



HAL
open science

Financial role of precious metals in portfolio diversification

Thi Hong Theu Dinh

► **To cite this version:**

Thi Hong Theu Dinh. Financial role of precious metals in portfolio diversification. Economics and Finance. Université Paris-Saclay, 2023. English. NNT : 2023UPASI001 . tel-04262955

HAL Id: tel-04262955

<https://theses.hal.science/tel-04262955>

Submitted on 27 Oct 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Financial role of precious metals in
portfolio diversification
Rôle financier des métaux précieux dans la
diversification du portefeuille

Thèse de doctorat de l'université Paris-Saclay

École doctorale no 630 : Droit, Économie, Management (DEM)

Spécialité de doctorat: Sciences économiques

Graduate School: Economie et Management

Référent : Université de Versailles-Saint-Quentin-en-Yvelines

Thèse préparée dans l'unité de recherche SOURCE (Université Paris-Saclay, UVSQ, IRD),
sous la direction de **Stéphane GOUTTE**, Professeur des universités/HDR, la co-direction
de **Duc-Khuong NGUYEN**, Professeur/HDR

Thèse soutenue à Guyancourt, le 24 Mars 2023, par

Thi Hong Theu DINH

Composition du jury

Membres du jury avec voix délibérative

Natalia ZUGRAVU-SOILITA Professeur des universités, UVSQ, Université Paris-Saclay, France	Présidente
Perry SADORSKY Professeur des universités, York University, Canada	Rapporteur et Examineur
Geogios SERMPINIS Professeur des universités, University of Glasgow, Scotland	Rapporteur et Examineur
Julien CHEVALLIER Professeur des universités, Université Paris 8, France	Examineur

Titre: Rôle Financier des Métaux Précieux dans Diversification du Portefeuille

Mots clés: Métaux Précieux, Avantages de la Diversification, Moteurs Économiques, la Structure de Dépendance de la Queue, Actifs Traditionnels, Copulas, la Crise Financière Mondiale

Résumé: Cette thèse étudie les rôles financiers de quatre principaux métaux précieux (c'est-à-dire l'or, l'argent, le platine et le palladium) dans les stratégies de diversification de portefeuille. À cette fin, tout d'abord, une technique d'échantillonnage de données mixtes a été utilisée, combinée à un modèle GARCH et DCC sur les données des pays du G7 et des BRICS pour identifier l'impact des moteurs macroéconomiques et financiers sur la volatilité quotidienne et la corrélation par paire de ces métaux. Il constate que les économies américaine et chinoise, en particulier, influencent les marchés des métaux précieux, mais de manière opposée. Les marchés boursiers et la balance commerciale des pays du G7 et des BRICS, ainsi que la confiance des consommateurs des pays du G7, sont les principaux moteurs de la volatilité des marchés des métaux précieux. Les moteurs de corrélation les plus influents sont les marchés boursiers, la masse monétaire et le taux d'inflation. Après avoir examiné les mouvements dynamiques des marchés des métaux précieux dans le contexte de l'économie mondiale, la thèse revisite le rôle de diversification des quatre métaux précieux en utilisant une méthodologie de répartition stochastique. Les résultats empiriques confirment les avantages de la diversification des métaux précieux pour les actifs traditionnels (c'est-à-dire les actions, les obligations, les liquidités et les devises) des marchés du G7, tant au comptant qu'à terme. Notamment, les contrats à terme sur métaux précieux ont nettement surperformé leurs rendements au comptant au lendemain de la crise financière de 2008. Enfin, la structure de dépendance de la queue entre les métaux précieux et les marchés boursiers des pays du G7 et des BRICS a été étudiée dans cette thèse afin de tester le rôle de valeur refuge des métaux précieux. En utilisant à la fois des copules bivariées (copules paires de vigne) et des copules multivariées (copules archimédiennes hiérarchiques), les résultats montrent des preuves d'une dépendance de queue asymétrique entre le métal précieux et les stocks à la fois dans les analyses bivariées et multivariées. Les résultats de la vigne-copule révèlent que chaque métal précieux peut servir de valeur refuge pour le marché boursier des États-Unis, du Royaume-Uni et du Canada lors des ralentissements et des reprises du marché, mais pas pour les marchés boursiers européens, en particulier en Allemagne et en Italie. Dans les copules multivariées, l'indépendance de la queue inférieure indique la propriété de valeur refuge des métaux précieux contre les mouvements baissiers extrêmes simultanés des marchés boursiers mondiaux. Cependant, cette propriété n'est pas vraie dans les reprises de marché. Fait intéressant, la crise financière mondiale de 2008 a eu un impact significatif sur les rôles financiers des marchés des métaux précieux. En résumé, cette thèse affirme le rôle important des métaux précieux, en particulier de leurs dérivés, pour les investisseurs dans la construction de portefeuilles pendant les périodes de volatilité des marchés.

