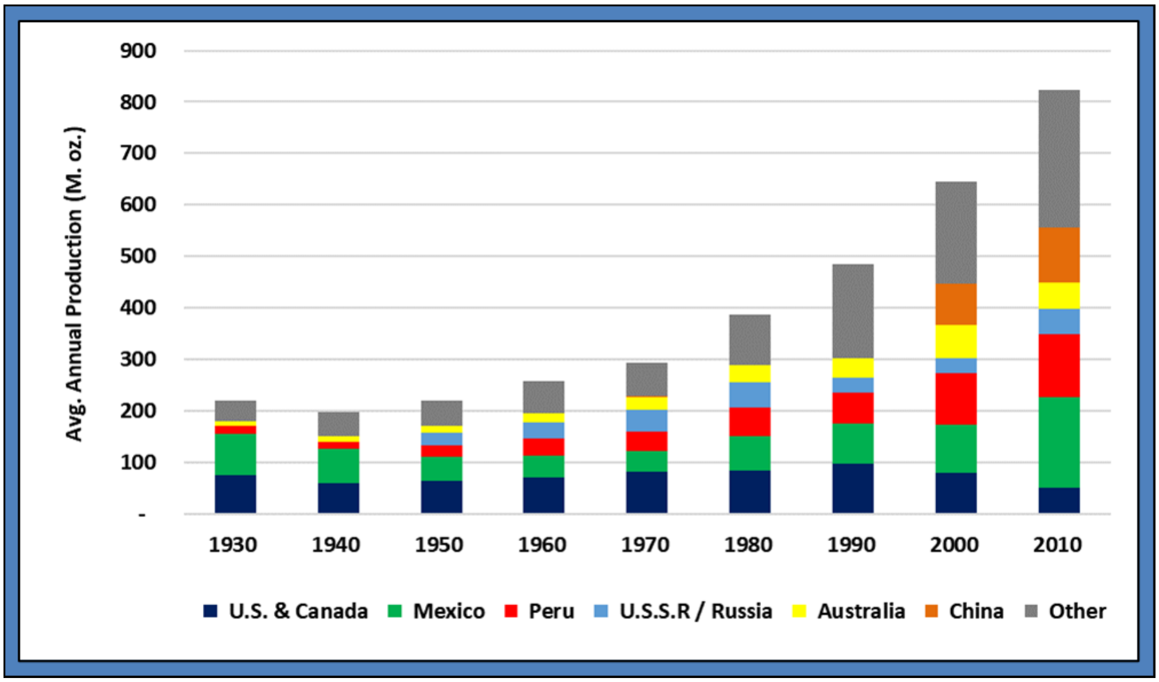
Key Silver Mine Producing Geographies (Average Annual Production in Million Ounces)



Sources: USGS, Silver Institute, CPM Group, Bloomberg, and Capitalight Research.

Figure 4 provides further silver mine supply detail by key producing countries. During the 1930s through the 1970s, cumulative average production from the U.S. and Canada averaged approximately 70M ounces annually. This increased to over 95M annual ounces during the 1990s, which has since declined to approximately 50M ounces per year during the 2010s. With the exception of a number of years during the late 1960s through mid-1970s and during the 2000s, Mexico has been the dominant annual producing country. During the last 10 years, annual supply from the country has averaged over 175M ounces. Notably, over the past 3 decades China has migrated from a relatively minor producer to mining in excess of 100M ounces over the last 10 years.

Figure 4
Key Silver Mine Producing Countries (Average Annual Production in Million Ounces)

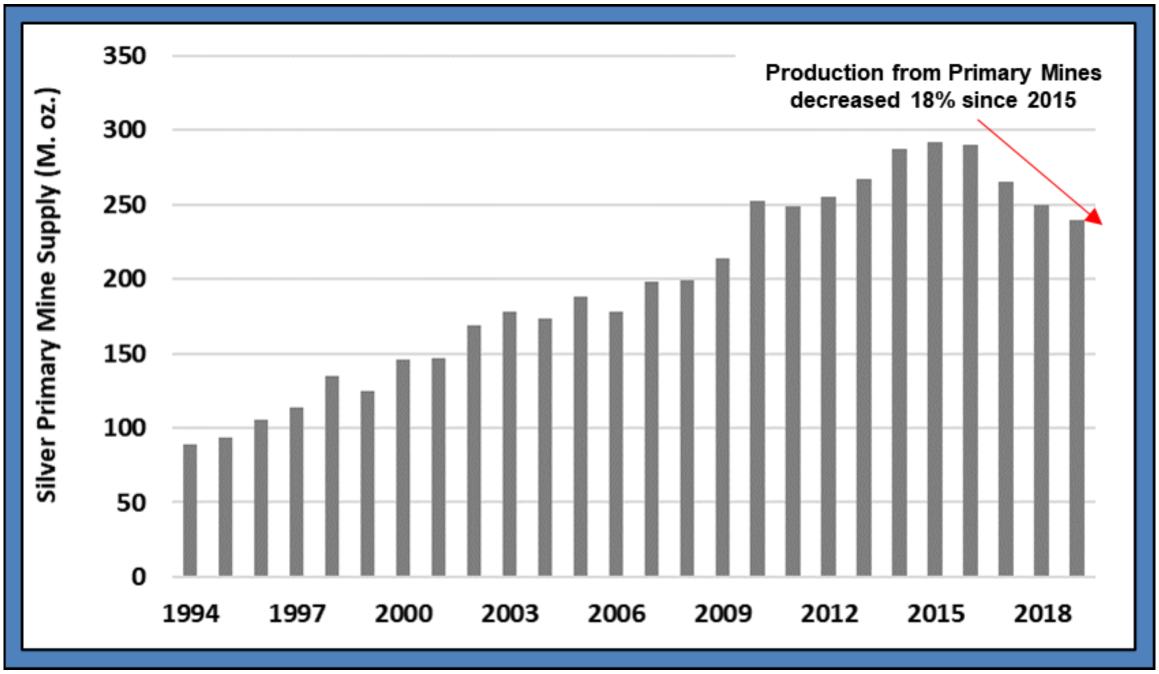


Sources: USGS, Silver Institute, CPM Group, Bloomberg, and Capitalight Research.

Expectations for Mine Supply Growth to Remain Very Challenged

As shown in Figure 1, over the past few years global silver mine supply has declined by approximately 6 percent to under 800M ounces in 2019. Figures 5 and 6 display production trends for primary silver and by-product operations, respectively. Silver mine production from primary mines has declined by over 50M ounces (or approximately 18 percent from 2015 through 2019).

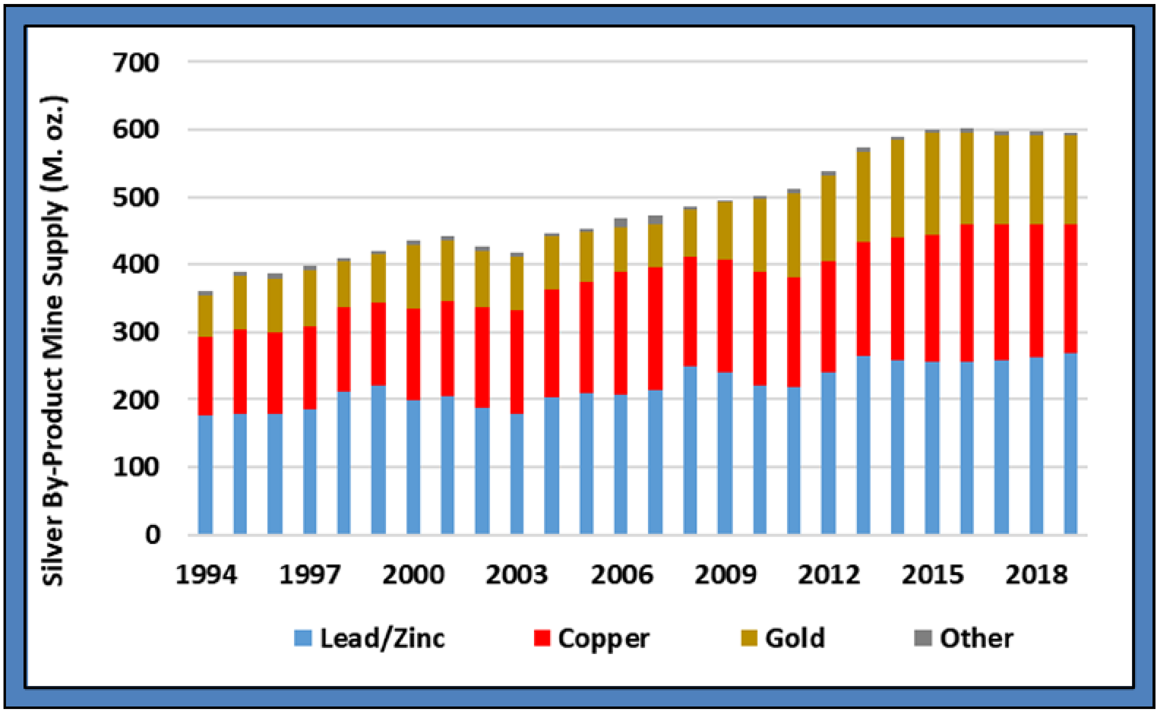
Figure 5
Primary Silver Mine Production (in Million Ounces)



Sources: USGS, Silver Institute, CPM Group, Bloomberg, and Capitalight Research.

Silver production as a result of by-product operations has only declined marginally since 2015 (down 4M ounces or less than 1 percent). The decrease in by-product production has been driven from lower silver from primary gold mines (down approximately 13 percent), offset by increases from lead and zinc, and marginally from copper.

Figure 6
By-Product Silver Mine Production (in Million Ounces)



Sources: USGS, Silver Institute, CPM Group, Bloomberg, and Capitalight Research.

Over recent years, both primary and silver by-product mine production have been impacted by continued lower processed ore grades as well as by disruptions. As an example, Fresnillo reported lower production of over 6M ounces (or nearly 12 percent in 2019 from the year prior driven by lower ore grades at its Fresnillo, Saucito and San Julián mines). Operational disruptions from blockades, labor strikes, and social challenges also continue to impede production. Blockades at Newmont's Penasquito mine last year drove production to approximately 21M ounces (or nearly 50 percent) below expected levels. Higher costs and lower grades also led Buenaventura to report silver production declining by over 20 percent in 2019 compared to 2018.

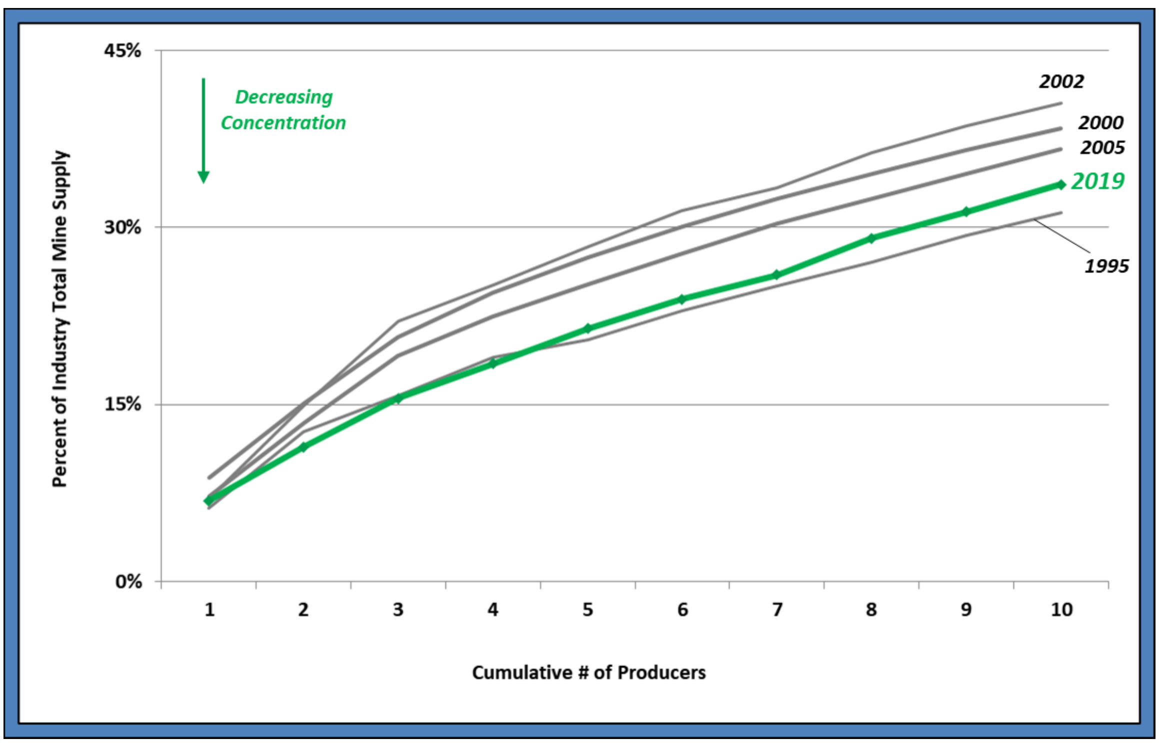
Going forward, we anticipate mine supply growth to remain very challenged. Lower processed grades, which in turn result from longer-term downward trends in exploration success, will pressure operating costs as well as production levels. Upticks from mining operations such as Penasquito returning to more normalized levels and the potential for the aforementioned Escobal mine to receive operating permits will likely be more than offset by structural trends with lower processed grades. Over the near-term, COVID-19 restrictions will also potentially impact production levels going forward. In the next section of this article, we will cover trends in global silver mine supply concentration.

Global Silver Mine Supply Concentration Trends

Since 2000, per Bloomberg, there have been approximately 400 completed mergers and acquisition (M&A) deals (totaling nearly $17B) in the silver mining segment. These range from the relatively large such as Pan American Silver's acquisition of Tahoe Resource in early 2018 (for nearly $1.1B) and First Majestic's take-over of Primero Mining (for approximately $320M, also in 2018) to numerous smaller deals for exploration assets. With this activity, it would seem logical to assume that global mine supply would become more concentrated with fewer firms dominating annual totals over time.

Figure 7 displays concentration of mine supply in the silver sector for various years with cumulative output from the 10 largest producers (on the x-axis) and the percent of total industry supply (on the y-axis). As shown, cumulative production from the top 10 mining companies was over 40 percent of the total in 2002. Since the turn of the millennia, supply concentration has declined with the top 10 producers contributing over 40 percent of the industry's total mine supply in 2000, compared to 33 percent last year. Concentration, however, is still marginally higher than in the mid-1990s when the top 10 contributed slightly over 30 percent of the industry total.

Figure 7
Silver Mine Supply Concentration Trends (% of Industry Total)



Sources: Silver Institute and Capitalight Research.

Table 1 provides a listing of the top 10 silver producers in 2019, with Fresnillo's total nearly 55M ounces, followed by KGHM and Glencore. Cumulatively, these three mining companies supplied nearly 130M ounces (or 16 percent) of the industry total of approximately 837M ounces, as reported by the Silver Institute. By comparison, in 2002, the three largest producers (Fresnillo, BHP and KGHM) accounted for slightly under 25 percent of industry output. On an annual basis since 2013, Fresnillo has been the largest silver producing company, with production increasing from approximately 39M ounces to nearly 55M ounces, last year.[4]

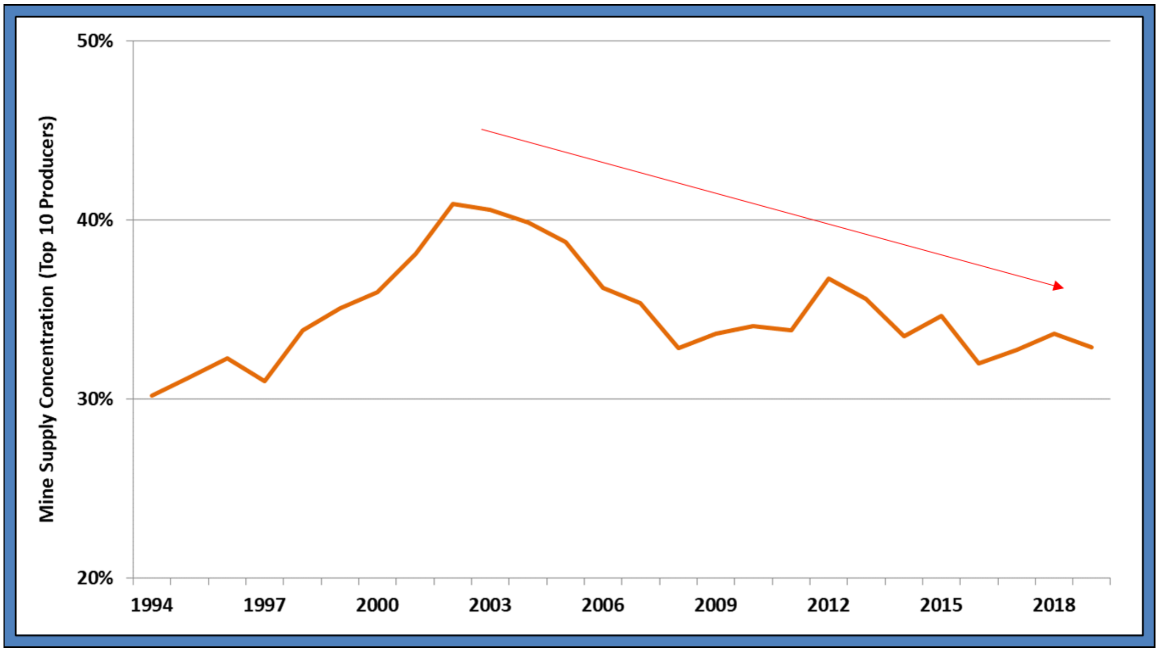
Table 1
2019 Top 10 Silver Producers

Rank	Company	2019 Silver Mine Supply (M. oz.)	Cumulative (% of Total)
1	Fresnillo	54.6	7%
2	KGHM	45.6	12%
3	Glencore	32	16%
4	PanAm Silver	25.9	19%
5	Polymetal	21.6	21%
6	Hindustan Zinc	20.4	24%
7	Southern Copper	20.3	26%
8	Buenaventura	20.1	29%
9	Codelco	17.9	31%
10	Hochschild	16.8	33%
	Industry Total	**836.5**	

Sources: Silver Institute and Capitalight Research.

Figure 8 summarizes annual supply concentration from the top 10 producers over the last 25 years. As shown, concentration increased from the mid-1990s through early 2000s, peaking in 2002 and 2003 when output exceeded over 40 percent of the industry total. As shown in the figure, concentration has since generally trended downward, but has yet to reach the lows that occurred in the mid-1990s.

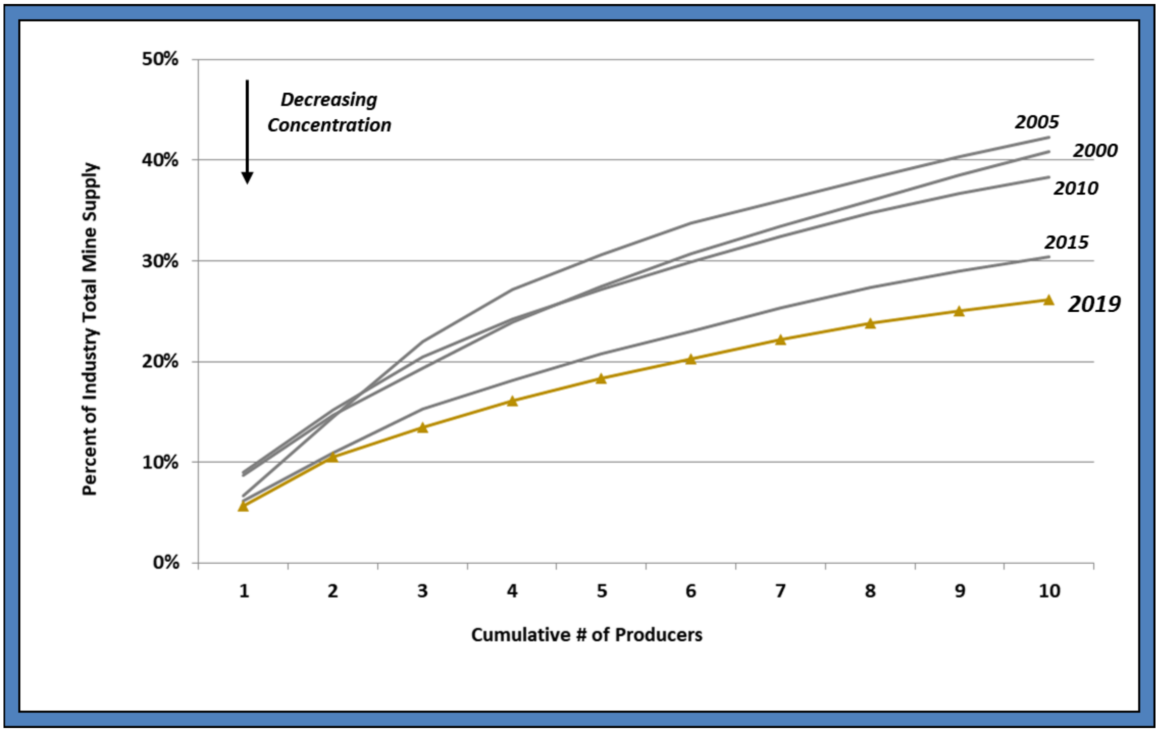
Figure 8
Silver Mine Supply Top 10 Producers (% of Industry Total)



Sources: Silver Institute and Capitalight Research.