Title: Financial Role of Precious Metals in Portfolio Diversification

Keywords: Precious Metals, Diversification Benefits, Economics Drivers, Tail Dependence Structure, Traditional Assets, Stochastic Spanning, Copulas, Global Financial crisis

Abstract:

This thesis investigates the financial roles of four main precious metals (i.e., gold, silver, platinum, and palladium) in portfolio diversification strategies. For this purpose, first, a mixed data sampling technique was employed, combined with a GARCH and DCC model on data from G7 and BRICS countries to identify the impact of macroeconomic and financial drivers on the daily volatility and pairwise correlation of these metals. It finds that the U.S. and Chinese economies, in particular, influence the precious metal markets, but in the opposite way. The stock markets, trade balance of both G7 and BRICS countries, and the consumer confidence of G7 countries are the key drivers for the volatility of precious metal markets. The most influential drivers for correlation are stock markets, money supply, and the inflation rate. After considering the dynamic movements of precious metal markets in global economics, the thesis revisits the diversification role of all four precious metals using a stochastic spanning methodology. The empirical results confirm the diversification benefits of precious metals for the traditional assets (i.e., stocks, bonds, cash, and currencies) of G7 markets in both spot and futures returns. Precious metal futures significantly outperformed their spot returns after the 2008 financial crisis. Lastly, the tail dependence structure between precious metals and stock markets of G7 and BRICS countries was studied in this thesis to test the safe-haven role of precious metals. The findings show evidence of asymmetric tail dependence between precious metals and stocks both in the bivariate and multivariate analyses. The vine-copula results reveal that each precious metal can serve as a safe haven for the U.S., the U.K., and Canadian stock markets, but not for European stock markets, especially in Germany and Italy. In the multivariate copulas, the lower tail independence indicates the safe-haven property of precious metals against simultaneous extreme downward movements of global stock markets. Interestingly, the global financial crisis of 2008 significantly impacted the financial roles of precious metal markets. In summary, this thesis affirms the vital role of precious metals, especially their derivatives, for investors in building portfolios during volatile market periods.

Declaration of Authorship

I, Thi Hong Theu DINH, declare that the thesis titled "Financial Role of Precious Metals in Portfolio Diversification" and the work presented are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University
- This work has not previously been submitted for a degree or diploma in any other university
- To the best of my knowledge and belief, this thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.
- Where I have quoted from the work of others, the source is always given. Except for such quotations, this thesis is entirely my own work.
- I have acknowledged all the main sources of help.

Acknowledgments

This Ph.D. has been an amazing and challenging journey for me. I also could not have undertaken this journey without the help and support of many people who, in one or another, have contributed to making my thesis possible.

First and foremost, I would like to express my deepest gratitude to my supervisor, Professor Stéphane GOUTTE, who agreed to supervise me right at the time I was in need most as well as his great patience, helpful guidance, high motivation, and immense knowledge during the production of this thesis.

I would also like to acknowledge and give my most sincere thanks to my co-supervisor, Professor Duc-Khuong NGUYEN. Truly, words cannot express enough my gratitude to him because I believe that I could not have completed this thesis without his continuous help and invaluable guidance in both academic and real life. He always comes to share his precious knowledge and experience in research work. Additionally, he helped make more sense of the confusion. I'm proud of and grateful for my time working with Prof. Duc-Khuong. Especially my warmest thanks also go to his wife, Dr. Thanh Huong DINH. She is my big idol both in the life and the work.

My appreciation also goes out to the jury members of my thesis committee for giving me their great pieces of advice as well as their helpful discussion about improving my thesis manuscript.

I am incredibly thankful to the Vietnamese Government for providing me with the financial means to complete this project. I gratefully recognize the help of the France Government (e.g., BCS, CAF, CPAM). Without these supports, I could not concentrate totally on my academic work.

From the bottom of my heart, I would like to say a big thank you to all professors and the administrative staff of University Paris 8 and Paris Saclay University, especially to Prof. Frederick Goodman, Prof. Jacqui Shykoff, Mrs. Mireille Morvan, Mrs. Noémie Moutty, Mrs. Maryse Chomette for their constructive support. Many thanks also to Dr. Calvin Peck, Dr. Melissa Ann Thomas of the Academic Writing Centre for their reviewing and their pieces of advice on my thesis. I am grateful for their precious time and insightful guidance.

I would be remiss in not mentioning Prof. Nikolas Topaloglou and Dr. Thomas Walther for the hard work done with them in the articles. I gained a lot of research-related knowledge from collaborating with them.

On this special occasion, I also would like to send my special thanks to all the teachers who have taught and guided me since I was in kindergarten until now. I sincerely thank Ms. Dinh Thi Thoa, who nurtured my love of math since I was in junior high school. And I want to express my heartfelt gratitude to Prof. Nguyen Quang Dong - my teacher in econometrics as well as the former Dean of the Faculty of Economic Mathematics, National Economics University, Hanoi - who gave me the opportunity to have my dream job as a lecturer, so I was motivated to make this Ph.D. journey. And especially, my thanks to the spiritual teachers in my life, which are Zen Master Thich Nhat Hanh and the Sangha of Plum Village, Venerable Thich Nu Dam Luong, Venerable Thich Hoang Thach, and Venerable Thich Minh Phuc who have lifted me after hardships and suffering so that I can continue on my path.

Immense gratitude as always to all my colleagues at National Economics University, especially in Mathematical Economics Faculty, for all their support by distance during my Ph.D. journey, and notably to Assoc. Prof. Nguyen Thi Minh and Dr. Nguyen Manh The, who have been my direct managers at the Faculty of Economic Mathematics, for their great help and support for me. And this special thank I also want to give to my close colleagues over the years when they were always with me and helped me whenever I had difficulties in life and academic work, including Dr. Le Duc Hoang, Dr. Phung Thanh Quang, Dr. Hoang Duc Manh, Dr. Vu Duy Thanh, Ms. Le Thuy Mai, Dr. Do Thi Thu Thuy, Dr. Nguyen Thi Thu Trang, Dr. Tran Phi Long, Dr. Nguyen Thi Kim Dung,...

I am forever thankful to all my friends in France and Vietnam for encouraging and supporting me whenever I need them. My immeasurable appreciation and deepest gratitude to Ms. Vu Thi Minh Luan, who I always consider my older sister, always giving me care, love, and understanding in every situation; to Nguyen Hoang Dung, who is always ready to help me solve technical problems whenever I encounter difficulties during my Ph.D. thesis work and the life as well; to Ms. Nguyen Thu Hang, Ms. Huguet, Jessyca Tran Dang, and Pham Minh Tu who have always supported my son and me unconditionally during our time living and studying in France; to Ms. Lam Dieu Thuy who helped me to improve my English writing in this thesis; to Ms. Dinh Thi Hanh and Ms. Dinh Thi Anh Hong who always supported me in my life. I would be remiss if I did not thank my friends in Annecy, like my second family in France, for their unconditional support for my son and me. And thanks to Ms. Khuc Hoang Tuyet Huong, Mr. Nguyen Ha Giang, Ms. Cao Mai Ly, Ms. Nguyen Thi Hoai An, Mr. Le Nguyen Minh Phuong, Ms. Nguyen Huong Giang, Ms. Pham Linh Nham, Ms. Bui Thi Thu Huyen, Ms. Pham Thi Lan, Ms. Le Huong Thao who encouraged me so much.

Most importantly, I am grateful for my family's unconditional, unequivocal, and

loving support. Words cannot express my gratitude to my parents, Mr. Dinh Tien Quy and Mrs. Pham Thi Dau, because without their endless sacrifice, this day would not have been possible. I am also deeply indebted to my siblings, including my older sister, Ms. Dinh Thi Hong Nhieu, my young sister, Ms. Dinh Thi Thao and my brother Phung Duc Hai Anh who are always by my side, supporting me unconditionally. Finally, the person I want to thank the most is my dearest friend, my son DINH Hieu Minh. He is my inspiration, my delight, and my love. I appreciate him coming into my life as an amazing gift from God, and I also appreciate his fantastic collaboration during my Ph.D. journey.