For comparative purposes, Figure 9 displays industry concentration trends in gold mine supply. Similar to silver, but relatively more dramatic, production from the top 10 gold companies has declined over the last 20 years. In 2005, production from the top gold miners accounted for 42 percent of the industry total, whereas in 2019 the total had declined to 26 percent. Gold production is less concentrated within the top miners in relation to silver.

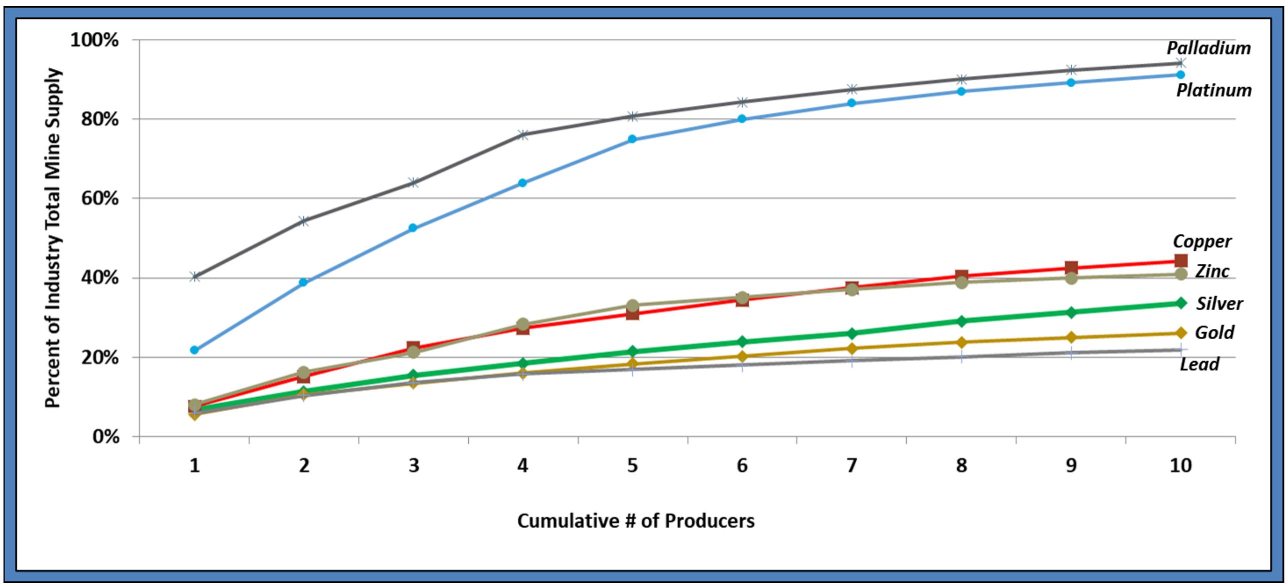
Figure 9
Gold Mine Supply Concentration Trends (% of Industry Total)



Sources: GFMS and Capitalight Research.
[GFMS, formally Gold Fields Mineral Services, is part of Thomson Reuters.]

To provide further context, Figure 10 expands the analysis to include industry supply concentration for platinum and palladium and for key silver by-product base metals (copper, zinc and lead). As shown, mine supply is highly concentrated in the platinum and palladium sectors with the top 10 producers accounting for over 90 percent of their respective industry totals. Further the top three mining companies in these segments generated well over 50 and nearly 65 percent of the platinum and palladium totals, respectively.[5] As mine production in these industries is geographically limited (platinum overwhelmingly dominated in South Africa and palladium production centered in Russia and South Africa), high concentration is logical due to higher barriers to entry (from relatively few commercially viable deposits).

Figure 10
Other Metal Mine Supply Concentration Trends (% of Industry Total)[6]



Sources: Silver Institute, GFMS, and Capitalight Research.

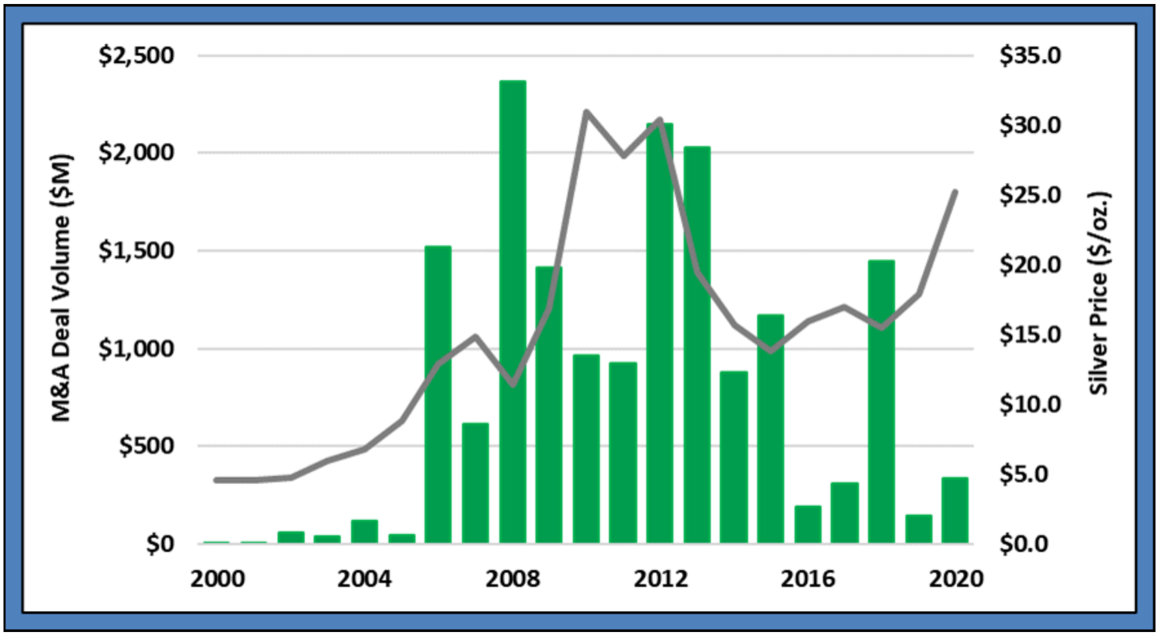
As covered previously, the vast majority of silver mine supply continues as a by-product, driven by production from zinc/lead and copper mining operations.[7] Concentration from the top 10 copper producers represents nearly 45% of the industry total. BHP, Codelco and Freeport are the three largest producers with combined production representing over 20 percent of the 2019 global total. As with silver and gold, copper production has become less concentrated. In general, during the 1990s and 2000s the top 10 producers accounted for approximately 55 percent of global annual totals.

Similar to copper, top zinc producers cumulatively produce slightly over 40 percent of the 2019 annual total with over 20 percent generated by the top 3 (BHP, Glencore and Teck) last year. As shown, lead is less concentrated with the largest 10 producers cumulatively providing slightly over 20 percent of the industry total with the top three including Glencore, Vendanta Resources and Teck.

Industry Concentration Outlook

Since the turn of the millennia, silver mining has seen considerable M&A activities, totaling nearly $17B. For the sector, Figure 11 displays annual deal volumes and average silver prices.

Figure 11
Annual Silver Mining M&A Deal Volume and Silver Prices



Sources: Bloomberg and Capitalight Research.

As shown, M&A deals, by value, peaked at nearly $2.4B in 2008 and again exceeded $2B in both 2012 and 2013.[8] The aforementioned PanAm Silver and First Majestic deals drove the total to nearly $1.5B in 2018. Such activity is expected to drive industry concentration; however, as discussed in the above analysis, supplier concentration has generally declined across the sector.

Going forward, we anticipate industry concentration levels to marginally increase in both silver and gold mine supply. The continuing mining challenges of lower processing grades and limited exploration success will force companies to look towards M&A to sustain production profiles.

Endnotes

This article is excerpted from Capitalight Research's *Silver Monitor*, https://www.capitalight.co/silvermonitor.

1 Currently, the largest haul truck is the Belaz 75710, with approximately 490 tons of capacity. The largest CAT truck is the 797F with 400 tons of capacity.

2 In general, silver by-product mine producing companies will record revenues from silver production sales to offset the costs of mining of the primary metal.

3 This continues a trend. Seventy-five percent of global mine supply originated in North America from 1900 through 1925.

4 Fresnillo produced over 58M ounces in 2018 with the company expecting the 2020 total to be in the 51 to 56M ounce range.

5 Platinum production is dominated by South African producers (Anglo American, Impala and Sibyane-Stillwater). The Russian mining company, Norilsk Nickel is largest palladium producer (with over 40 percent of the industry's total in 2019).

6 Production data is for 2019 annual totals with the exception of platinum and palladium where 2018 data is used.

7 Since the late 1980s, well over 70 percent of annual silver mine supply results from being a by-product of mining other metals with the remainder from primary silver mines.

8 These deals include completed merger and acquisitions, investments and joint ventures with disclosed dollar-amounts.

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Prior to rejoining Newmont, Dr. Brady was a Senior Manager at Risk Capital Management, a consultancy that advised energy and natural resource companies on financial risk, valuation and commodity hedging.

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Ms. Schieven joined Dundee Economics in 2008 in Toronto where her skills in economic research and analysis and her ability to translate data into concise, meaningful charts and graphs made her a principal contributor to Dundee Economics publications. She also regularly contributed articles about the effect of the actions of Central Banks on global markets.

In 2016, she joined Murenbeeld & Co., rebranded in 2021 to Capitalight Research, also in Toronto, where she continues to contribute articles, research, and analyses in weekly and monthly publications. She specializes in research and analysis with a focus on the effects of macroeconomic events and data on gold and silver prices, equity markets, exchange rates, and interest rates.

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Dynamic Commodity Valuations

Nick Vasserman
Founder and Chief Investment Officer, Integrated Portfolio Intelligence, LLC

Introduction

Although the trading of commodities can be traced back to Ancient Babylon, until recently the pricing of these markets was rather complex and opaque. Valuations evolved from long-term fixed price regimes to arcane bilateral markets. Over the years, a host of reporting agencies played a critical role in identifying pricing benchmarks and facilitating trades. According to Johnson (2018), there are presently over 100 organizations — both private and public — throughout the world that produce a wide array of commodity benchmarks. These "price reporters" generate in excess of 100,000 assessments of commodity prices every week and thousands of fundamental data points per day across a vast range of global markets. This paper proposes that in today's information age it is possible and necessary to construct a globally consistent investment framework that integrates all available fundamental data and technology into dynamic stocks-to-use ratios to assess commodity valuations in near real-time.

What is the Value Factor for Commodities?

Upon identifying and tracking structural premia like carry, momentum, and volatility across different asset classes, traders and analysts use mean-reversion as a proxy for commodity value. That is to say, mean-reversion is the current observed price relative to an average (deflated) price over an extended lookback period. In contrast, the equities market is informed by a row of transparent basic measures for computing the value factor. For example, MSCI draws on sales, earnings, cash flow, and book value. Irrespective of one's favorite metric, it is worth noting that all balance sheet data adhere to Generally Accepted Accounting Principles (GAAP), thereby ensuring a modicum of consistency and transparency. Whereas any yardstick is subjective and perhaps even biased to some extent, investors can assume that the numbers are indeed directly comparable for all publicly traded stocks.

Mean-reversion is certainly a documented structural premium for commodity price dynamics that can be observed over the long haul. However, following this statistical metric is hardly indicative of fundamental analysis. Therefore, mean reversion should not be deemed a fitting substitute for value.

Commodity Supply and Demand Analysis: Theory and Practice

While equity instruments are forward-looking, commodities can be viewed as spot assets that reflect current fundamentals of supply and demand. Commodities are typically priced in relation to the marginal cost of supply and the marginal willingness of consumers to pay. As such, the price is grounded on fluctuations in, and the levels of, supply and demand. More often than not, the fundamental changes are on a sequential basis. At other times, though, the price can abruptly shift due to weather or other events.

Table 1
The Classical Balance Sheet for all Major Commodities Sectors, Including Energy, Metals, and Agriculture

Annual Balance Sheet	**Energy**	**Metals**	**Agriculture**
Beginning stocks	Global stocks	Known exchange & off exchange stocks	Prior season crops in storage
Production	Local/global aggregated production	Global mine supplies adjusted for disruptions	Aggregate of regional acreage, yield
Global trade (imports - exports)	Producer & consumer countries: exports & imports	Producer & consumer countries: exports & imports	Producer & consumer countries: exports & imports
Consumption	Global and local industrial and consumer consumption	Global and local industrial and consumer consumption	Global and local industrial and consumer consumption
Ending stocks	Beginning stocks + production + imports - exports - consumption	Beginning stocks + production + imports - exports - consumption	Beginning stocks + production + imports - exports - consumption

Challenges with Traditional Commodities Balance Sheets

Historically speaking, commodities balance sheet entries were not observable in a timely fashion. Data was typically published by government agencies and often substantially revised in later releases. The classical balance sheet for all major commodities is shown in Table 1.

Reporting agencies and organizations adopt different accounting standards. A case in point are the varying estimates released for corn stocks held by the People's Republic of China (PRC) in February 2021. The United Nations Food and Agriculture Organization (FAO) lowered Chinese corn reserves by 54 million tonnes to 139 million tonnes. Conversely, the United States Department of Agriculture (USDA) raised its estimate by 4.5 million tonnes to 196.18 million tonnes in their monthly World Agricultural Supply and Demand Estimate (WASDE). Both of these numbers sharply diverge from local sources and surveys that put reserves at significantly lower levels. According to Integrated Portfolio Intelligence (IPI) estimates, China accounts for over 25% of global corn consumption (a projected 295 million tonnes in 2020/21). Consequently, the different model assumptions can have a material impact on decision makers. These disparities stem from the lack of generally accepted commodity accounting principles governing the sundry reporting agencies, public organizations, and buy-or-sell side analysts. Hence, each body adopts their own conventions and guidelines. This lack of uniformity severely hinders the efforts to gauge international commodities balances and compare individual commodities to other tightly linked markets.

Dynamic Stocks-to-Use Ratios as a Valuation Factor

For the sake of overcoming this informational discord, the author champions the *dynamic* stocks-to-use ratio as a global measure of commodity values. More specifically, this ratio should be used to measure ending stocks/consumption for a particular annual or seasonal global commodity balance sheet and importantly it should be dynamically modified as each component is updated. To facilitate a direct comparison and ranking of all commodities via their stocks-to-use ratio, a consistent and global analytical framework should be established. Let us expound on this proposition by delving a bit deeper into the corn market.

Recent advances in technology and data science enable us to deploy a single global framework across all global commodities and parse supply and demand in near real time. As a result, analysts can monitor shifts in commodity valuations at a higher frequency than traditional methods.

Case Study: 2020/21 World Corn Balances

Table 2
Global Corn Balances

Beginning Stocks	Prior Season	303.0 Mt
Harvested Area	Acreage Analysis	196.8 MH
Yield	Yield Analysis	5.76 tonnes per hectare
Production	= Acreage * Yield	1132.7 Mt
Total Supply	Beginning Stocks + Production	1435.7 Mt
FSI Use	Food, Seed & Industrial	424.2 Mt
Feed & Residual Use	FSI & Residual Use	720.1 Mt
Total Use	FSI, Feed & Residual	1144.3 Mt
Ending Stocks	Total Supply - Total Use	291.4 Mt
Stocks to Use	Ending Stocks/Total Use	25.50%

Sources: IPI, USDA.

Notes: Mt is an abbreviation for million tonnes, and MH is an abbreviation for million hectares.

Table 2 presents a concrete example of the inputs used in calculating the stocks-to-use ratio by showing the global corn balances for marketing year 2020/21 as of February 2021. This balance sheet is aggregated by IPI from single country balances and includes major exporters such as the U.S., Argentina, Brazil, Ukraine, Russia and the European Union (EU) and major importers such as China, Japan, South Korea, and Mexico. Single country exports and imports play a key role in determining supply and demand.

A globally consistent and dynamic framework for global commodity balance sheets should be comprised of databases and models that comply with the same guidelines, principles, and models. In the next section, we shall briefly review the key models for our case study, continuing with the international corn market.

Corn Supply Side Production Analysis

Model 1: Analysis of Acreage

The aggregate survey analysis incorporates macro and micro surveys. The former involves multiple visual field surveys of numerous random spots throughout the crop development cycle. Plantings are a function of the weather and economics. Price advantages of one crop over another in a particular season might derive from weather conditions that allow for a greater share of total plantings. Alternatively, the micro surveys consist of visits to a smaller number of individual fields at set intervals.

Model 2: Analysis of Yield and Crop Conditions

Yield-and-crop-conditions models focus on aggregated real-time indices of bearish/bullish conditions, which are highly dependent on the specific time of year, crop, and region. For instance, dry weather may be favorable during planting or harvest season, but otherwise deleterious. Therefore, it is incumbent upon observers to account for this seasonality. A combination of, say, hot and arid weather in the U.S. during July would place more stress on corn growth than a cool and dry spell.

As a rule, models should factor in daily raw inputs from individual weather stations of maximum and minimum temperature, precipitation, and subsoil moisture as well as Normalized Difference Vegetation Index (NVDI) data. Shorter-term weather models such as the American and European models should be incorporated along with long-term teleconnection models. (The American model is also known as the Global Forecast System (GFS) model and is operated by the National Weather Service. The European model is also known as the European Center for Medium-Range Weather Forecasts (ECMWF) model.) For the sake of consistency, forecasts are to be performed on a single crop weighted by region of production. In other words, all the producing countries should be identified along with the key regions of the major players – the United States, China, and Brazil. The crop calendar for each region should be closely observed and may differ for all the key crop stages, namely planting, silking, and grain fill.

Model 3: Analysis of Global Trade Imports and Exports

Tracking maritime shipping of grain via satellite allows for a granular analysis of global ship types by port, terminal, and berth. Data from premium vendors and public sources can be molded into an up-to-date and comprehensive database tracking the flow of commodities. Likewise, keeping tabs on physical loadings, movements, and discharges provides insights into actual progress *vis-a-vis* announcements and general market talk. Under this heading, we can include analyses of single and aggregated vessel performance; congestion and delays at major ports, terminals, and berths; vessel berthing activity; and commodity flows and trends. All this information can be obtained ahead of official publications.

Before proceeding to the next model, let us touch upon a pertinent development in the global corn market. In 2020, China was a major buyer of corn on the world market for the first time in many years. This spawned a major global expansion in the demand for this commodity, not least U.S. corn. Demand for the latter picked up thanks to a lack of, or tepid, competition from the Ukraine, Brazil, and Argentina. In fact, the United States now has the lowest priced corn in the world. This state of affairs will probably last until the next harvests of the two Latin American rivals.

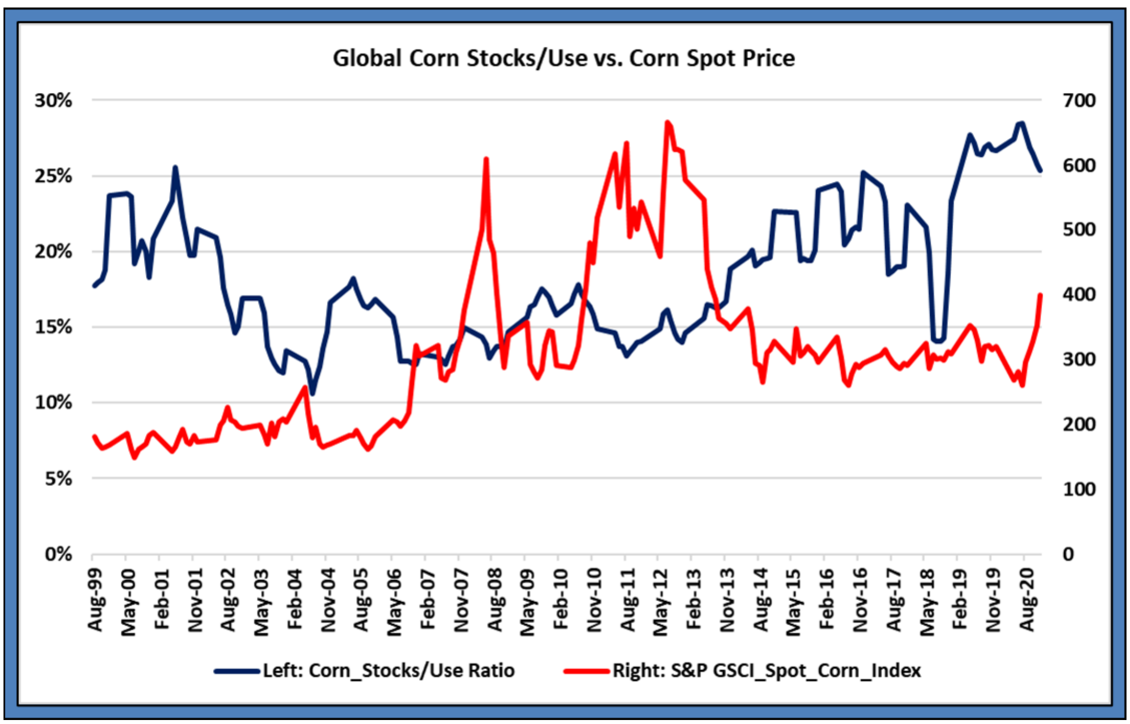
Model 4: Consumption-Side Analysis

With respect to ethanol production and margins analysis, the corn ethanol grind estimate is a key model for domestic consumption. The same can be said for the food, seed, and industrial use of high-fructose corn syrup (HFCS), glucose, and dextrose. Nowcasting, econometric models, and surveys further help observers understand deviations in the aforementioned macro variables.

The net result of employing the above four models is to create an updated global corn balance sheet with which to calculate a current global stocks-to-use ratio.

Historical Corn Stocks-to-Use Ratios and Corn Prices

Figure 1
Global Stocks-to-Use Ratios and Corn Prices Between August 1999 and August 2020



Source of Data: Bloomberg.

When the level of stocks-to-use increases, this is usually accompanied by a surplus and price dips. Conversely, signs of global shortages tend to command a bullish price reaction. As Figure 1 demonstrates, the spot corn price is sensitive to both the level of, and fluctuations in, the stocks-to-use ratio. During the fourth quarter of 2020, a drop from record highs for this ratio was followed by a spike in corn prices. The main catalyst behind this *volte-face* was the surge in Chinese demand.

Conclusions

Market Efficiency Implications

An integrated and dynamic commodities balance sheet analysis is conducive to a more efficient market. When the balance sheet tightens due to acute commodity shortages, a near real-time analysis supports a long speculative position that pushes up prices, rations demand in a timely fashion, and encourages marginal supply before the onset of alarming shortages. By identifying deficits and shortages in advance, consumers and producers can prudently adjust their behavior. As a result, the market is better placed to avert serious disruptions.

Investment Management Implications

For asset managers, near real-time fundamental analysis provides an important potential edge. By swiftly discerning emerging fundamental imbalances, managers can net potential uncorrelated alpha returns to trend-following strategies with earlier position entries and exits. Trend-following strategies by comparison are backwards looking and lag the price action. As large investment funds enter the commodities market following popular trend-based signals, they are liable to create a structural positioning imbalance and a less desirable risk/reward trade-off to holding a mature position.

Observing a potential divergence in the relative stocks-to-use dynamics of commodities with tight fundamental linkages, such as corn and wheat or soybeans, can also provide critical insights into market-neutral relative-value opportunities that should exhibit reduced correlations to most common investment themes.

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Author Biography

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Mr. Nick Vasserman has over twenty years of experience in developing and deploying quantitative macro-oriented systematic programs globally. He has managed systematic macro trading portfolios in New York, London and Toronto since 1996 at major investment banks and is now offering 4th generation evolutions of the strategies and portfolio risk framework. Before launching Integrated Portfolio Intelligence (previously Momenta Capital), Mr. Vasserman spent several years at J.P. Morgan in a variety of senior trading and risk management roles. He founded and was Head of J.P. Morgan's Americas Cross Asset Quantitative Strategies business. Mr. Vasserman was previously Global Head of Index Trading, Quantitative Index Strategies and Electronic Market Making within the renowned Global Commodities Group at J.P. Morgan. Prior to joining J.P. Morgan in 2009, he was Global Head of FICC (Fixed-Income Currencies & Commodities) Proprietary Systematic Trading at UBS Investment Bank. Mr. Vasserman has also held roles in Interest Rate Derivatives Trading as well as Exotic and Structured Derivatives Trading at UBS in New York and London. He holds a Bachelor of Administrative Studies (B.A.S.) degree from York University in Canada and a finance M.B.A. from Canada's University of Toronto, Rotman School of Management, where he conducted research with Professor John C. Hull on pricing and hedging exotic options.

The Impact of the Energy Transition on Wholesale Power Pricing and Market Risk

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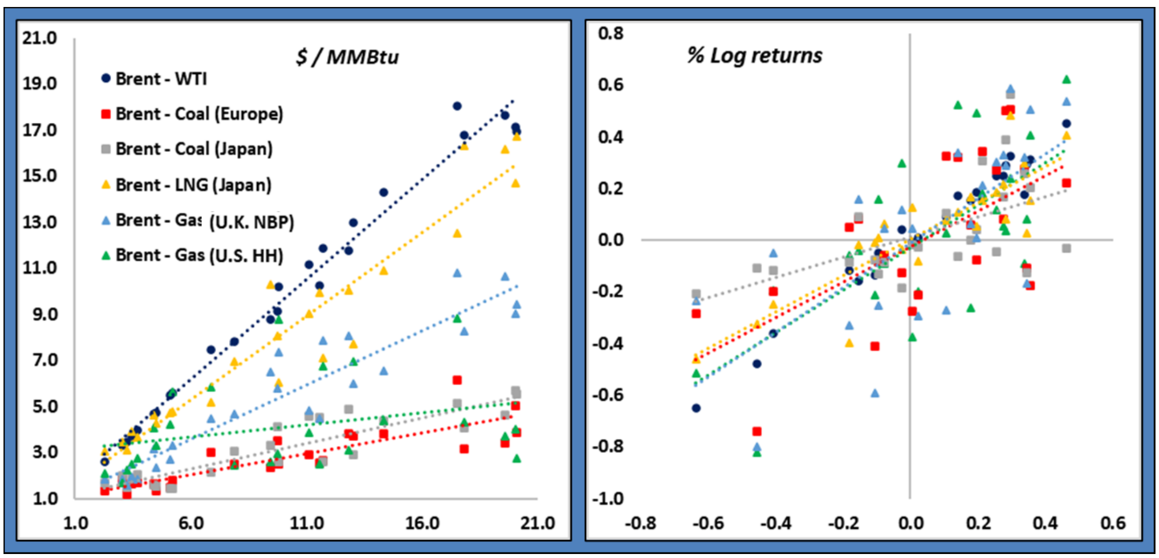
Low carbon power generation is gaining market share in many key markets around the world. Underpinned by displacing traditional thermal power generation with renewables like wind and solar, this trend introduces supply intermittency that drives new pricing patterns and changes the profile of risk. The scale and complexity of the intermittency challenge will increase as the share of renewable generation rises in energy systems. Understanding these challenges are key to investment, strategy, and policy decisions. This article explores these trends using evidence from the U.K. power market, followed by a discussion on future implications and recommendations.

Background

For decades, key energy commodities - crude oil, natural gas, coal, electricity - were interlinked. As globally traded energy commodities, crude oil and liquid fuels like heavy fuel oil (HFO) and gasoil were generally the dominant driver of other energy commodity prices. They drove gas and Liquefied Natural Gas (LNG) prices via contractual linkage, by influencing upstream costs for gas exploration, as competing feedstock into petrochemicals, and as competing fuels in power generation. They also influenced traded coal prices via mining and shipping costs. These historical relationships are illustrated in Figure 1.

Figure 1
Historical Relationship Between Oil, Gas, and Coal Prices and Returns (Annual Average, 1995-2019)[1]

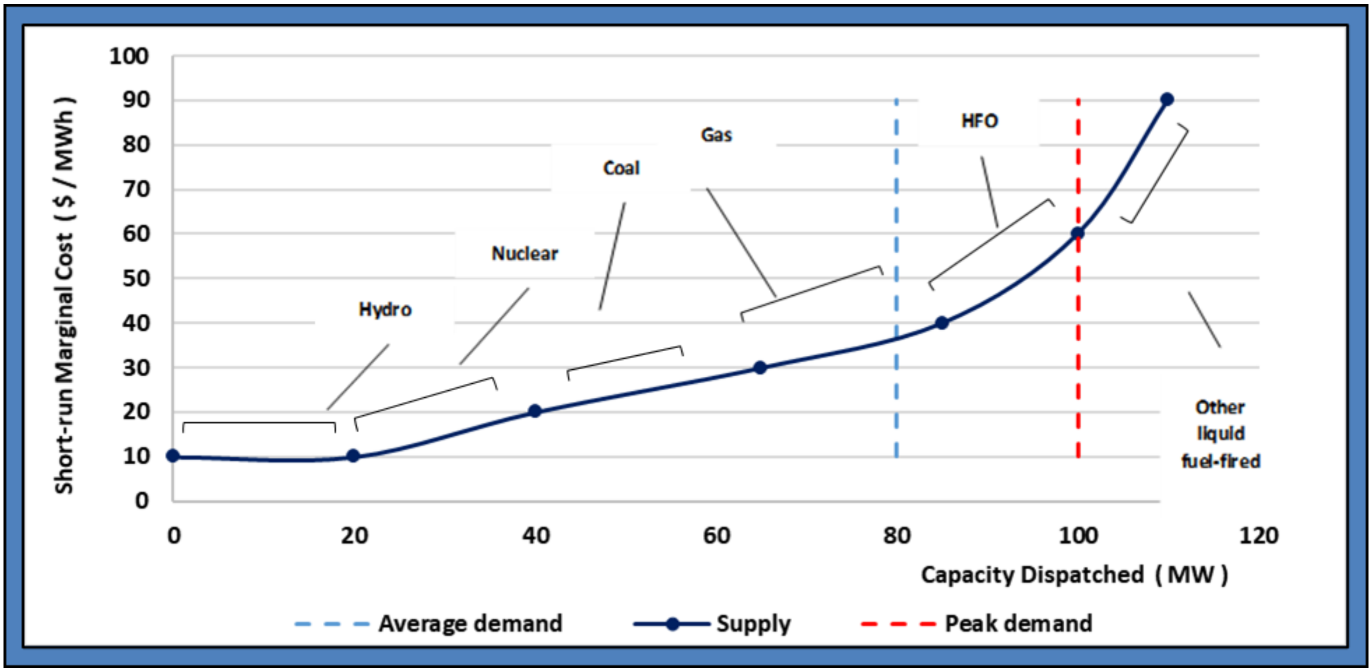


Abbreviations: MMBtu stands for million British thermal units (Btu). A Btu is a measure of heat energy and is a common unit for comparing fuels. U.K. NBP stands for the U.K. National Balancing Point while U.S. HH stands for the U.S. Henry Hub in Louisiana.

Notes: In the left-hand-side graph, the y-axis displays Brent crude oil prices, converted to $/MMBtu, while the x-axis displays six comparison fuels that are identified in the graph's color-coded legend. The right-hand-side graph uses the same color-coded legend to show % log returns of Brent versus the six comparison fuels.

These relationships underpinned power generation costs and price formation in traded markets across the world, which typically were in equilibrium with a fossil fuel-fired power plant setting the power price at the margin. See Figure 2.

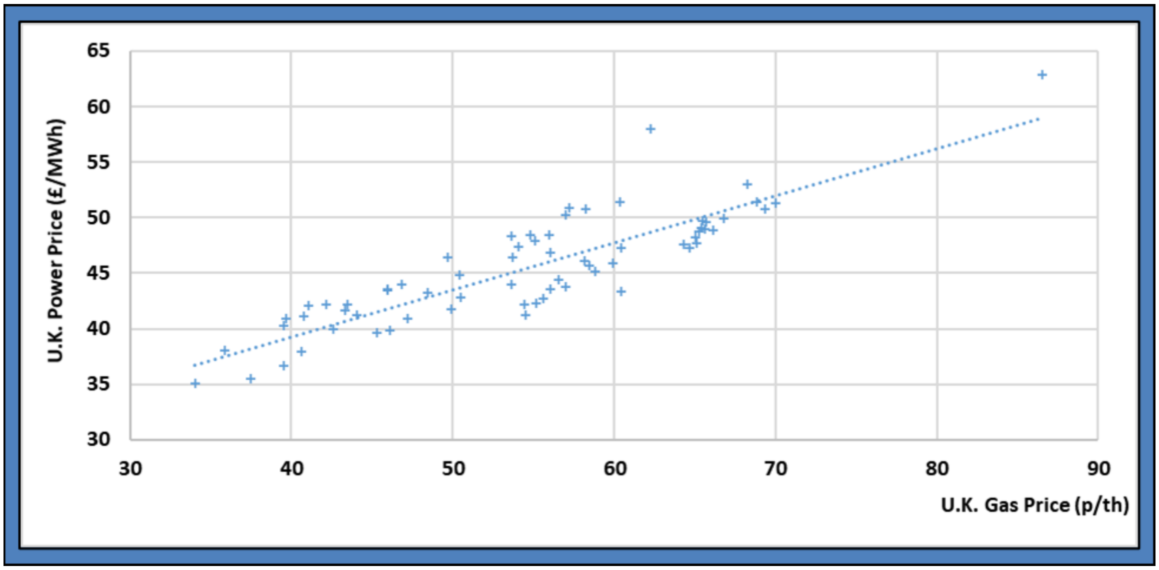
Figure 2
Make up of a Typical "Traditional" Power Supply Stack at a Given Point in Time



Abbreviations: MW stands for Megawatts, a unit of power, while MWh stands for a Megawatt of electricity used continuously for one hour.

The influence of fuel prices on power prices could be seen in the strong association between prices of power and fuels, especially gas, which were only broken for short periods of time due to localized shocks to demand and supply, *e.g.*, cold weather inducing high demand or outages removing supply. See Figure 3 on the next page.

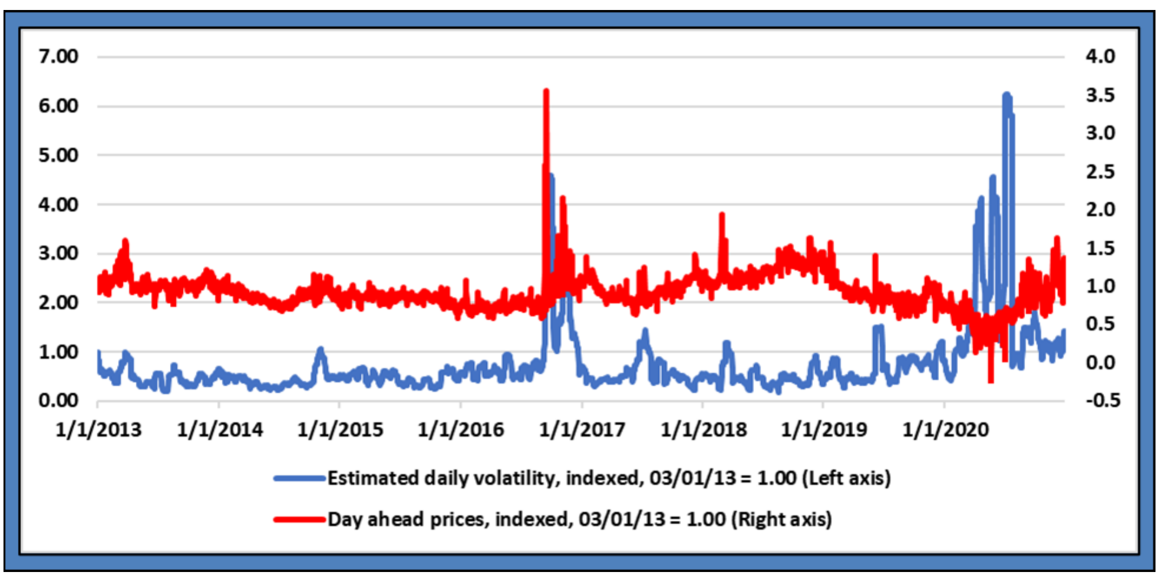
Figure 3
Historical Relationship Between U.K. Gas and Power (Monthly Average Spot Prices, 2010-2015)[2]



Abbreviation: p/th stands for pence per therm (in the U.K.).

It was also the case especially in electricity markets that price dislocations tended to be biased to the upside rather than downside; as during periods where supply relative to demand was limited, the probability of being short in a costly blackout event drove up prices much faster compared to how prices reacted during periods of oversupply. See Figure 4. On the supply side, plants could always turn off temporarily when they were "out of money," restoring balance while they would always be limited by their maximum capacity.

Figure 4
U.K. Power Spot Price and Volatility Trends (Daily, 2013-2020)[3]



Unhedged generation assets had the opportunity to recover higher profits during these periods of positive price spikes, which, if sustained, would signal the need for investment on the supply side. Conversely, downstream suppliers needed to be good at demand forecasting and hedge price risk typically via forward purchasing, and also via direct investment in generation assets, in the absence of liquid markets.

Effects of Low Carbon Renewable Generation in the Power System

As the transition towards a low carbon energy system progresses, renewables are displacing fossil fuels in the power generation sector. Oil and coal fired power plants are disappearing from the fuel mix altogether in many of the key markets.

The intermittent nature of the incoming renewable generation technologies, which are largely wind and photovoltaic solar, is changing how power markets function. Photovoltaic solar and wind generation technologies do not provide a controllable form of capacity due to their dependence on weather and other environmental conditions. This introduces new patterns and high levels of intraday as well as seasonal variability, which naturally also differ by location.

In addition to this, over a year, on average, these generation technologies typically provide a lot less than their maximum potential output compared to a traditional fuel-fired or nuclear power plant.[4] Therefore, in the absence of large-scale power storage, they need to be built in much larger quantities to ensure there is enough supply around when needed. The key challenge from a market risk point-of-view is that these plants sometimes do generate at or close to their maximum capacity. When that happens, there can be excess supply that is difficult to curtail, leading to strong downward swings in prices.

In sizeable power markets which experienced a quick buildout of wind and solar generation,[5] we have indeed started to observe changes in market pricing especially within-day where downside shocks, and in some cases even negative prices, are realized. Table 1 on the next page presents evidence from the U.K. power market where the ratio of the five highest and lowest hourly prices to the annual average price are compared across the years 2013, 2017, and 2019. These years were selected as they have similar average price and volatility characteristics and exclude periods of very high volatility as shown in Figure 4 on the previous page.