Résumé en français

Récemment, de nombreux pays du monde ont été confrontés à une série de problèmes considérables en raison de la propagation rapide et continue du coronavirus et des facteurs de risque mondiaux antérieurs (par exemple, la guerre commerciale prolongée entre les États-Unis et la Chine, les fluctuations monétaires, les mouvements d'intérêts à long terme, le Brexit). De nombreux experts ont fortement averti que ces événements extrêmes pourraient conduire à une autre crise financière mondiale. En conséquence des chocs de marché, les investisseurs préfèrent conserver des actifs sûrs et rester à l'écart des actifs risqués, phénomène connu sous le nom de phénomène de "fuite vers la qualité" sur les marchés financiers (Bernanke et al. 1994). Selon cela, les métaux précieux ont été largement acceptés comme alternatives potentielles aux actifs traditionnels (par exemple, actions, obligations, devises), en particulier en période de forte incertitude (Hillier et al. 2006a, Baur & Lucey 2010a, Lucey & Li 2015a). De plus, la résilience des métaux précieux aux conditions de marché extrêmement défavorables a également attiré une attention particulière des chercheurs et des praticiens (Baur & Lucey 2010a, Ciner et al. 2013a, Agyei-Ampomah et al. 2014, Lucey & Li 2015a, Batten et al. 2015).

Les métaux précieux sont particulièrement intéressants pour être considérés comme d'importantes réserves de valeur et d'actifs monétaires, ainsi que pour être utilisés dans une variété d'activités industrielles. Cependant, par le passé, les investisseurs ne tenaient

généralement pas compte des métaux précieux dans la construction de leurs portefeuilles d'investissement. Ces dernières années, la situation a considérablement changé puisque les métaux précieux ont joué un rôle de plus en plus important en tant qu'actifs de placement sûrs. Ces métaux semblent surperformer les actifs traditionnels (par exemple les actions, les obligations), en particulier dans un environnement aussi turbulent. En outre, l'introduction de nouveaux titres et intermédiaires commerciaux liés aux métaux précieux (par exemple, contrats à terme, options, fonds négociés en bourse) a renforcé l'attrait des métaux précieux en tant qu'actifs d'investissement. On s'attend donc à ce que ces métaux deviennent une classe d'actifs commune, semblable aux actions et aux obligations. Cependant, certains soutiennent qu'investir dans des ETF de métaux précieux et d'actions minières de métaux précieux est beaucoup plus risqué (Cao et al. 2010, Daskalaki & Skiadopoulos 2011a). Tant les chercheurs que les praticiens doutent que cette surchauffe des marchés des métaux précieux puisse réduire leurs avantages de diversification. Par conséquent, il est crucial de clarifier les rôles financiers précis des marchés des métaux précieux dans le système financier mondial.

Les rôles financiers des métaux précieux incitent énormément les chercheurs et les praticiens à en savoir plus sur leurs comportements complexes. La plupart des études suggèrent les avantages favorables des métaux précieux pour l'investissement, tels qu'une cible d'investissement refuge, un outil de couverture contre divers risques et l'inflation, des actifs bien diversifiés, ou un investissement à haute liquidité, etc. (Jaffe 1989a, Baur & McDermott 2010, Jain & Biswal 2016a). Jusqu'à présent, il existe un grand nombre de travaux antérieurs qui se concentrent sur l'étude des trois rôles largement acceptés des métaux précieux, notamment: couverture, diversification et valeur refuge (Baur & McDermott 2010, Batten et al. 2015, Lucey & Li 2015a). Pour être plus précis, les métaux précieux seraient considérés comme des couvertures si, en moyenne, ils sont non

corrélés (couverture faible) ou négativement corrélés (couverture forte) avec un autre actif ou portefeuille. Pendant ce temps, ce métal deviendrait un diversificateur s'il a une corrélation faiblement positive avec un autre actif ou portefeuille en moyenne, ce qui suggère qu'il peut donner des avantages de diversification pour l'ensemble du portefeuille. Enfin, selon la définition de [Baur & McDermott \(2010\)](#), les métaux précieux seraient considérés comme une valeur refuge contre les cours boursiers si ces métaux étaient non corrélés (faible valeur refuge) ou négativement corrélés (forte valeur refuge) avec les actions en période de marché extrême mouvements.

De plus, le développement émergent des marchés des métaux précieux a récemment suscité un débat public et scientifique houleux sur le rôle de ces métaux. Des preuves largement répandues, notamment [Jaffe \(1989a\)](#), [Chua et al. \(1990a\)](#) and [Hillier et al. \(2006a\)](#), ont étudié l'idée que l'investissement dans les métaux précieux peut aider à améliorer la performance globale des portefeuilles traditionnels. [Hillier et al. \(2006a\)](#), [Baur & Lucey \(2010a\)](#) and [Jain & Biswal \(2016a\)](#), notamment, ont mis en évidence une faible corrélation des métaux précieux avec les rendements boursiers et obligataires en période de turbulences ou de crises financières, ce qui permet à ces métaux de devenir des valeurs refuges au fur et à mesure. ainsi que de bons diversificateurs. Certains auteurs ([Cao et al. 2010](#), [Daskalaki & Skiadopoulos 2011a](#)), cependant, s'opposent à de tels rôles. Ils ont affirmé que la surfinanciarisation actuelle des marchés des métaux précieux, ainsi que l'augmentation considérable des entrées de capitaux sur ces marchés, pourraient entraîner une corrélation accrue entre les métaux précieux et les actifs traditionnels, ce qui réduirait ainsi leur contribution à la diversification. Ce débat me donne une forte motivation pour revisiter ces trois rôles financiers clés des métaux précieux en employant des méthodes avancées.