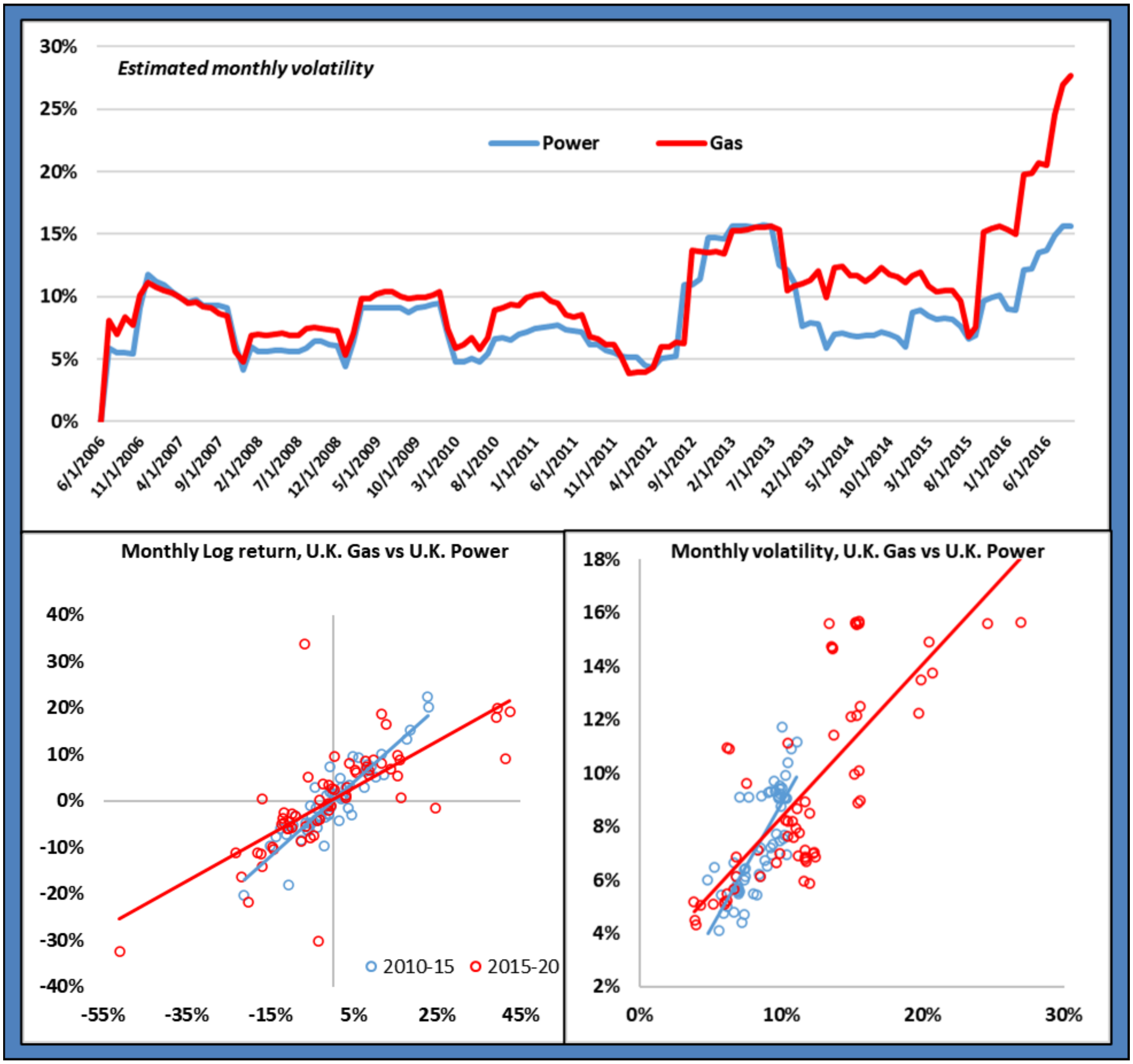
Table 1
Ratio of Highest and Lowest Hourly Power Prices to the Average Price within the Respective Year

		2013	2017	2019
	Highest			
	1	309.1%	330.8%	643.9%
	2	271.0%	322.4%	510.8%
	3	259.3%	308.8%	313.5%
	4	259.2%	299.2%	279.5%
	5	259.1%	293.0%	279.5%
	Lowest			
	1	29.9%	3.5%	-6.6%
	2	30.0%	4.2%	0.0%
	3	30.0%	10.1%	0.0%
	4	30.0%	10.3%	0.0%
	5	30.1%	11.0%	0.0%
Average day-ahead power and gas price (indexed to 2013=100%)				
Power		100.0%	90.4%	85.6%
Gas		100.0%	66.2%	51.0%
Ratio of Installed Wind and Solar to Total Installed Capacity				
		15%	31%	36%

It is immediately noticeable in Table 1 that despite similar price and volatility levels, we are seeing more extreme price movements as the ratio of wind and solar capacity in the power system increases.[7]

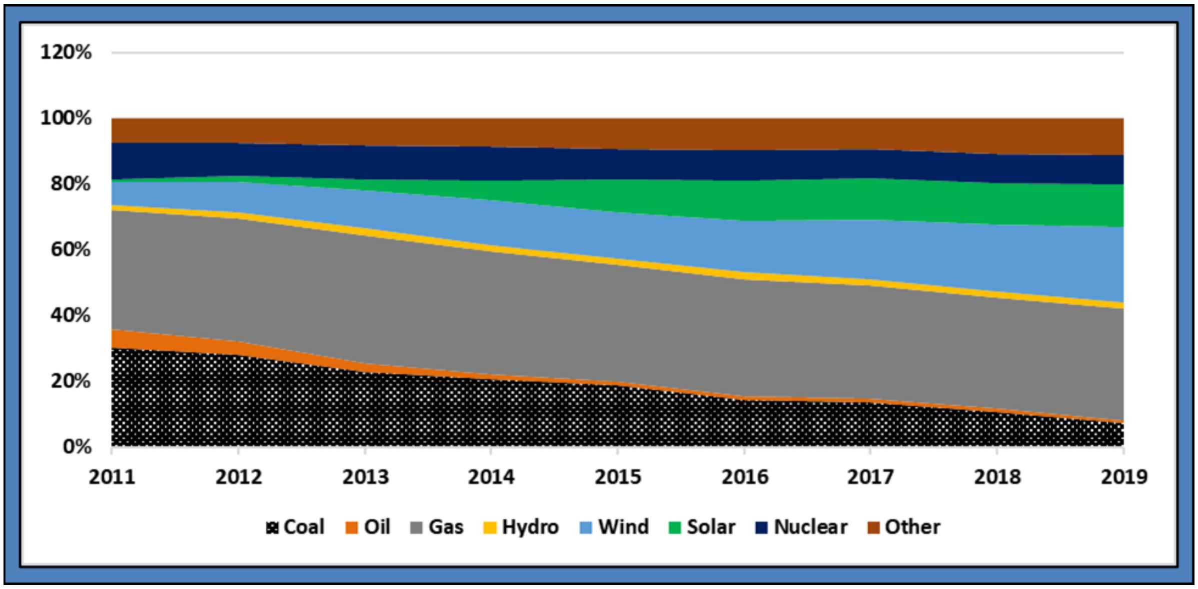
In addition to this, although a considerable amount of the variation in U.K. power prices is still driven by gas prices (as the marginal generator is still predominantly gas-fired), we are starting to see this relationship weakening with the relationship between renewable generation volumes and market price response strengthening. Figure 5 on the next page shows that during the earlier part of the last decade, U.K. gas and power price volatilities were highly correlated; however, the relationship became weaker in the second half of the decade, as evidenced by the flatter linear regression line as well as the dispersion of the data.

Figure 5
U.K. Gas and Power Returns and Volatility Trends (Monthly Data, 2010-2020)[8]



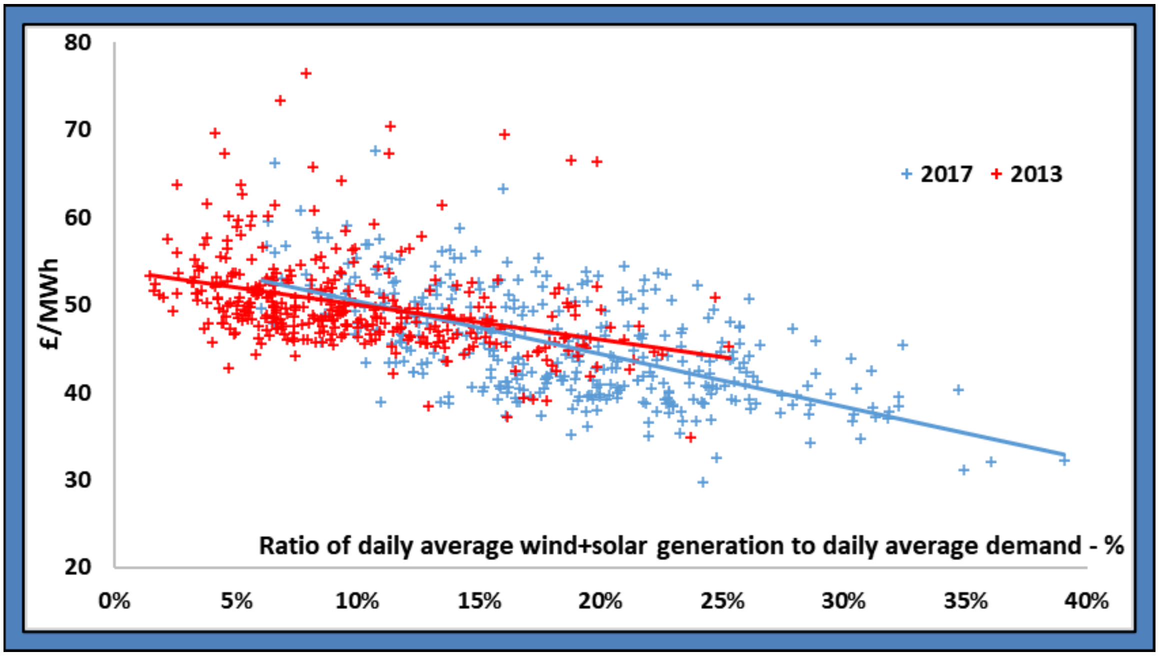
This is notable as gas-fired plants became the dominant thermal capacity over the same period as coal plants came off the system as new gas fired plants were built, which is illustrated in Figure 6 on the next page.

Figure 6
Installed Capacity in the Great Britain (GB) Power System, % of Total[9]



Intuitively, the consequence of this trend should be a stronger relationship between the price of gas and power. However, a combination of factors, including changes to plant efficiency as old plants retired and new plants came online, new interconnection capacity, and in particular, a substantial increase in the capacity of near-zero marginal cost plants (wind and solar), changed the market pricing dynamics. The impact of wind and solar generation on market prices is further examined in Figure 7 on the next page where the evolution of the relationship between day-ahead market prices and daily wind and solar generation as a percentage of daily average demand between 2013 and 2017 is shown.

Figure 7
Impact of Wind and Solar Generation on Power Prices in the U.K.



The data indicate that wind and solar generation became a stronger driver of power prices in 2017 vs. 2013, evidenced by a steeper regression line and less dispersion in 2017 vs. 2013. This is consistent with how the capacity mix evolved. Nameplate capacity of wind and solar in the Great Britain (GB) system increased from about 14 gigawatts (GW) to 31GW while peak demand fell in the same timeframe.

Transitioning to "Net Zero" and Implications for the Future

While the future evolution of the energy supply mix in a given geography is uncertain, on trend, power systems will include growing levels of renewable generation, in particular wind and photovoltaic solar. This will mean an amplification of the patterns driven by the intermittent nature of these technologies that we have briefly analyzed in this article.

An increasing share of these technologies will lead to the displacement of gas and other traditional thermal power plants as the marginal price setter. Initially this will increase short-term price volatility – a trend that has already started in some markets. In the longer term, in markets where the majority of generation comes from renewable sources, power prices could trend lower, leading to lower revenues captured by assets exposed to market prices. The impact of this on the wider market can range from lower returns for market participants to a slowing down of new investment. This impact could continue until or unless the market pricing regime evolves to reflect the long-run cost of investment in renewable generation or energy storage technologies (*e.g.*, lithium-ion (Li-Ion) batteries or hydrogen as an energy vector), which would need to become economic at large scale to take over as the marginal price setter.

In theory, energy storage presents a solution to the physical balancing challenges and hence a substantial commercial opportunity depending on future costs and other operational characteristics. In practice however, there are challenges to making storage work at large scale in competitive markets, as the "last" incremental new capacity has the potential to arbitrage away the profits for all incumbents. Adjustments to energy policy and regulation may be required to ensure different storage technologies have the chance to develop and become viable as a long-term solution to intermittency.

Conclusion

Low carbon power generation is gaining market share in many key markets around the world. Underpinned by displacing traditional fuel-fired power generation with renewables like wind and solar, this is introducing supply intermittency, the scale and complexity of which will increase as the trend advances. Based on an extrapolation of the impacts we see today we can predict that the magnitude of market (price) risk will increase in the coming years in the markets where low carbon generation gains market share.

Investors and market participants will need to build the skills to manage the changing risks as well as the analytical capabilities to stress test their portfolios against long-term directional shifts in market pricing. Policymakers will need to ensure markets continue to function as intended since markets will continue to play an instrumental role in meeting customers' energy needs as well as the decarbonization of economies in a commercially sustainable manner.

Endnotes

The *GCARD* previously covered the transition to next generation energy sources in an article based on a J.P. Morgan Center for Commodities' Research Council meeting that was summarized by the *GCARD*'s Contributing Editor, Hilary Till, and which is available at the following link:
http://www.jpmcc-gcard.com/wp-content/uploads/2018/10/JPMCC-Research-Council-Report-120415.pdf.

1 Source: BP Statistical Review.

2 Sources: U.K. Office of Gas and Electricity Markets (OFGEM) and Author's calculations.

3 Sources: Nordpool and Author's calculations.

4 Exact yields vary greatly by generation technology and specific location. For example, photovoltaic solar could be generating power throughout the entire day almost every day of the year in places with a sunny climate like in the Mediterranean region, reaching annual capacity factors close to 40-50% while they can be close to 10% in Northern Europe. Similarly, wind turbines can have higher yield when deployed offshore and at an elevation where wind speeds are more stable, promising yields above 40% while many onshore locations yield significantly less. It is also important to note that advances in both wind and solar technologies, including how they are deployed (*e.g.*, floating vs. fixed offshore wind), are improving yields.

5 For example, Germany, U.K., and California markets.

6 Sources: Nordpool, the U.K. Government Digest of United Kingdom Energy Statistics (DUKES) 5.12, and Author's calculations.

7 We can also see the confirmation of this trend in the distributional characteristics of the daily returns where we see an excess kurtosis of 2.9 in 2013 which rises to 5.9 and 7.4 in 2017 and 2019, respectively.

8 Sources: U.K. OFGEM and Author's calculations. Volatility estimated by 12-month rolling standard deviation of logarithmic returns.

9 Sources: U.K. Government DUKES 5.12 and Author's calculations.

Author Biography

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Mr. Nazim Osmancik is a senior executive with extensive experience in macro research, strategy, market analysis, trading and risk management gained in the energy sector and professional services. His professional experience includes leading risk, treasury, foreign exchange and cash management operations as Chief Risk Officer of Centrica Energy Marketing & Trading, as well as leading the global market analysis and price forecasting functions within Centrica Plc, U.K. Prior to Centrica, he held various posts in consulting firms including IPA, PwC, and ICFi. Mr. Osmancik studied Economics and Mathematics at Macalester College and has a Master's degree in Finance from the London School of Economics. His research interests include market pricing in fully decarbonized energy systems, non-linear interactions between energy commodity markets, forecast evaluation and enhancement, and developing systematic trading strategies. Mr. Osmancik had last contributed an article to the *GCARD* on "Evaluating Forecasts for Better Decision-Making in Energy Trading and Risk Management: An Industry Practitioner's View on How to Enhance the Usefulness of Forecasts Including Potential Applications of Machine Learning."

Disclaimers

Volatility in Dairy Markets:
Towards a Dynamic Value at Risk Model for Dairy Commodity Trading

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Commodity prices are subject to extreme price volatility and are a prominent source of risk for treasurers, as highlighted in Treasury Today (2020). The current geopolitical uncertainty is one of the main causes behind the recent uptick in volatility in many markets, complicating the ability of a treasurer to manage risk. Inevitably, the dairy sector is also affected by these developments and is on the lookout for more advanced market risk management tools. One promising tool is volatility modeling. This paper will focus on how volatility modeling can benefit commodity traders by dynamically managing price risk in the European Union (EU) dairy market with time series models.

Introduction

Commodity trading has shown significant growth over the last century due to trade liberalization, urbanization and the opening of new markets. Large trading firms have emerged with a strong foothold in multiple countries in order to span the entire supply chain. These firms are in the business of transforming commodities in space (logistics), in time (storage), and in form (processing). If the price of a material plus the transformation costs (*e.g.*, processing, transportation, and financing) is less than the price of the transformed product in a particular market, traders will be motivated to engage in this activity until the price differential nears zero (Pirrong, 2014).

Commodity trading firms keep a close eye on local market conditions since demand and supply imbalances or updated rules and regulations can suddenly close arbitrage windows. They are diverse and vary in size, product offerings, locations and asset strategy. Large > 10€ billion commodity trading firms that trade a vast variety of commodities invest heavily in fixed assets such as plantations, storage locations, and processing facilities while at the other end of the spectrum, smaller and highly specialized commodity trading firms operate in a niche segment of the market and carry almost no fixed assets on their books.

While engaging in these activities, commodity trading firms face a wide array of risks that can be managed by hedging, insurance and/or diversification. Risks typically translate into price swings which can be measured by the underlying volatility of an asset. Volatility is rarely seen as a positive signal because it increases uncertainty about returns, potentially preventing investors to enter a particular market. With margins generally being thin, large capital expenditures financed with debt (*e.g.*, production facilities or storage centers) could bankrupt a company with an ill-timed investment or a disadvantaged unhedged position. Concerns about increased price volatility are usually voiced by producers and processors who, in the absence of risk management tools, are exposed to uncertainty associated with changing prices.

These parties could use some help in managing the risks and returns on their product portfolio especially when input costs are high and certain utilization rates have to be met (Soutter and Manuel, 2019).

Most commodity trading firms are willingly exposed to market risk because it allows them to arbitrage between markets and take positions. A firm's risk metrics compare its current risk exposure to the risk appetite of the firm. These metrics are typically reviewed at regular intervals as markets rarely operate in a steady state. This triggers the need for management to understand and, when possible, estimate the short-term "riskiness" of the markets in which they operate.

Research Methodology

Risk management is at the center of many commodity trading firms since they cannot control how asset prices will develop over time despite their extensive knowledge of commodity markets. This paper focuses on the open position of a trading firm which is the main source of (market) risk. Risk metrics at commodity traders are frequently based on historical data, rules of thumb and typically remain static over time. In practice, markets are rarely constant, and warrant a more dynamic approach towards risk management. The objective of this article is *to characterize the existence of price volatility in EU dairy markets and utilize historic time series analysis to predict future volatility to manage price risk*. This should lead to a more advanced and dynamic set of risk management tools.

<u>Scope</u>

The scope of this study is the EU Dairy Market. Despite being a mature market, it is highly volatile as regulatory changes, weather effects, and demand changes have significant implications on the prices of dairy products. The products of interest are Skim Milk Powder (SMP) and Butter. These two commodities represent the protein and fat content of milk and can be traded both physically as well as on the futures market. Weekly public price information for SMP and Butter published by the EU Agriculture and Rural Development board for the period 2001-2017 (European Commission, 2018) have been used as the input of this research.

<u>Academic Relevance</u>

The agricultural commodity sector has been an important subject of economic research, for example the effects of changes in local legislation or the impact of pricing mechanisms on the supply chain (Moyer and Josling, 2002). Johnson (1975) already described how the effect of agricultural price stabilization in one market amplifies the volatility in the markets of its trading partners. Mathematically modeling volatility has been a subject of many debates. Several authors concluded that modeling volatility is inherently difficult as it is rarely constant, asymmetric, and exhibits certain properties (*e.g.*, autocorrelation) that do not easily fit into standard statistical models (Pagan and Schwert, 1990). Volatility however does encompass specific behaviors that can be captured by mathematical models; *e.g.*, the Moving Average (MA) and Autoregressive (AR) models are used by economists to model time series of assets returns.

Value at Risk (VaR), defined as the value of a portfolio of assets that can be expected to be lost during adverse market conditions, became a popular concept in the mid ’90s. VaR has been widely adopted by banks and other financial institutions to manage risk (Linsmeier and Pearson, 1996). Despite some criticism, regulatory frameworks such as Basel refer to the use of VaR models for capital requirement ratios and stress testing purposes. Volatility estimates are a critical input in VaR models. Several articles combine conditional volatility estimates from time series models with Value at Risk, but few turn it into a practical application (Engle, 2001).

Moledina *et al*. (2004) published an article on how to estimate the volatility of various soft commodities with the help of time series models. O’Connor *et al*. (2011) used the method described by Moledina *et al*. (2004) to measure the volatility in dairy markets for the period 1990 to 2007 to verify whether the EU’s price policy had the desired dampening effect on EU dairy prices. This paper will investigate how time series models can describe the underlying volatility patterns in dairy prices and assess if the conditional volatility estimates are able to outperform traditional methods (*e.g.*, a historic volatility assumption). In addition, we explain how these volatility metrics can be used in a trading environment to enhance the risk management practice of a commodity trading company.

Global Dairy Markets

Soft commodities, *e.g.*, dairy, wheat, grain, and coffee, are typically grown rather than mined or extracted, lose their value over time and tend to be more volatile when compared to regular commodities. Many governments try to protect local agricultural markets by imposing import tariffs, offering private storage programs, set intervention prices or have other means to subsidize local farmers which can result in significant prices difference among regions.

Milk is produced by over 260 million cows worldwide and equals an annual milk volume of 600 million metric tons (MT’s) of which 42% comes from Europe (FAO, 2016). The EU and the US are the two largest producers of dairy products and have well developed domestic demand markets which consume the majority of the dairy products they produce. The remainder is traded internationally, which accounts for 7% to 10% of the world’s milk output. A small change in global milk production, *e.g.*, due to severe weather conditions or diseases, has an amplified effect on the global supply of dairy products. In monetary terms, dairy is the largest soft commodity market in the world with an annual production value of 328 billion USD (FAO, 2016).

Three prominent factors that influence the volatility in dairy volumes/prices are as follows: (1) the impact of small changes in the quantities on internationally traded volumes, (2) the delayed response in the demand or supply of dairy products, and (3) the effect of government bodies that regulate agricultural policies. These factors make it difficult for farmers to predict in which direction the market is heading and whether they need to sell forward part of their production volumes. Stocking dairy commodities may help to reduce price fluctuations by balancing demand and supply. However, speculation by traders or government intervention programs could lead to the build-up of large stock reserves.

Agricultural derivatives markets allow farmers and cooperatives to hedge positions and trade in physical or cash-settled contracts. The development of dairy derivative markets has made it easier for participants to manage outright price risk. The presence of speculators is often seen as a necessary condition for functioning markets, but volatility can attract speculative activity, which may destabilize markets. The ramp-up of the EU dairy derivatives markets coincided with a period of increased volatility (2010-2017).

Dairy Data Analysis

Analyzing financial data is usually done using returns rather than prices or absolute returns. The benefit of using relative returns is the normalization of the data which gives the ability to compare datasets. Logarithmic returns provide the additional benefit of time-additivity, ease of calculation (*e.g.*, log normality) and numerical stability. Market volatility can be defined as the degree to which prices fluctuate over time. Volatility is often regarded as an important measure of risk in financial markets and consequently has become the price of uncertainty. Let's denote S_t as the price of a financial asset, *e.g.*, the price of a metric ton of Butter at time t, which should have a positive value at all times. The log return of holding such an asset during time period t is given by:

$$r_t = \ln\left(\frac{S_t}{S_{t-1}}\right);\ S_t \geq 0 \tag{1}$$

The log return of an asset is considered to be a random variable and is characterized by an expected value µ and a volatility σ. Volatility measures to what extent a return fluctuates around its sample mean and is measured by the sample standard deviation of a return in a time period T:

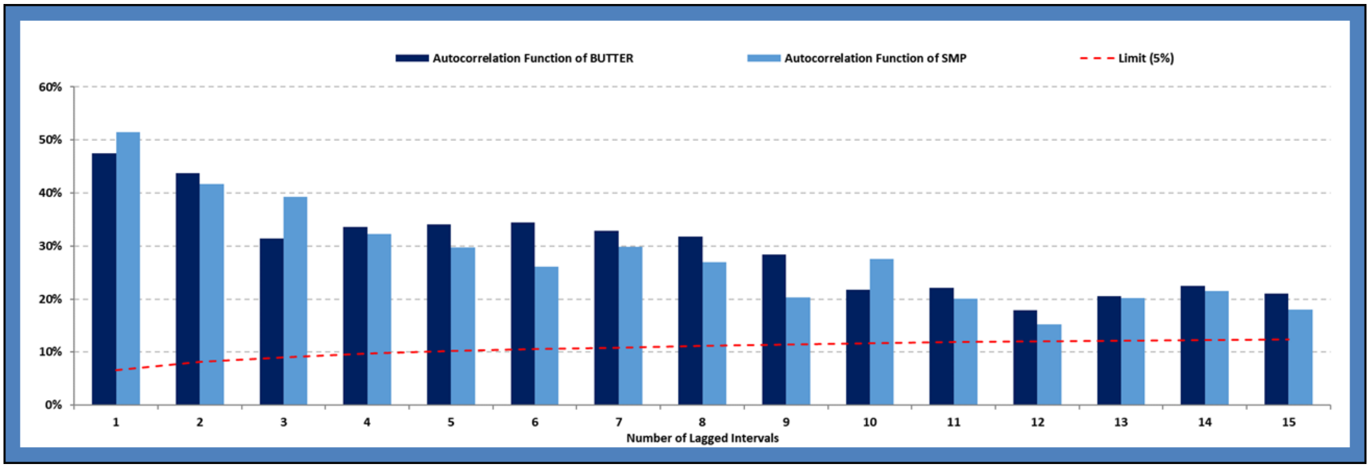
$$\hat{\sigma} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_t - \hat{\mu})^2} \tag{2}$$

The volatility of an asset has interesting statistical properties which can be of use in forecasting it; *e.g.*, volatility in commodity prices may cluster, are likely to persist or even may reverse to the mean in time. The next section visualizes these three important statistical properties in the Butter and SMP time series.

Positive autocorrelation signals volatility clustering (Piot-Lepetit and M'Barek, 2011). Autocorrelation can be measured between returns and historical returns for various numbers of lagged intervals. Figure 1 on the next page shows the autocorrelation for 1 to 15 lagged intervals in the absolute weekly returns for Butter and SMP prices. The one lag interval autocorrelation has the highest value after which the autocorrelation gradually decays for larger intervals.

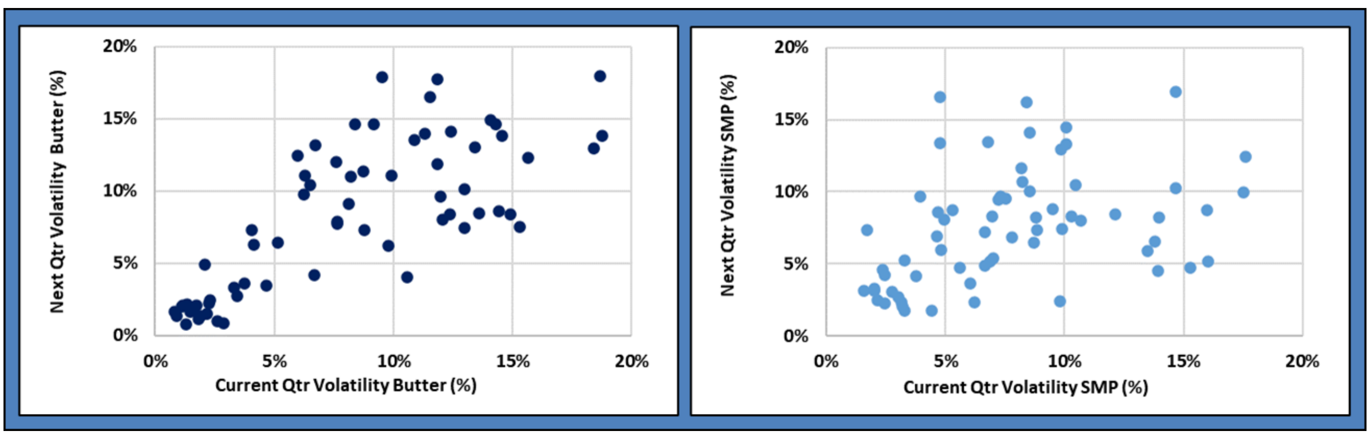
The volatility of an asset is rarely constant. When the *volatility* of a time series itself is fluctuating, the time series is referred to as "heteroskedastic" compared to "homoscedastic," which refers to a time series with constant volatility. Heteroskedastic properties challenge statisticians in time series regression as the error term is not time invariant, a standard condition for standard regressions. Error terms might be larger in some ranges of the dataset compared to others.

Figure 1
Autocorrelation of SMP & Butter Measured in Absolute Weekly Returns (2001-2017)



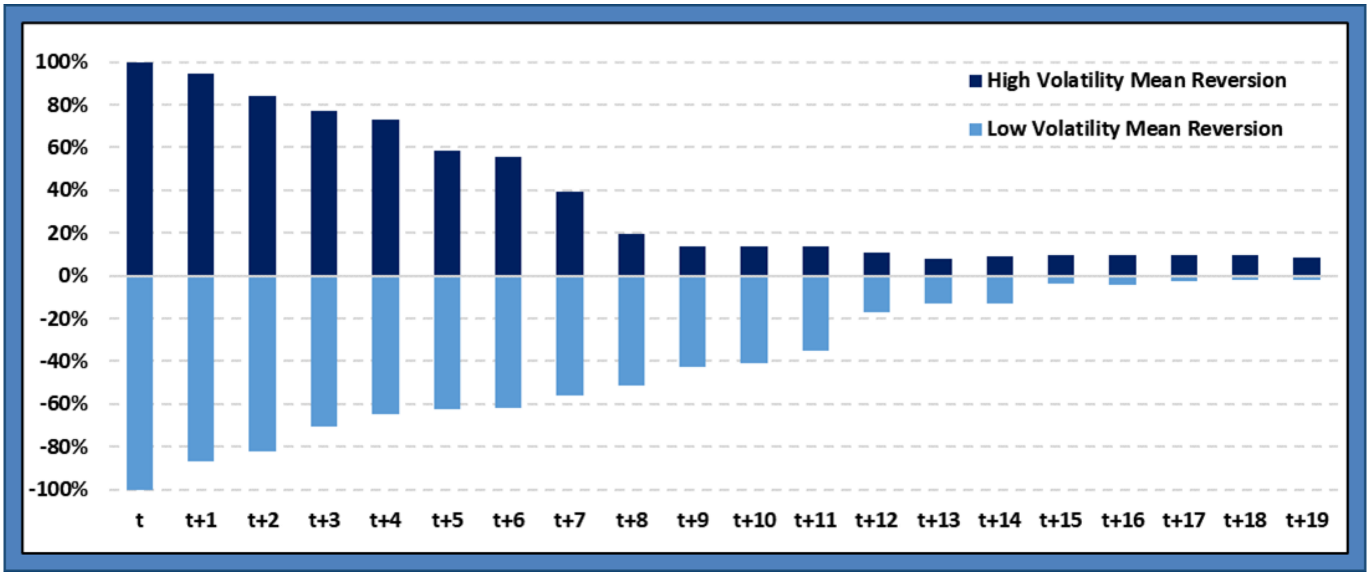
The volatility of Butter and SMP has been calculated for 16x4 quarterly periods in the past 16 years. The quarterly volatility figures ranged between 2% to 19% for both Butter and SMP. The volatility is far from constant but both times series do exhibit a certain level of volatility persistence (Figure 2). The R^2 value of the linear regression between the volatility of two consecutive quarters for Butter is (59%) and for SMP (17%). The correlations are positive and the standard deviation of the returns of the past quarter may predict to some extent the next quarter's volatility.

Figure 2
Annualized Volatility of Returns Qtr on Qtr for Butter and SMP (2001-2017)



Another common empirically observable feature for return volatility, as mentioned by Engle and Patton (2007), is its tendency to revert to the mean. In other words, the volatility gradually returns to its long-term average. From 2007 to 2017, eleven quarterly periods of high volatility (1σ > the mean volatility) and eight quarterly periods of low volatility (1σ < the mean volatility) were observed in the Butter time series. The delta between the average volatility and the extreme value in the high or low volatility period was noted for each consecutive week and converted into a percentage improvement to the long-term average.

Figure 3
Mean Reversion Effect of the Butter Dataset in Weeks (2007-2017)



Mean reversion is clearly observable in Figure 3. The time it takes for the volatility of Butter to move to halfway its long-term average (half-life), is about 7 to 8 weeks. After about 13 weeks the volatility levels are back to the long-term average. The effect is however not symmetric; periods of low volatility take a slightly longer time to revert to the mean in our sample. This analysis gives an idea of how frequent volatility estimates have to be updated and reflects the short-term risk in the order book at a commodity trading firm.

These three typical properties of volatility in the EU dairy commodity market can serve as inputs to model volatility. Additional statistical tests show that log returns of the Butter and SMP time series follow a stationary process with no trend, zero mean ($\hat{\mu}$) and are not normally distributed at the 95% significance level, warranting further research on the type of non-normality and possible correlations between individual data points.

Volatility Modeling

A prerequisite to modeling the dynamics of a time series is to determine whether the series behaves as a stationary or non-stationary process (Moledina *et al.*, 2004). The Augmented Dickey-Fuller (ADF) test will help to verify this property. If there is no unit root, the data is considered stationary. The regular returns for Butter and SMP show signs of non-stationarity because the presence of a unit root (the null hypothesis, H_0) cannot be rejected. This is significant for the first two variants of the ADF test (p-value > 0.05). The first difference of the time series did completely remove the non-stationarity from both datasets.

The time series are also checked for the presence of higher order, non-linear, forms of autocorrelation with the help of the Autoregressive Conditional Heteroscedastic (ARCH) test, which can detect a time-varying phenomenon in the conditional volatility. The ARCH effect is present in both datasets and is significant at the 1% level for at least the first 3 lags. The next period's volatility is likely dependent upon both the past volatility and the past innovations of the same series.

In order to start forecasting, let's define the following standard equation for the log return of an asset in time series with a zero mean:

$$r_t = \sigma_t \, Z_t \tag{3}$$

where Z_t, the error term, is a sequence of $N(0,1)$. We will utilize four models to obtain an estimate for the future volatility $\hat{\sigma}_t$, based on certain properties of the time series.

Model 1: Historical average model (HIS): This model assumes that the future volatility is equal to the volatility over a fixed period (training period) and does not take any time conditional information into account.

$$\hat{\sigma}_t^2 = \sigma^2 \tag{4}$$

Model 2: Exponential Weighted Moving Average model (EWMA): The EWMA model computes $\hat{\sigma}_t^2$ based on historical values. The weighting decreases exponentially with each historic time period. The smoothing parameter λ is estimated by minimizing the Mean Square Error function on the training data.

$$\hat{\sigma}_t^2 = \lambda \, \sigma_{t-1}^2 + (1-\lambda) \, r_{t-1}^2 \; with \; \lambda \sim \{0,1\} \tag{5}$$

Model 3: Autoregressive Moving Average model (ARMA): ARMA (p,q) models, popularized by Box and Jenkins in the 1970's, are moving average models that adjust the weights of historic observations to optimize the predictive power over the training period (Box *et al.*, 1995). The conditional volatility is expressed as a function of its past values σ_{t-i} along with an error term ε_{t-j}.

$$\hat{\sigma}_t = c + \sum_{i=1}^{p} \varphi_i \sigma_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \tag{6}$$

Model 4: Generalized Autoregressive Heteroskedastic model (GARCH): Autoregressive conditionally heteroskedastic ARCH (q,p) models were introduced by Engle in 1982 and later extended by Bollerslev into a generalized version (Bollerslev, 1986). In a GARCH model the $\hat{\sigma}_t^2$ is calculated from a long-run average variance rate, as well as from the last squared return r_{t-i}^2 and the last period's forecast σ_{t-j}^2.

$$\hat{\sigma}_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, r_{t-i}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2 \;\; with \;\; \alpha_i \geq 0 \; and \; \beta_j \geq 0 \tag{7}$$

The parameter estimation of these models is performed with the help of NumXL™, an advanced statistical plug-in for Excel which estimates the parameters by maximum likelihood methodology on the training data. NumXL™ also evaluates the statistical fit by the Akaike Information Criterion (AIC) which is used as a metric for model selection. Additionally, AIC penalizes models with many parameters (*e.g.*, overfitting).

Testing and Validation

After estimating the model parameters on the training dataset (2001-2013), all four parameterized models are tested in the 2014-2017 period. The models have to forecast the conditional volatility for $t+1$ week and the results are compared to the realized volatility. The realized volatility is calculated by averaging the past quarter's intraweek log returns and using it as a proxy for the realized weekly volatility. The Root Mean Square Error (RMSE) (8) and the Mean Heteroscedastic Square Error (MHSE) (9) error functions are used to compare the realized and the forecasted volatility, where $\hat{\sigma}_t$ is a forecast of the volatility, σ_t is the realized volatility in week t and T is the number of weeks in the test period.

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\hat{\sigma}_t - \sigma_t)^2} \tag{8}$$

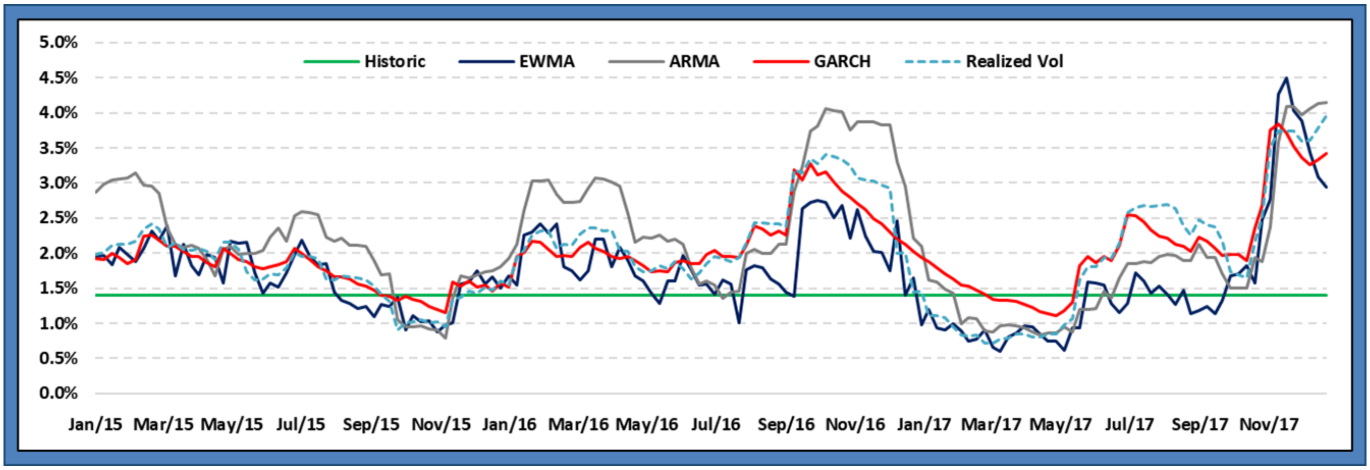
$$MHSE = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{\sigma_t}{\hat{\sigma}_t} - 1\right)^2 \tag{9}$$

The RMSE is commonly used among practitioners, but it has some drawbacks; *e.g.*, the RMSE uses the absolute delta and does not proportionally relate estimates to each other (Bollerslev and Ghysels, 1996). MHSE addresses the issue of the RMSE by measuring the error in relation to its estimate. A lower number on each of the error functions indicates a better fit.

Volatility Modeling Results

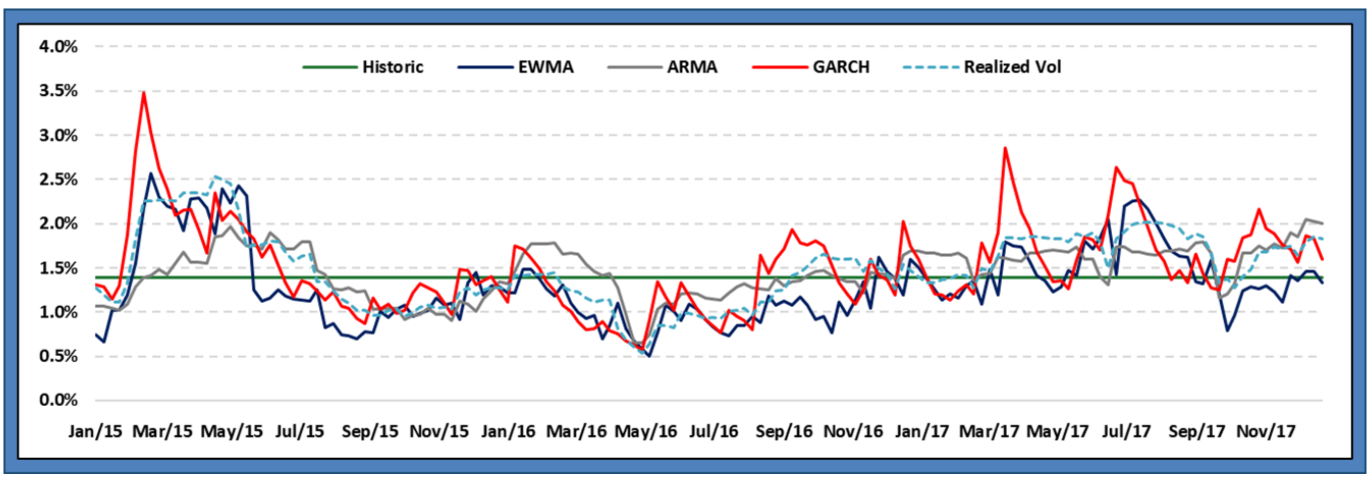
Figure 4 on the next page shows the result of the four volatility models versus the realized volatility (dotted blue line) for Butter for a period of 3 years. The realized weekly volatility of Butter in the period 2015-2017 clearly exceeds the historical average of the training dataset (dark green line). The GARCH and EWMA models track the realized volatility of Butter more accurately than the ARMA model which seems to overestimate the volatility in most periods.

Figure 4
Conditional Volatility Forecasting Result for Butter (2015-2017)



The weekly volatility of SMP, as seen in Figure 5, is more in line with its long-term average although periods of low volatility (2016) and increased levels of volatility (2017) can be observed. The ARMA and EWMA models seem to outperform the GARCH model as the latter reacts more strongly to changes in the realized log returns. This can be explained by the higher value of the estimated α parameter in the GARCH model of the SMP dataset compared to Butter (0.26 vs. 0.09).

Figure 5
Conditional Volatility Forecasting Result for SMP (2015-2017)



Comparing Results

The historical model (HIS), which acts as a proxy for a *static* risk approach, performed the worst for both Butter and SMP. The EWMA model did a better job and was able to reduce the MHSE by half for Butter compared to the historical average. The next class of models, ARMA and GARCH, further improved the result with GARCH scoring the highest on both error measures: RMSE (.28) and MHSE (16.6%) criteria for the Butter returns. The volatility of the SMP dataset was best predicted by the ARMA model, with an MHSE score of 19.4%, and the GARCH model at 19.8%.

Test Dataset	*Error Function*	*Historic*	*EWMA*	*ARMA (1,1)*	*GARCH (1,1)*
Butter	RMSE	0.96	0.54	0.51	**0.28**
(2014-2017)	MHSE	68.7%	36.9%	22.8%	**16.6%**
SMP	RMSE	0.43	0.32	**0.29**	0.32
(2014-2017)	MHSE	31.2%	29.8%	**19.4%**	19.8%

The standardized residuals analysis for both the GARCH and ARMA models have a mean of 0, standard deviation near 1, indicating that the residuals were showing signs of randomness/white noise. Full normality could not be established (p value > 0.05), mainly due to excess kurtosis. The ARCH effects did largely disappear in the residuals, although still present in the ARMA case, which could warrant the search for a more complex ARMA-GARCH model for SMP.