En ce qui concerne la méthodologie, il est nécessaire de mesurer les mouvements

dynamiques ainsi que la relation dynamique entre les métaux précieux et les autres actifs financiers afin d'étudier les rôles financiers des métaux précieux dans le cadre de cette thèse. Cependant, ces mesures ont encore été vigoureusement contestées, en particulier dans les analyses multivariées. Étant donné que les marchés des métaux précieux sont très volatils et difficiles à prévoir, la modélisation appropriée de la dynamique de volatilité et de corrélation est cruciale sur ces marchés. Les investisseurs et les gestionnaires de portefeuille peuvent prendre de meilleures décisions d'investissement s'ils disposent d'une représentation plus précise de la dynamique, y compris la volatilité ainsi que la corrélation, des marchés des métaux précieux. De nombreuses études révèlent qu'en plus d'être influencées par la dynamique de l'offre et de la demande, la volatilité et la corrélation des marchés des métaux précieux sont également liées à l'évolution des activités économiques. De plus, selon les stratégies d'investissement de portefeuille, les investisseurs pourraient détenir une large gamme d'actifs disponibles sur les marchés financiers. Compte tenu des avantages de la diversification (par exemple, réduction du risque pour tout niveau de rendement attendu sur un actif ou un portefeuille), il peut sembler que les investisseurs devraient s'efforcer de dépenser de l'argent sur autant d'actifs que possible. Cependant, ce n'est pas tout à fait vrai. La diversification a encore ses limites ([Bodie et al. 1992](#)) car l'ajout de plus d'actifs pourrait même conduire à une réduction de la performance du portefeuille en raison des frais de transaction ou d'autres coûts. Par conséquent, lors de l'évaluation du rôle de diversification des métaux précieux, il est principalement basé sur le cadre M-V de [Markowitz \(1952\)](#). Même ainsi, la limitation de l'approche M-V repose sur ses deux hypothèses strictes. La première correspond à l'étude de [Hanoch & Levy \(2013\)](#) qui requiert des rendements des actifs normalement distribués. La seconde vient de l'hypothèse de [Von Neumann et al. \(2007\)](#), qui demande des fonctions d'utilité quadratiques. Si ces hypothèses sont brisées, les

résultats deviennent peu fiables. Notamment, la recherche actuelle a continué à faire face à des défis importants pour mesurer les co-mouvements extrêmes entre les actifs financiers, y compris les métaux précieux, en particulier lorsque la distribution conjointe des rendements des actifs n'est pas elliptique et que leurs co-mouvements ne sont pas symétriques. Pour gérer tous les problèmes mentionnés ci-dessus, il est crucial d'appliquer les méthodes avancées qui peuvent traiter à la fois les distributions non linéaires, les queues épaisses et les distributions de rendement financier asymétriques, en particulier dans le modèle multivarié.

Malgré le fait qu'il s'agisse d'un sujet controversé jusqu'à présent, le rôle des métaux précieux a clairement évolué, en particulier en période de marchés extrêmes. En particulier, plus le système financier mondial est incertain, plus le rôle des métaux précieux est renforcé ([Białkowski et al. 2015a](#), [Balcilar et al. 2015](#)). En conséquence, il existe une littérature en plein essor démontrant que les chocs d'incertitude liés aux crises financières ont un impact significatif sur la dynamique du marché des métaux précieux ([Morales & Andreosso-O'Callaghan 2011a](#), [Hammoudeh et al. 2011a](#)). Étonnamment, il existe si peu de recherches approfondies sur l'impact des crises financières sur le rôle financier des métaux précieux. En effet, mesurer le rôle financier des métaux précieux dans différentes conditions de marché reste difficile. Cela nécessite une modélisation précise des modèles de dépendance multi-actifs. Par conséquent, dans ma thèse, j'étudie explicitement le rôle financier de l'or, de l'argent, du platine et du palladium à travers les trois scénarios de période financière de la crise financière mondiale de 2008: la période pré-crise, la crise et la période post-crise.