We ran a few more simulations with more complex model variants, *e.g.*, EGARCH, and higher order ARMA (X,X) and GARCH (X,X) models for both time series, but despite the additional parameters, no significant improvement was found. In general, we can conclude that in our datasets the basic ARMA (1,1) and GARCH (1,1) model fits the time series best. The next section explains how these volatility estimates facilitate the implementation of a dynamic risk management approach supported by the VaR.

Application in Practice

The Value at Risk (VaR) metric is a useful method to determine the (market) risk of carrying a position. Although it has received some criticism, it is still widely used by financial institutions, asset managers and trading houses. The VaR is essentially a function of three parameters: the time horizon, the confidence level (X%), and an estimate of the forward-looking volatility of a portfolio of assets which is usually the most difficult one to estimate.

We will use the volatility estimates made by the ARMA and GARCH models from the previous section to calculate a Value at Risk, based on the notion that the future volatility can be derived from past innovations of the same time series. In a second application the logic of the VaR model is reversed to define the maximum position limits at regular time intervals to ensure that the risk, expressed as the Value at Risk as % of equity, stays within the predefined limits.

1. <u>Calculating a Dynamic VaR</u>

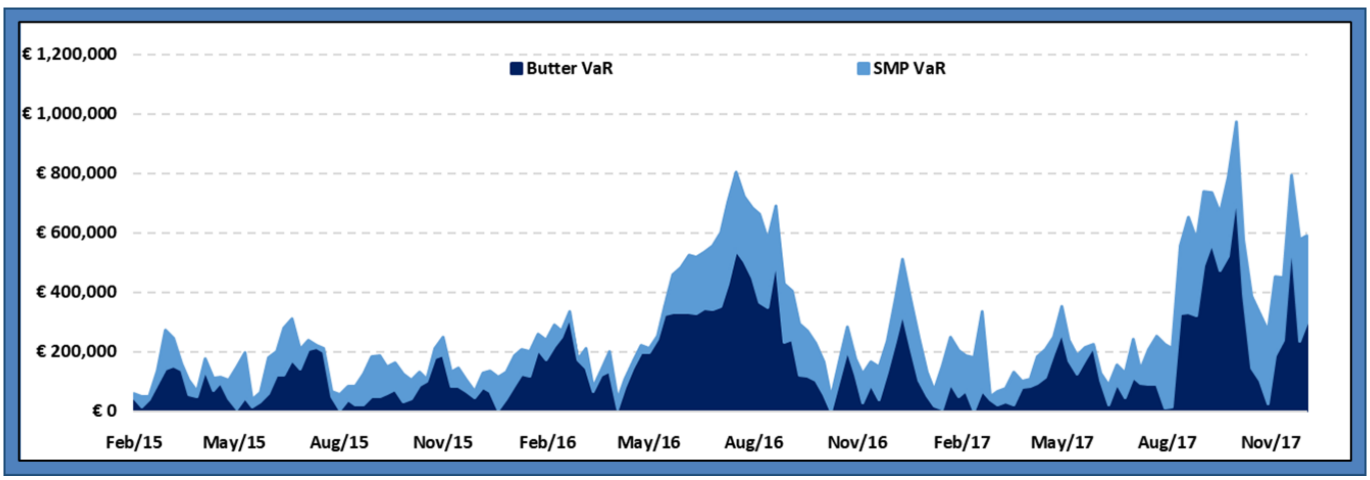
Let's set the maximum position limit for Butter at 5,000 MT's and SMP at 10,000 MT's and that traders are only allowed to trade outside these position limits with the consent of their management. The position limit is transformed into a one-day VaR (in EUR) with the help of the following formula:

$$One\ day\ VaR_t = \frac{|O_t| \cdot p_t \cdot (e^{\hat{\sigma}_t \cdot P_{95\%}} - 1)}{\sqrt{5}} \tag{10}$$

with O_t the maximum product position in metric tons, p_t the weekly price of the commodity in EUR, $\hat{\sigma}_t$ the weekly conditional volatility estimate and $P_{95\%}$ as the 95th percentile of the standardized residuals of the error term. A histogram was used to determine the range in which 95% of the standardized residuals would fit. For a standard normal distribution this is 1.65x the standard deviation, but for the Butter and SMP errors the 5% quantile amounts to 1.99x and 2.14x respectively, which is caused by the non-normality of the returns (Engle, 2001). At each t the GARCH model was used to estimate the conditional volatility $\hat{\sigma}_t$ for Butter and the ARMA model for SMP.

Figure 6 sums the one-day VaR's of both product positions without correcting for the correlation between them. It shows that the overnight VaR ranges from less than 100kEUR to almost 1,000kEUR, which might be above the risk appetite of a firm. Although the Butter position was smaller compared to SMP, it represented on average, 60% of the total VaR due to the higher volatility levels.

Figure 6
The Overnight VaR for Butter and SMP Combined in EUR



Q3'16 and Q4'17 were two periods in which Butter prices were highly volatile; weekly price changes of >300 EUR/MT were no exception. This analysis illustrates that in times of high volatility the accompanying risk level increases significantly. Traders should be vigilant in times of increased volatility and consider hedging their open positions in order not to increase the exposure of the firm beyond predetermined risk levels.

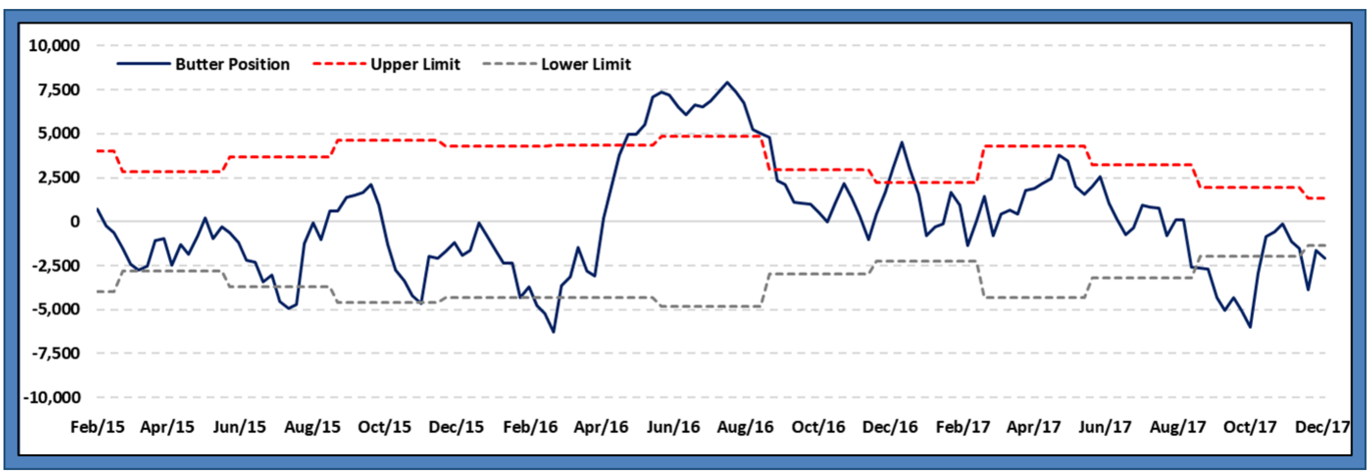
2. Calculating Dynamic Position Limits

The conditional volatility estimate could also be used to implement a strategy in which a firm employs *dynamic* position limits with the goal to stay within the agreed VaR as % of equity. Product positions consist of multiple products and traders can maximize one position at the expense of the other. Without correcting for the correlation of the returns of SMP and Butter and given the traders' intent to create a position in both products, what would have been the appropriate position limits for each product?

Assume that the traders are allowed to allocate 60% of the VaR on Butter and 40% on SMP, reflecting the average allocation of the VaR over the past three years. Position limits are recalculated quarterly with the help of formula (10) and the average limit of the past five weeks will set the limit for the quarter ahead. Position limits can be either long and short and the one-day 95% VaR is capped at 1% of equity. Maximum position limits should be reassessed periodically. The frequency depends on the nature of the business and the maturity of the commodity market in which the firm operates.

Figure 7 clearly illustrates the effect of the conditional volatility estimate; it narrows the boundaries (dotted lines) when the volatility increases and widens the position limits again in periods of relative calm. In most instances, the Butter position stayed within its precalculated limits. The same exercise was done for SMP, resulting in positions limits between 4,000 and 7,000 MT. When comparing these dynamic position limits to the static limits of 5,000 MT (Butter) and 10,000 MT (SMP) respectively, the static limits underestimate the actual volatility in the market and would not allow a company to maintain its 1% VaR over equity target.

Figure 7
The Butter Position and the Dynamic Position Limits in MT's



Dynamic limits may allow a company to anticipate volatility trends and to timely adjust positions before the associated position risk level increases. It is worth noting that the somewhat weak correlation between weekly Butter and SMP returns does reduce the overall risk of the portfolio. The positive correlation between Butter and SMP of 0.33 over the past three years gives an approximate 15% to 20%

reduction of the VaR of the combined portfolio. However, correlations are not constant and if the positions are managed independently, the offsetting effect of weak correlations can be limited in practice.

These two practical applications illustrate that the conditional volatility estimates are useful in the calculation of a weekly VaR metric and can also be used to dynamically set position limits for commodity traders to allow for better risk management.

Embedding a Dynamic VaR model in an Organization

One of the first questions that the shareholders of a company have to decide upon is: "*What is the level of risk we feel comfortable with*?" Once the risk appetite is defined (*e.g.*, position limits, VaR as % of equity), the firm has to create a proper risk management framework within the organization. This section explains how commodity traders can embed dynamic risk management in their risk routine.

A middle office desk is typically concerned with daily risk management responsibilities and could calculate the dynamic product position and VaR limits based on the current volatility outlook. Conditional volatility estimates are derived with the help of a preselected volatility model, *e.g.*, the GARCH or ARMA variants. Historical returns are usually publicly available, and with the help of a statistical software package, model parameters can be established with little effort. Care should be taken to ensure the data is stationary before modeling since financial time series are rarely independent. A supporting organization is essential in execution and maintenance of a dynamic risk management model.

- **Traders**: the traders are responsible for maintaining an accurate position and should get a basic understanding of volatility estimates and obtain training on the logic behind a VaR model.

- **Middle Office**: this is the center of risk management and is ideally positioned to reconcile trades, perform desk research, update volatility estimates and advise management on position limits.

- **Management**: the firm's management has to determine the risk appetite of the firm and needs to be fully aware of the VaR metric and is in charge of reviewing it on a regular basis.

- **Finance department**: this department serves as the reporting and accounting backbone of the organization and checks if limits are respected and/or if escalations are performed in accordance to internal guidelines.

- **Treasury**: the treasury department is typically interested in the results of the model as they need to ensure sufficient liquidity is available for margin calls or provide credit support.

The decision to reduce or increase a certain position should be carefully considered as other factors may be at play. The breach of a VaR or position limit serves as a trigger to investigate. The position accuracy has to be verified first, in addition to a review of the current market circumstances. If, for example, the recent uptick in volatility can be explained, and the traders are comfortable with the level of risk, they could be given the consent of the management's board to maintain their positions. Despite the popularity of VaR models, it remains just one measure in the toolkit of a risk manager. Stress tests and sensitivity analysis amongst others have to be run in parallel to ensure a proper assessment of the risk is made.

Summary and Conclusion

This paper studied the time series properties of price volatility in EU dairy markets and has tested models to forecast the price volatility. Second, it showed how to use these forecasted volatility estimates to manage price risk at a commodity trader.

Volatility in dairy is predominately driven by external factors far beyond the control of a typical commodity trading firm and are not easily captured in a model. On the positive side, time series of EU Butter and SMP commodities demonstrated significant positive autocorrelation, strong forms of volatility persistence and quantifiable levels of mean reversion. This heteroskedastic behavior combined with leptokurtosis and non-normality is modeled best with the help of an ARMA or GARCH time series model. These models provided a conditional estimate of the expected future volatility, which is a welcome input for Value at Risk models that are frequently used to assess the risk of the open positions at trading firms.

This paper discussed how product positions in combination with a volatility outlook can be translated into a dynamic VaR number. In addition, in times of high volatility, the accompanying risk level increases significantly, and could exceed the risk appetite of the firm. Another application was to use the conditional volatility estimates to dynamically set position limits. When the expected volatility increases, the model narrows the position limits and widens the boundaries again in periods of relative calm. We conclude that volatility modeling is an interesting field to further explore and offers multiple opportunities for commodity trading firms to enhance their risk management suite. A dynamic VaR model could replace some "static" tools or methods currently in place, but it cannot be a sole substitute for a prudent risk management practice at any firm.

Further Research

This research can be expanded by including dairy commodity prices from other geographical areas, or more advanced time series models to obtain a better volatility estimate. It would also be interesting to understand if the parameter estimation method can be improved with the help of semiparametric approaches since the assumptions about the underlying distributions are often violated. Lastly, the dairy futures market has grown rapidly in the past few years and has become a key platform to mitigate price risk. The volatility of futures could, for instance, help to estimate the forward-looking volatility of dairy products.

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Commodity Portfolio Management: Strategy Structuring Considerations

Vito Turitto
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This article expands on research into commodity portfolio management that was published in the Winter 2019 edition of the Global Commodities Applied Research Digest. Commodity markets are often used to diversify portfolio risk and as a hedge against inflation but, in order to maximize returns and hedging effectiveness, it is necessary to develop an approach that examines each commodity market separately. Accordingly, this article analyzes individual commodity returns and provides guidance on how extreme returns can impact commodity portfolio strategies.

Introduction

Diversifying an investment portfolio as well as hedging against inflation using commodity markets is a well-established need within the portfolio management industry; nevertheless, citing the Winter 2019 *GCARD* article on "Commodity Portfolio Management," "it is crucial to point out that for commodities, metrics such as volatility and seasonality deserve to be addressed specifically and separately: an equity-style approach would ignore the strong idiosyncratic features characterizing each commodity, inevitably leading to inefficient portfolio construction and to a suboptimal allocation of resources."

The present research is entirely based, for consistency purposes, on the same commodities that were analyzed in the previous *GCARD* article. Specifically, the data is drawn from liquid, exchange-traded (Intercontinental Exchange and Chicago Mercantile Exchange Group) commodity futures contracts and includes three different commodity sectors: energy (which can be further subdivided into crude grades and petroleum products), agriculture, and metals (which can be further subdivided into precious and base metals.) The time period of this dataset ranges from January 2010 to January 2020. The study's three commodity sectors contain the following sets of futures contracts:

1. Energy: Brent Crude, West Texas Intermediate (WTI) Crude, European Low Sulphur Gasoil (diesel), New York Reformulated Blendstock for Oxygenate Blending (RBOB) Gasoline, and Dutch Title Transfer Facility (TTF) Natural Gas;

2. Agriculture: U.S. Sugar Number 11 and White Sugar - Europe; and

3. Metals: Gold, Silver, and Copper.

This article will cover the nature of return fluctuations in different commodity markets in order to provide insights that may be useful for the efficient structuring of commodity portfolio strategies. This research will be subdivided into two sections: (a) the returns in commodity markets and (b) the "fat tails" in commodity returns.

Returns in Commodity Markets

This section includes the calculation of the various commodity markets' log-normal returns and, in order to simplify and facilitate the comparative analytics, the results will be discussed in the following subgroups:

1. Brent, WTI, and Dutch TTF;
2. Gold, Silver, and Copper;
3. Intercontinental Exchange (ICE) Gasoil and RBOB Gasoline; and
4. White Sugar - Europe and U.S. Sugar Number 11.

<u>Brent, WTI, and Dutch TTF Futures Returns</u>

Brent, WTI, and Dutch TTF are the most liquid and well-established commodity futures markets within the energy space. Those who trade these markets are not just speculators such as hedge funds, asset managers, and pension funds but also commercials (such as energy producers, refiners, and miners.) Hence, the returns generated in these markets result from the price discovery process among the aforementioned counterparties. The daily return series for these three contracts are shown in Figure 1.

Figure 1
Daily Log-Normal Returns (in %) for Brent, WTI, and Dutch TTF Futures Contracts (January 2010 through January 2020)

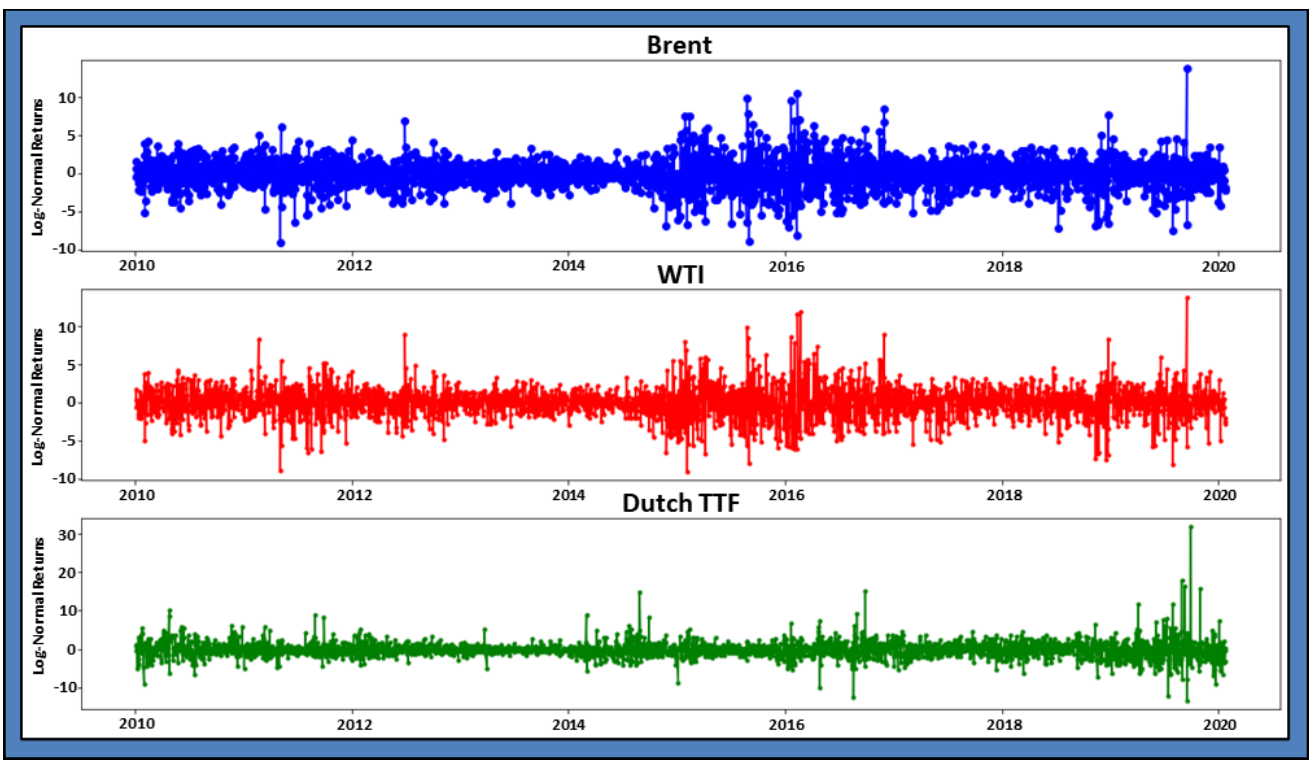


Table 1 compares the returns in each of the three energy markets. In this article, we are using the convention of the higher the returns, the higher the quartile metric is. Correspondingly, we are using the convention of the lower the returns, the lower the quartile metric is. This convention is also used in Tables 2 through 4.

Table 1
Median, 3rd Quartile and 1st Quartile Returns for Brent, WTI, and Dutch TTF Futures Contracts (January 2010 to January 2020)

	Median Daily Futures Returns
Brent	0.04%
WTI	0.03%
Dutch TTF	-0.01%
	3rd Quartile Daily Futures Returns
Brent	0.93%
WTI	1.06%
Dutch TTF	0.93%
	1st Quartile Daily Futures Returns
Brent	-0.93%
WTI	-1.09%
Dutch TTF	-1.03%

Over the time horizon of this study, Brent had the highest median daily returns while the Dutch TTF contract had the lowest median daily returns, which, in turn, were negative. The WTI contract had the highest difference in returns across the 1st and 3rd quartiles.

Gold, Silver, and Copper Futures Contracts

The daily return series for Gold, Silver, and Copper futures contracts are shown in Figure 2.

Figure 2
Daily Log-Normal Returns (in %) for Gold, Silver, and Copper Futures Contracts (January 2010 through January 2020)

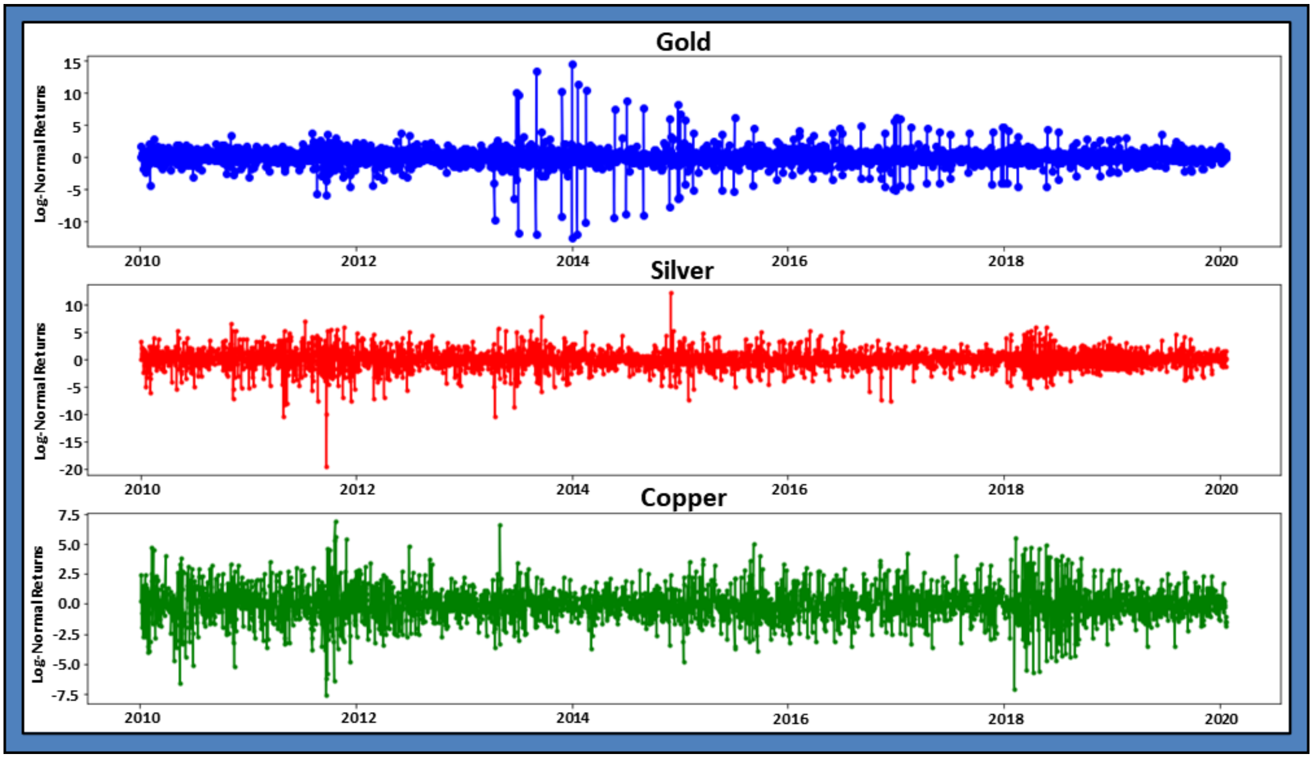


Table 2 compares the returns in each of the subgroup's three metals markets.

Table 2
Median, 3rd Quartile and 1st Quartile Returns for Silver, Gold, and Copper Futures Contracts (January 2010 to January 2020)

	Median Daily Futures Returns
Silver	0.05%
Gold	0.01%
Copper	0.00%
	3rd Quartile Daily Futures Returns
Silver	0.83%
Gold	0.52%
Copper	0.76%
	1st Quartile Daily Futures Returns
Silver	-0.74%
Gold	-0.45%
Copper	-0.71%

Over the time horizon of this study, Silver had the highest median and 3rd quartile returns while Gold had the lowest difference in returns across the 1st and 3rd quartiles.

Intercontinental Exchange (ICE) Gasoil and RBOB Gasoline Futures Contracts

The daily return series for ICE (European) Gasoil and RBOB (American) Gasoline futures contracts are shown in Figure 3.

Figure 3
Daily Log-Normal Returns (in %) for ICE Gasoil and RBOB Gasoline Futures Contracts (January 2010 through January 2020)

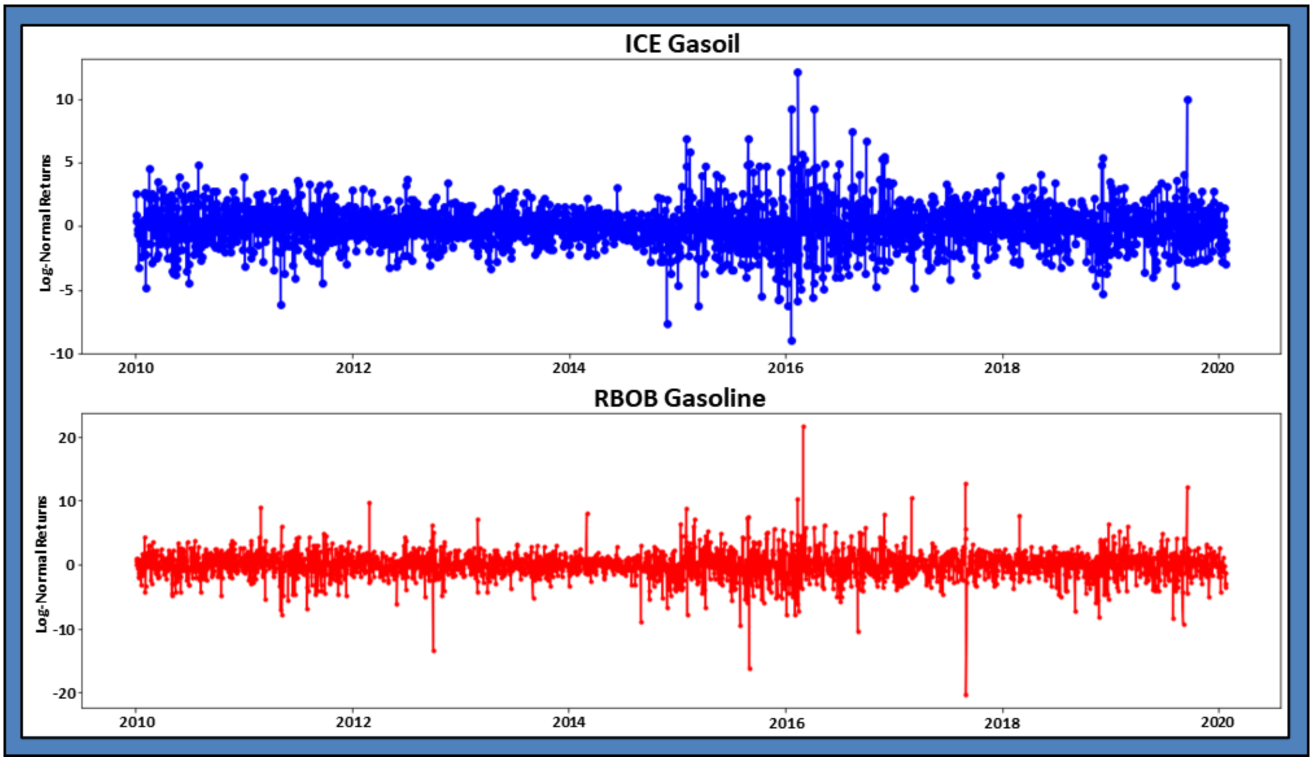


Table 3 compares the returns in the subgroup's two crude oil product contracts.

Table 3
Median, 3rd Quartile and 1st Quartile Returns for ICE Gasoil and RBOB Gasoline Futures Contracts (January 2010 to January 2020)

	Median Daily Futures Returns
ICE Gasoil	**0.00%**
RBOB Gasoline	**0.02%**
	3rd Quartile Daily Futures Returns
ICE Gasoil	**0.81%**
RBOB Gasoline	**1.14%**
	1st Quartile Daily Futures Returns
ICE Gasoil	**-0.82%**
RBOB Gasoline	**-1.12%**

In terms of median returns, the two underlying crude contracts, Brent and WTI, outperformed the product returns of ICE Gasoil futures and RBOB Gasoline futures contracts.

White Sugar – Europe and U.S. Sugar Number 11 Futures Contracts

The daily return series for White Sugar – Europe and U.S. Sugar Number 11 futures contracts are shown in Figure 4.

Figure 4
Daily Log-Normal Returns (in %) for White Sugar – Europe and U.S. Sugar Number 11 Futures Contracts (January 2010 through January 2020)

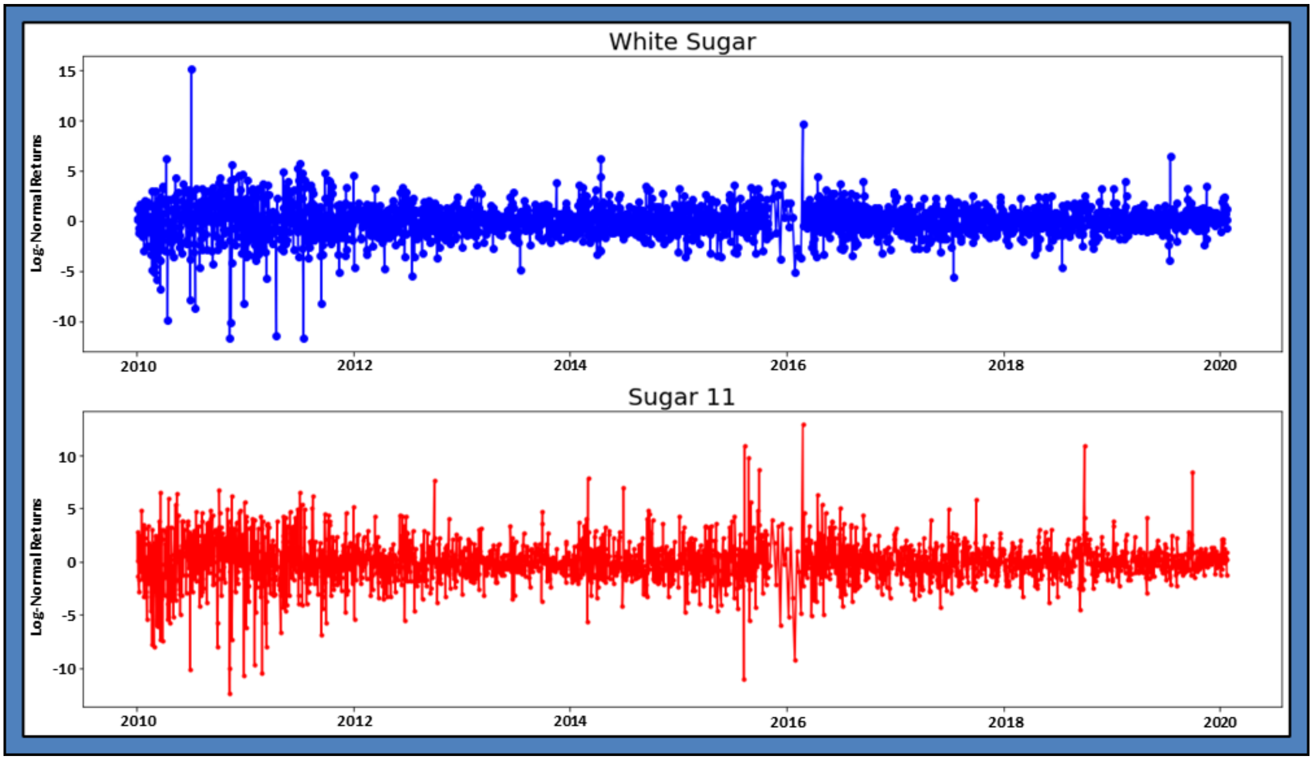


Table 4 compares the returns amongst the two sugar futures contracts.

Table 4
Median, 3rd Quartile and 1st Quartile Returns for White Sugar – Europe and U.S. Sugar Number 11 Futures Contracts (January 2010 to January 2020)

	Median Daily Futures Returns
White Sugar – Europe	**0.00%**
U.S. Sugar Number 11	**-0.05%**
	3rd Quartile Daily Futures Returns
White Sugar – Europe	**0.71%**
U.S. Sugar Number 11	**0.90%**
	1st Quartile Daily Futures Returns
White Sugar – Europe	**-0.77%**
U.S. Sugar Number 11	**-0.98%**

Over the time horizon of this study, the White Sugar – Europe contract outperformed the U.S. Sugar Number 11 contract in terms of median returns while the U.S. Sugar Number 11 contract had the higher difference in returns across the 1^{st} and 3^{rd} quartiles.

Section Summary

The main takeaways from this section are as follows:

- Silver futures contracts provided the highest median returns;
- The Dutch TTF and U.S. Sugar Number 11 futures contracts had negative median returns; and
- RBOB Gasoline futures had both the highest 3^{rd} quartile returns and the lowest 1^{st} quartile returns.

"Fat Tails" in Commodity Returns

Commodity returns frequently do not follow a normal distribution, and this is a well-documented phenomenon in finance. In the previous section, we solely calculated the returns that range between the 1^{st} and the 3^{rd} quartiles. One should also review how "fat tailed" a commodity futures market's distribution is, where 3-sigma, 4-sigma or even 5-sigma events occur more frequently than one would expect under a standard normal distribution. (Here, sigma means standard deviation.) The dispersion in market returns can quite quickly and aggressively skew investment performance. To understand how aggressive such moves can be in individual commodity markets, one needs to calculate the dispersion of daily returns, and, in particular, document each market's extreme returns. We will examine the same commodities as in the previous section and use box plots to provide a visual summary of the kind of extreme moves that have occurred in our dataset's commodity markets.

Box Plots

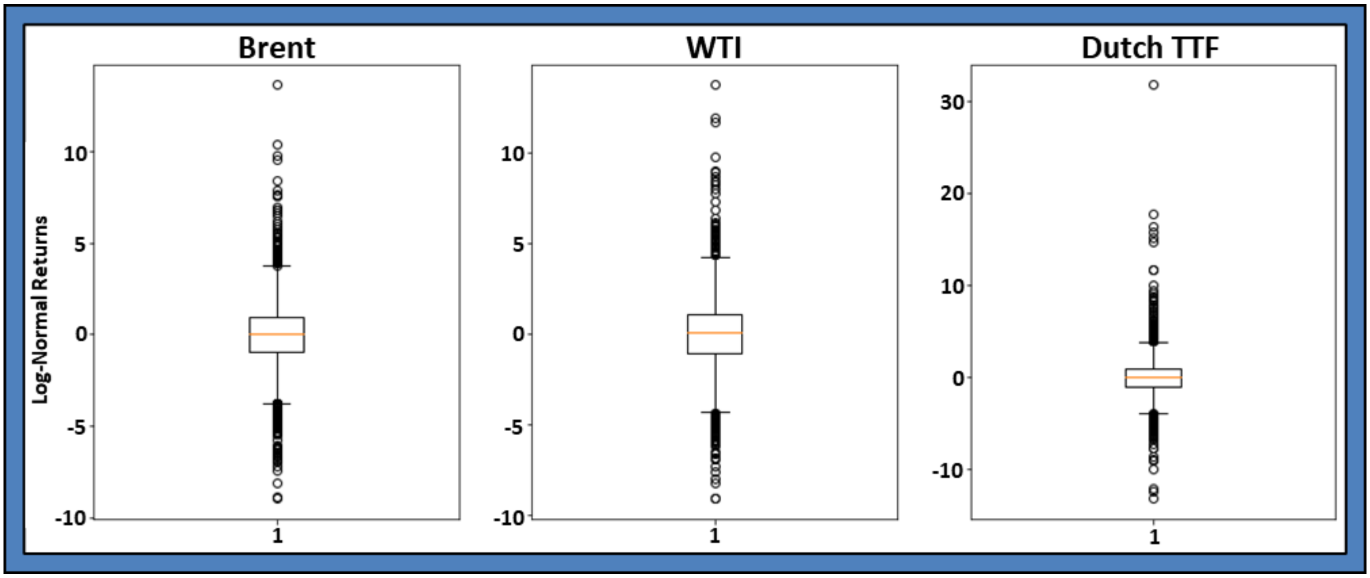
Box plots are a great way to visualize and compare the distribution of different market returns and this is particularly true when outliers are considered. Furthermore, box plots provide a clear and concise way to summarize large quantities of data. In particular, the analyst can readily compare financial time series even if they have different distributions, and they provide an easy-to-understand way to understand how "fat" the distribution tails can be, no matter how far-from-the-median returns may be.

The box plots in Figures 5 through 8 use the following conventions. The red horizontal line is the median return. The box demarcates the 1^{st} and 3^{rd} quartile of returns. The interquartile range is calculated as the 3^{rd} quartile of returns minus the 1^{st} quartile of returns. The top horizontal line (the top "whisker") is arrived at by adding 1.5 times the interquartile range to the 3^{rd} quartile of returns and identifying the largest return within that distance. The bottom horizontal line (the bottom "whisker") is arrived at by subtracting 1.5 times the interquartile range from the 1st quartile of returns and identifying the lowest return within that distance. The circles outside the "whiskers" are the outliers in the data and include the highest and lowest returns observed in the data.

Brent, WTI, and Dutch TTF Futures Returns

Despite the interconnections between energy markets, the Dutch TTF futures contracts have exhibited the wildest fluctuations between the minimum and maximum returns. See Figure 5.

Figure 5
Box Plots of Daily Log-Normal Returns (in %) for Brent, WTI, and Dutch TTF Futures Contracts (January 2010 to January 2020)

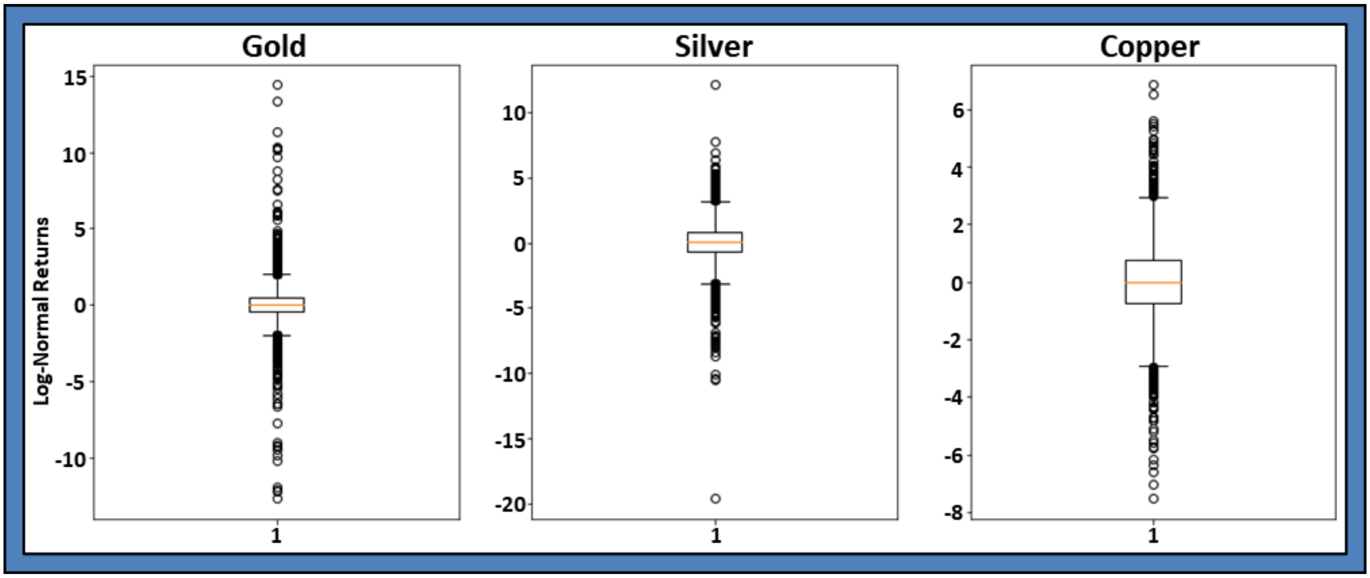


Specifically, the highest daily return in Dutch TTF futures was a staggering 31.7% while the lowest ever return recorded, within the time frame of the present analytics, was -13.2%. In comparison, the highest returns for Brent and WTI futures contracts were 13.7% for both markets while the lowest returns amounted to -9.0% and -9.1%, respectively. Overall, at least historically, it would have been much easier to manage a portfolio of both crude grades rather than including Dutch TTF futures which, despite the extremely high returns they could potentially yield, have carried substantial downside risk.

Gold, Silver, and Copper Futures Returns

Dispersion has historically been different in the metals. None of the metals markets in our study experienced positive returns as high as observed in the Dutch TTF market, and the highest positive performance is no higher than 14.4% (in Gold futures.) See Figure 6.