Comme indiqué ci-dessus, dans l'économie mondiale, la guerre commerciale entre les États-Unis et la Chine, les deux plus grandes économies du monde, est devenue plus compliquée, faisant craindre un ralentissement économique mondial. De nombreux experts

s'inquiètent de l'escalade des tensions entre les États-Unis et la Chine après 2018 et de son vent contraire persistant pour tous les marchés financiers. Du fait qu'entre 2014 et 2017, environ 80% des métaux précieux utilisés par les États-Unis étaient importés de Chine, les métaux précieux jouent un rôle crucial dans la guerre commerciale entre ces deux pays. Outre les États-Unis et la Chine, d'autres pays du G7 (c'est-à-dire le Royaume-Uni, le Canada, le Japon, l'Allemagne, la France et l'Italie) et les pays BRICS (Brésil, Russie, Inde et Afrique du Sud) sont également au premier rang des échanges de métaux précieux. Cependant, jusqu'à présent, la plupart de la littérature académique sur les rôles financiers des métaux précieux ne s'est concentrée que sur les marchés américains, ce qui semble ignorer d'autres marchés importants tels que la Russie ou l'Inde et l'Afrique du Sud, qui représentent déjà environ 30% du total. monde dans l'importation de lingots et de pièces d'or (World gold Council, 2016), etc. Pour ces raisons, j'ai décidé de choisir les économies très développées (Groupe des Sept, G7) et émergentes (Brésil, Russie, Inde, Chine, Afrique du Sud, BRICS) pour l'échantillon de recherche de ma thèse sur les marchés des métaux précieux.

Par ailleurs, force est de constater que les métaux blancs dont l'argent, le platine et le palladium, sont généralement éclipsés par l'or dans le volume de la littérature académique. Dans certaines circonstances, ils surpassent même l'or bien que les deux servent le même objectif que des véhicules d'investissement importants. En particulier, [Lucey & Li \(2015b\)](#) ont conclu que l'argent, le platine et le palladium agissent comme une valeur refuge lorsque l'or ne remplit pas ce rôle. En conséquence, il est nécessaire d'étudier les quatre métaux précieux, y compris l'or, l'argent, le platine et le palladium, dans des relations dynamiques avec d'autres classes d'actifs.

En tant qu'actifs d'investissement efficaces, les métaux précieux sont récemment devenus plus attrayants en raison de l'avènement de nouveaux instruments et intermé-

dières commerciaux associés à ces marchés, tels que les contrats à terme, les options, les fonds négociés en bourse, etc. La financiarisation accrue des marchés des métaux précieux au cours des dernières décennies a-t-elle profité aux marchés financiers mondiaux? Pendant de nombreuses années, cela a été une question controversée à la fois dans le milieu universitaire et dans la pratique, alors qu'il y a jusqu'à présent un manque de recherche holistique sur le rôle des métaux précieux et de leurs dérivés. Pour cette raison, ma thèse propose une vaste enquête sur deux types différents de ces métaux, en testant séparément et en comparant les performances des rendements au comptant et futurs de quatre métaux précieux.

Par conséquent, dans le chapitre 1, je donne un aperçu général de ma thèse ainsi que le contexte et la motivation pour mener à bien cette recherche. Dans le cadre de ce chapitre, les informations les plus générales sont présentées, du contexte mondial actuel à l'évolution et aux enjeux des marchés financiers mondiaux qui sont directement liés aux rôles financiers des métaux précieux. De plus, j'explique également clairement la raison pour laquelle j'ai choisi l'échantillon de recherche à la fois dans l'espace et dans le temps pour ma thèse. Les principaux résultats et leurs importantes contributions à la littérature actuelle concernant le marché des métaux précieux sont présentés plus loin dans ce chapitre. Enfin, la structure de ma thèse est également esquissée dans ce premier chapitre.

Chapitre 2 - **Moteurs économiques de la volatilité et de la corrélation sur les marchés des métaux précieux**, dont l'objectif principal est d'analyser l'impact individuel des moteurs économiques et financiers les plus importants sur la volatilité et la corrélation temporelles des marchés des métaux précieux, j'emploie des données mixtes technique d'échantillonnage pour identifier l'impact d'un total de dix-neuf facteurs macroéconomiques et financiers des pays du G7 et des BRICS sur la volatilité quotidienne