Figure 6
Box Plots of Daily Log-Normal Returns (in %) for Gold, Silver, and Copper Futures Contracts (January 2010 to January 2020)

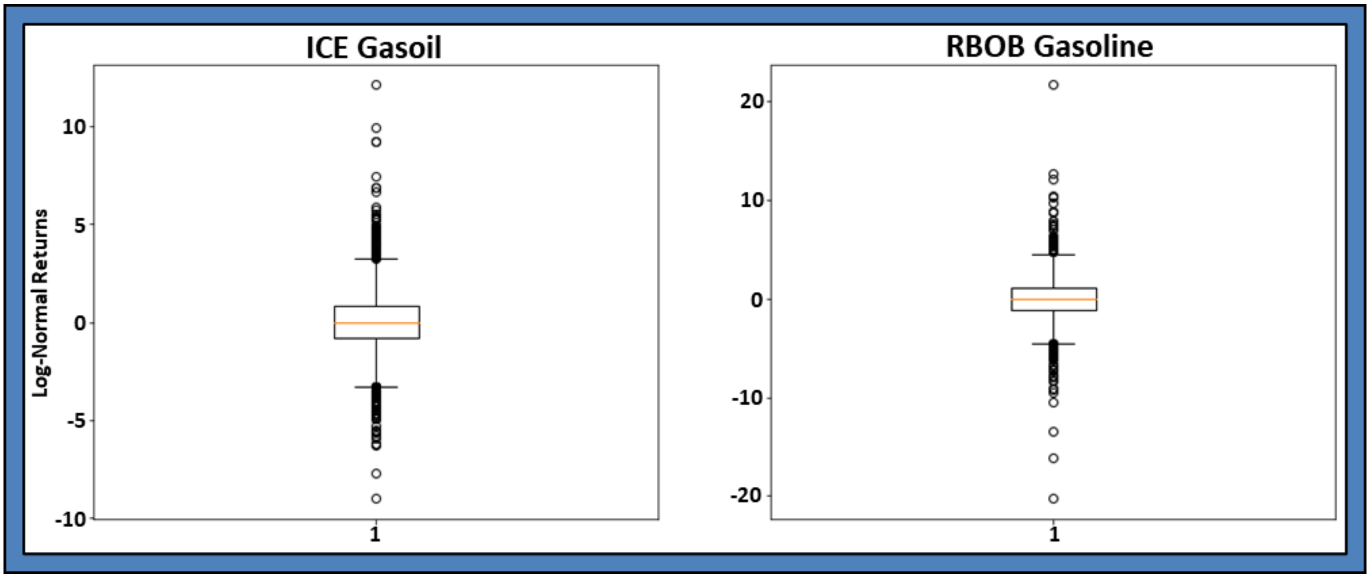


The highest return in the Silver market was around 12.0% while Copper futures did not experience as aggressive buying pressure; Copper's highest return is just 6.8%. Conversely, the lowest return recorded in our dataset's metal markets was achieved by Silver futures (-19.6%), followed by the Gold market (-12.6%) and then the Copper market, whose most negative return amounted to -7.5%.

Intercontinental Exchange (ICE) Gasoil and RBOB Gasoline Futures Returns

RBOB Gasoline futures experienced minimum and maximum returns as extreme as -20.2% and +21.7%, respectively. See Figure 7.

Figure 7
Box Plots of Daily Log-Normal Returns (in %) for ICE Gasoil and RBOB Gasoline Futures Contracts (January 2010 to January 2020)

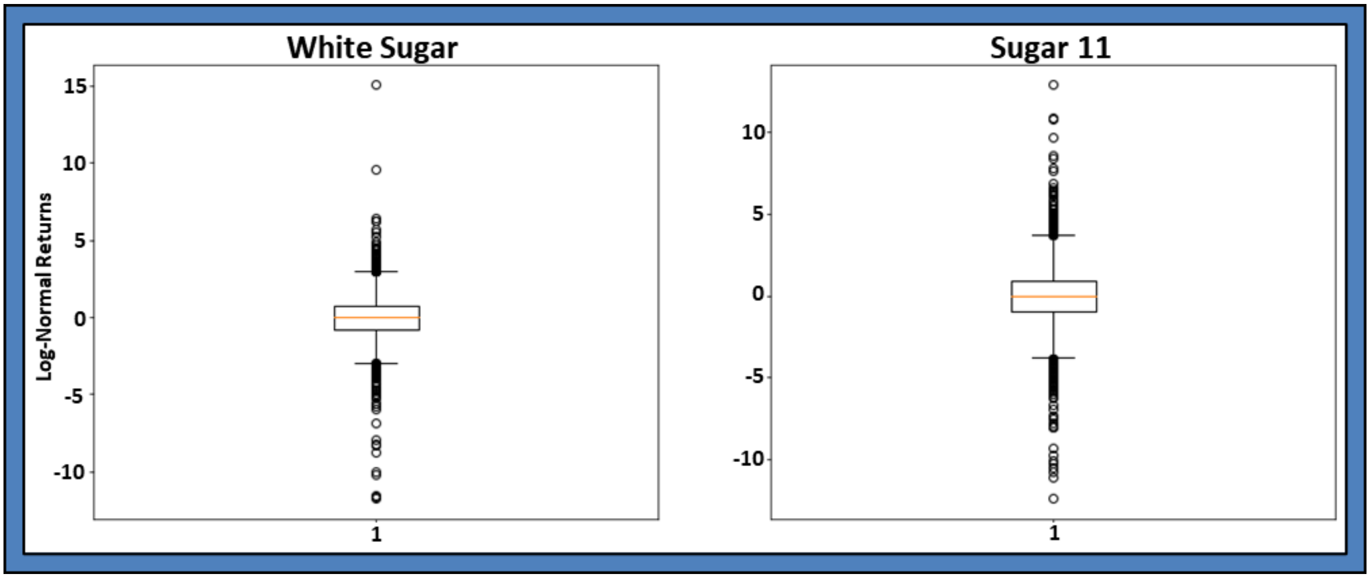


ICE Gasoil futures experienced positive returns of no higher than 12.1% while the downside risk was almost identical to the returns observed for Brent, the global crude benchmark (-9.0%).

White Sugar – Europe and U.S. Sugar Number 11 Futures Returns

The European and American sugar markets were similar when it comes to extreme returns. Their lowest returns were around -12.0%. The buying pressure on European white sugar futures was more aggressive with the highest return at 15.0% while the American sugar market's highest return was 13.0%. See Figure 8.

Figure 8
Box Plots of Daily Log-Normal Returns (in %) for White Sugar – Europe and U.S. Sugar Number 11 Futures Contracts (January 2010 to January 2020)



Section Summary

The main takeaways from this section are as follows:

- RBOB Gasoline futures experienced the lowest one-day return in the entire portfolio of examined futures contracts;
- The highest, positive return ever recorded, in the examined time period, was observed in the Dutch TTF market; and
- The second highest, positive return was observed in the RBOB Gasoline futures market.

More generally, the dispersion of returns differs markedly from one commodity to another and can drastically alter the outcome of an investment strategy, if overlooked. In addition, there are additional analyses that one can undertake that show how important seasonality and idiosyncratic returns are within the commodity futures markets.

Conclusion

The primary goal of this straightforward study is to provide a simple yet important reminder that commodity markets should be treated with care because an equity-style investment approach can easily yield returns orders of magnitude below expectations.

Further, the summary statistics of this paper reinforce the need, already identified in the Winter 2019 article on “Commodity Portfolio Management,” to view each commodity market as quite idiosyncratic. Therefore, a deep focus on each commodity market is crucial to understanding how changing the portfolio weights on individual commodities can impact portfolio stability and risk exposures.

Our next *GCARD* article will further explore commodity strategy structuring themes.

Author Biography

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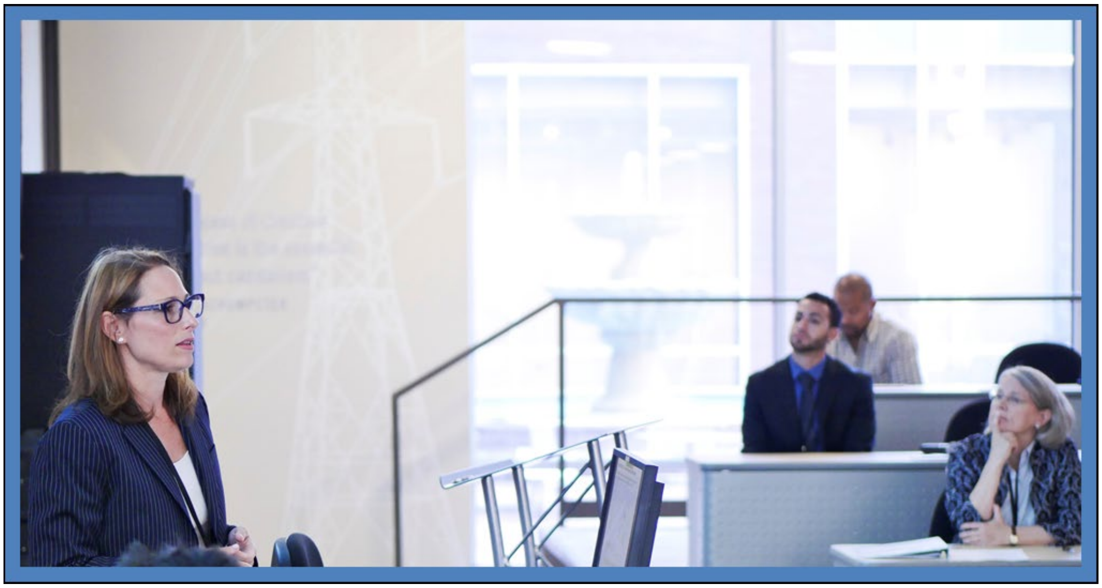
Mr. Vito Turitto joined the S&P Global Platts Commodity Risk Solutions team in 2015. Prior to joining Platts, he started his career in the City of London trading options on crude oil and other energy markets and went on to build HyperVolatility Ltd., a boutique quantitative investment consultancy. Mr. Turitto’s field of expertise is in volatility trading, analysis, and modeling. Mr. Turitto holds a B.A. in International Economics Relations from the University of Rome “La Sapienza” and received his Master of Science in International Finance and Investment from London South Bank University after completing a dissertation on forecasting volatility in the American crude oil market via stochastic volatility models.

Interview with Jodie Gunzberg, CFA

Managing Director and Chief Institutional Investment Strategist, Morgan Stanley Wealth Management; and Member of both the J.P. Morgan Center for Commodities' Advisory Council at the University of Colorado Denver Business School and the *GCARD*'s Editorial Advisory Board



Jodie Gunzberg, CFA, Managing Director and Chief Institutional Investment Strategist at Morgan Stanley Wealth Management, presented on Chinese commodity demand during a session at the J.P. Morgan Center for Commodities' (JPMCC's) inaugural international commodities symposium. The panel session was moderated by Hilary Till, the *GCARD*'s Contributing Editor and Solich Scholar at the JPMCC.

In this issue of the *GCARD*, we are delighted to interview Jodie Gunzberg, CFA. Gunzberg is the Managing Director and Chief Institutional Investment Strategist for Morgan Stanley Wealth Management. Previously Gunzberg was the Managing Director and Head of U.S. Equities at S&P Dow Jones Indices (S&P DJI). She had originally joined S&P DJI as the Director of Commodities product management.

Gunzberg is a founding member of the *GCARD*'s Editorial Advisory Board and recently joined the JPMCC's Advisory Council. She has contributed as an author to the *GCARD* and participated as a panel member on Chinese commodity demand during a session at the J.P. Morgan Center for Commodities' inaugural international commodities symposium.

In addition to her impressive track record of professional achievement, Gunzberg has retained a deep passion for education, whether it concerns early-childhood tutoring, university-level mentoring, or professional development for young finance professionals. Specifically, she is a Science, Technology, Engineering, and Mathematics (STEM) volunteer at an elementary school as well as serving on the Advisory Board for Hofstra University's Department of Finance; she is also a Chartered Financial Analyst (CFA) Institute Curriculum Consultant. Even though her professional responsibilities span asset classes, Gunzberg holds a strong interest in the many nuances of the commodity markets. In this interview, we ask Gunzberg about advice on career development, and we also explore both commodity- and education-based themes with her as well.

Interview

You have been an investment professional for over 20 years. How has your career evolved across asset classes?

I can describe my career of moving across asset classes as an accelerated course in managing risk through market crises. My first role on the buy-side was as a fixed-income analyst in the late 1990s when bonds posted some of their worst ever returns after the economies in Asia, Russia and Argentina struggled. We needed to quickly automate and adjust our screens with flexible parameters as extreme cases were becoming the new normal, and we had to build out the risk management and scenario testing capabilities as we were experiencing a risky scenario in real-time. Our edge came from using test versions of new technology to feed the latest data into customized models and adjust the portfolios accordingly to stated goals.

Speaking of technology, through this, I watched my colleagues on the equity side flourish during the tech bubble, and felt excited about the potential upside. So, in April 2001, I joined Driehaus Capital Management, an aggressive growth equity firm at the time. While the equity math was not as complex as the bond math, the quantitative models based on fuzzy logic were interesting, and the precipitous stock market drop made the stock picking and portfolio management fascinating but required a new layer of risk management. We had to get creative with portfolio strategies and structures so launched two hedge funds (long/short equity and equity-market neutral) at the start of 2003, just as equities were making a comeback. My timing was wrong again, but in the process, I learned technology enabled far fewer resources to generate quantitative portfolios that were competitive with similar fundamental strategies.

Next, I attended business school and built various hedge fund risk management systems while I studied, then went on to incorporate alternative investments into asset allocation models at Ibbotson, later acquired by Morningstar. While at Ibbotson and Morningstar, we built a family of commodity indices to fill the asset class in the models. Commodities immediately captivated my attention from the structural nature of the contracts as with bonds, but with the volatility and return potential of equities. Plus tangible goods are easy to understand and are relatable as resources that people need every day.

I followed my passion and joined S&P Dow Jones Indices as the Director of Commodities in 2010, and I learned more than I ever imagined about indexing and navigating difficult markets. The perfect commodities storm ensued as demand slowed from the Global Financial Crisis, and as Saudi Arabia's oil supply cuts became impotent in lifting prices after inventories built from U.S. fracking. My time specializing in commodities was through its worst decade, once again, driving the need for innovation and risk management to stay competitive in indexing. Subsequently, many strategies were born to manage risk including dynamic rolling, market-neutral alpha strategies, managed futures and real assets. Once I realized the power of indexing, I moved back into consulting to bring efficient choices across asset classes to investors. Then the global pandemic, a tragedy of epic proportions, hit the markets. I felt right at home as my career has centered around navigating through difficult markets. Though I may have done better financially with better timing, I learned tremendous lessons at an accelerated pace about staying focused on long-term goals while managing risk to get through short-term volatility and drawdowns.

What are some of the major changes that you have experienced in the investment industry, and what are some of the challenges, including with Environmental, Social, and Governance (ESG) investing?

The greatest advancement I have experienced is in the development of technology and data availability that enabled more sophisticated systematic strategies to capture returns traditionally generated by fundamental analysis. The growth in standardized data and contracts, coupled with product innovations from derivatives to Exchange-Traded Funds (ETFs), has allowed investors to access strategies at a lower cost with more transparency and liquidity. That said, the evolution has been quicker in some areas than others. For example, the development in commodity indices, and the structured products based on them, drove explosive growth in assets-under-management-tracking in the decade from 2000-2010, gaining nearly $400 billion, according to Barclays. This was driven by the story at the time about how commodities provided diversification and inflation protection while the growth in the futures market promoted liquidity and standardization, setting a higher bar for quality and enabling production to continue with less risk through insurance, while stabilizing prices for consumers. As commodity markets tumbled from demand declines and supply innovations, the demand for ESG has increased exponentially.

According to the Morgan Stanley Institute for Sustainable Investing, 85% of active individual investors and 95% of millennial active investors describe themselves as interested in sustainable investing. Also, 95% of asset owners are either already integrating ESG criteria or are actively considering the integration of ESG criteria within their investment process, and among asset owners integrating ESG criteria, 73% have begun doing so in the last 4 years, with 45% doing so in the last 2 years. There are a range of motivations driving this demand, including risk management, mission alignment, return potential, evolving policies and regulations, and constituent and stakeholder demand. The returns have been increasingly attractive post the Global Financial Crisis and the COVID-19 Crash, which serve as proof that the risk management employed in ESG strategies is working. Now the challenge remains with the variability in definitions, data integrity, and methodologies underlying scores, rankings and calculations of data providers for selecting, constructing and evaluating these investments.

You have served in many advisory capacities in the investment and education space. What are some ways that you see commodities' education influencing careers and the commodities industry?

Commodities education comes in many different forms. On the most basic level, while everyone – not just investors – knows what a commodity is, very few understand the vocabulary. For example, most, if not every kid knows what corn is. They have the basic understanding of knowing it is grown and eaten. If commodities businesses are framed as constituting the industry that feeds and fuels life, it may be a more relatable and tangible field that will generate career interest for students. Also, describing the parts of the industry across the supply chain in basic terms about how natural resources are brought from the earth to the consumer may draw more interest. Linking skills to various parts of the supply chain, whether in growing, mining or drilling to transportation, processing, marketing and sales – or to overall financing, can guide students towards the areas that suit their strengths and passion. Helping students realize the value that they can bring to the supply chain or in the investment programs that fund a commodity business, or in helping investors hedge inflation, diversify or generate higher returns will influence their career choices for making an impact.

Jodie Gunzberg, CFA, former board member of the CFA Society in New York, celebrated founder, Benjamin Graham's birthday by ringing the NASDAQ Stock Market Closing Bell. Gunzberg is currently an Editorial Advisory Board member of the *GCARD* and, in addition, serves on the JPMCC's Advisory Council.

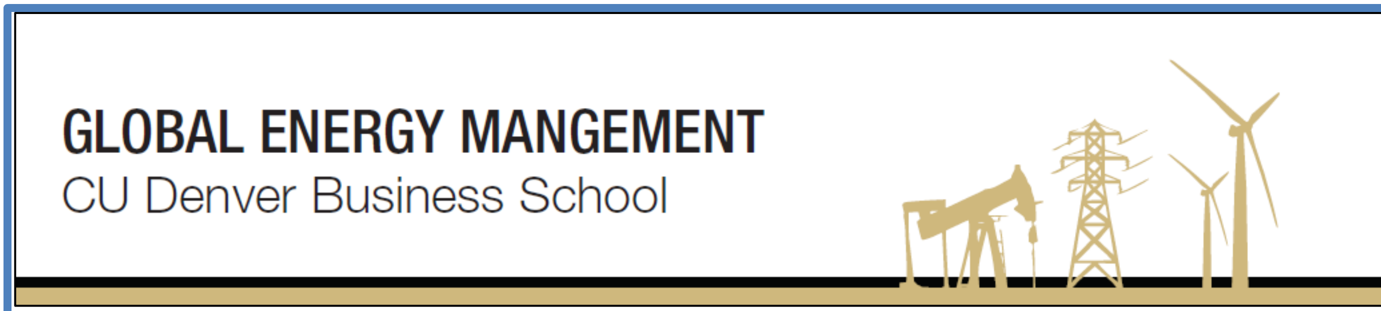
What, in your opinion, are some of the pressing issues currently in the commodity markets, and how do you see educational programs helping to address them?

The pressing issues we see in commodities today involve supply and demand issues that are highly driven by technological improvements, de-globalization, demographics, fiscal stimulus programs, and ESG. Also, other new innovations like cryptocurrencies and standardizations like diamonds bring current issues into well-established economics and finance. So breaking down each of the forces into how the supply/demand balance forms the spot market price, then explaining how that drives inventory excess or shortage to form investment opportunities by using various investment vehicles may prepare students for opportunities that arise in real-life roles in the industry. However, commodity-market education needs to be placed in the context of broader investments first to explain why these details matter. This includes education on defining asset classes and then commodities as an asset class. Next, how to get returns that represent the asset class is vital and that can include discussions about the physical markets, equities and futures or other products. Breaking down the fundamental sources of returns is key to determine how the current pressing issues influence these components including returns from collateral, convenience yield, supply shocks, the insurance premium and rebalancing. It all boils down to the basics and pinning each real-life event from weather to war or just everyday eating and driving to the sources of return in how we can address the applications.

What advice would you give those students and young professionals interesting in pursuing a career that touches on the commodity markets?

Think about how commodity markets improve our world by enabling more efficient food and energy access. While technical skills of math, programming, economics, finance and operations may be required, many other interesting fields of studies are applicable such as history, social sciences or psychology. Study something different and interesting that you can take with you for unique perspectives on the ways the world works and how different cultures contribute to the production and consumption of commodities. If possible start more generally, then with more experience, specialize in an area you find interesting and fulfilling.

Thank you, Jodie, for this opportunity to interview you!



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GLOBAL COMMODITIES
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The JPMCC is the first center of its kind focused on a broad range of commodities, including agriculture, energy, and mining. Established in 2012, this innovative center provides educational programs and supports research in commodities markets, regulation, trading, investing, and risk management. The JPMCC's Executive Director is Dr. Thomas Brady, Ph.D.

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