et la corrélation par paires de l'or, de l'argent, du platine et du palladium. Parce que, dans le passé, de nombreuses études ont montré que la volatilité et la corrélation des marchés des matières premières en général et des marchés des métaux précieux en particulier ne sont pas seulement liées à la dynamique de l'offre et de la demande, mais sont également associées à des changements dans les activités économiques ([Anson 2008](#), [Belousova & Dorfleitner 2012a](#)). Cependant, les recherches pertinentes à ce jour ont fait état de conclusions contradictoires concernant l'impact des facteurs économiques sur les mouvements des marchés des métaux précieux. Il est également généralement limité pour déterminer les moteurs économiques de la volatilité conditionnelle et de la corrélation des marchés des métaux précieux. [Tully & Lucey \(2007a\)](#), [Batten et al. \(2015\)](#), [Mo et al. \(2018\)](#) étudient le fait que les variables macroéconomiques et financières sont les principaux moteurs potentiels des mouvements dynamiques sur les marchés des métaux précieux. Cependant, jusqu'à présent, le problème d'inadéquation des fréquences entre les données économiques et les données sur les métaux précieux a entraîné le fait que les études antérieures se concentrent principalement sur un seul moteur ou sur un petit nombre de variables macrofinancières données. À ce jour, diverses méthodes ont été appliquées pour mesurer l'impact des sources économiques sur la volatilité et la corrélation temporelles des actifs financiers, telles que les modèles modifiés d'hétéroscédasticité conditionnelle autorégressive généralisée (GARCH) ([Hammoudeh et al. 2011b](#), [Pan et al. 2017](#)), des classes populaires de modèles à équations multiples, notamment l'autorégression vectorielle (VAR, [Andersen et al. 2003](#), [Apergis et al. 2014](#)), les approches basées sur le modèle de correction d'erreur vectorielle ([Kucher & McCoskey 2017](#)) et modèles de corrélation conditionnelle (DCC) ([Fernandez-Diaz & Morley 2019](#)), entre autres. Cependant, ces études n'étudient principalement que l'effet séparé d'un seul moteur ou se concentrent uniquement sur un petit nombre de variables macrofinancières données. L'une des raisons

à cela peut provenir du problème de la faible fréquence des données économiques alors que les analyses des mouvements temporels des métaux précieux reposent principalement sur des données à haute fréquence.

Dans ce chapitre, donc, en appliquant le modèle d'échantillonnage de données mixtes à hétéroscédasticité conditionnelle autorégressive généralisée (GARCH-MIDAS, [Engle et al. 2013](#)) et le modèle d'échantillonnage de données mixtes à corrélation conditionnelle dynamique (DCC-MIDAS, [Colacito et al. 2011](#)), je peux résoudre efficacement le problème de décalage de fréquence. Le principal avantage des modèles GARCH-MIDAS et DCC-MIDAS est qu'ils séparent la composante à long terme de la composante à court terme de la volatilité et de la corrélation, respectivement. En particulier, les progrès des modèles GARCH et DCC-MIDAS permettent de prendre en compte l'impact des variables exogènes sur la composante à long terme respective on the respective long-term component ([Conrad et al. 2014](#), [Asgharian et al. 2015](#)).

En particulier, j'utilise les données mensuelles des variables économiques des pays du G7 et des BRICS et les données quotidiennes des métaux précieux à la fois en rendements au comptant et futurs. Ce jeu de données couvre une longue période de 1998 à 2018 et il est divisé en trois sous-périodes liées à la crise financière mondiale de 2008 : la période pré-crise (mars 1998-août 2007), la période de crise (septembre 2007-décembre 2010) et la période suivant la crise (janvier 2011-septembre 2018), respectivement, pour étudier les changements dans l'impact des moteurs de la macro-finance sur les mouvements dynamiques des marchés des métaux précieux. Mes résultats empiriques indiquent l'impact inverse des moteurs économiques des pays du G7 et des BRICS, notamment entre les États-Unis et la Chine. Parmi les facteurs économiques et financiers pris en compte, les rendements boursiers, les taux d'intérêt et la confiance des consommateurs sont identifiés comme les prédicteurs les plus utiles pour modéliser la volatilité et la corrélation. En

outre, la croissance de la balance commerciale est la variable la plus importante dans la dynamique de la volatilité tandis que la masse monétaire et le taux d'inflation sont des déterminants importants de la corrélation à long terme entre les métaux précieux. Notamment, la crise financière mondiale de 2008 a eu un impact significatif sur l'influence des moteurs économiques et financiers sur la dynamique des marchés des métaux précieux, car de nombreux moteurs ont changé la direction de leur impact après la crise.

À partir des résultats ci-dessus, ce chapitre apporte plusieurs contributions à la littérature existante. Premièrement, à ma connaissance, il s'agit du premier travail qui analyse les moteurs macroéconomiques et financiers de la corrélation dynamique au sein des marchés des métaux précieux, bien que de nombreuses études antérieures aient étudié les déterminants des corrélations dynamiques entre les métaux précieux et d'autres actifs, tels que les actions ([Mensi et al. 2013](#), [Jain & Biswal 2016a](#), [Klein & Walther 2022](#)), oil ([Šimáková 2011](#)), les taux de change ([Pal et al. 2014](#), [Apergis et al. 2014](#)), ou les cryptomonnaies ([Klein et al. 2018](#)). Quelques articles analysent la corrélation variable dans le temps entre les métaux précieux eux-mêmes ([Sensoy 2013](#), [Klein 2017](#)), mais ils ne considèrent pas leurs moteurs. Deuxièmement, pour tenter de répondre à la question de savoir si l'impact des moteurs économiques sur la volatilité dynamique et la corrélation des métaux précieux change entre les périodes tranquilles et turbulentes, j'ai divisé l'échantillon complet en trois sous-périodes liées à la crise financière mondiale de 2008. Cela permet de fournir des recommandations précieuses aux décideurs politiques, aux investisseurs et aux gestionnaires de portefeuille pour faire face à toute crise mondiale à l'avenir. Troisièmement, nous contribuons en étudiant l'impact différent d'un ensemble de 19 variables économiques et financières de 12 pays (G7 et BRICS) sur la volatilité et la corrélation des métaux précieux. La plupart des études susmentionnées se concentrent uniquement sur les déterminants basés aux États-Unis ([Batten et al. 2015](#)).

Le chapitre 3 - **La crise financière mondiale de 2008 et les avantages de la diversification des marchés des métaux précieux**, vise à évaluer le rôle de l'utilisation des métaux précieux pour obtenir des avantages de diversification en utilisant une méthodologie de répartition stochastique (Arvanitis et al. 2019) en se concentrant sur la dominance stochastique de second ordre (SSD). Au meilleur de ma connaissance, il existe un grand nombre d'études qui évaluent les avantages de la diversification du portefeuille d'investir dans les matières premières en général (Gorton & Rouwenhorst 2006a, Chong & Miffre 2010, Belousova & Dorfleitner 2012b, Gao & Nardari 2018, Bessler & Wolff 2015, Daskalaki et al. 2017a) ou l'or en particulier (Johnson & Soenen 1997, Ratner & Klein 2008, Bedoui et al. 2018a). Parmi lesquelles, l'étude de Daskalaki et al. (2017a) ont appliqué pour la première fois une approche d'efficacité de dominance stochastique (SDE) pour analyser l'avantage de la diversification des matières premières. Cette recherche montre que les produits de base offrent des avantages de diversification à la fois dans l'échantillon et hors de l'échantillon. En outre, les auteurs ont constaté que les marchés des matières premières sont segmentés des marchés boursiers et obligataires. Avant cette étude, Van Hoang et al. (2016) ont utilisé la méthode de la dominance stochastique (SD) pour évaluer la contribution de l'or coté à Paris à la diversification des portefeuilles de 1949 à 2012. Cette recherche a souligné que les portefeuilles d'actions augmentés d'or domineraient significativement ceux sans or aux deuxième et troisième ordres. Cependant, ces résultats ne sont pas vrais pour les portefeuilles obligataires et sans risque. Dans le test de robustesse, ils ont effectué une analyse de dominance stochastique d'un portefeuille mixte (50% d'actions, 30% d'obligations et 20% d'actifs sans risque) et cette analyse fournit également des résultats similaires à un portefeuille avec des actions uniquement, sauf pour la période 1971-1983. Pendant ce temps, d'autres métaux précieux dont l'argent, le platine.

De plus, la financiarisation des marchés des métaux précieux a récemment suscité un débat houleux sur les avantages de la diversification d'investir dans ces marchés. Malgré le fait qu'il s'agisse d'un sujet controversé jusqu'à présent, le rôle des métaux précieux en tant que diversificateur a clairement évolué, en particulier en période de marchés extrêmes (Białkowski et al. 2015a, Balcilar et al. 2015). En particulier, plus le système financier mondial est incertain, plus le rôle des métaux précieux est renforcé (Morales & Andreosso-O'Callaghan 2011b, Hammoudeh et al. 2015). Étonnamment, il existe si peu de recherches approfondies sur l'impact des crises financières sur le rôle des métaux précieux en tant que bons diversificateurs.

Le test de gain stochastique est appliqué dans ce chapitre pour traiter les inconvénients de l'approche M-V. Parce que l'approche de recouvrement M-V repose sur ses deux hypothèses strictes. La première correspond à l'étude de Hanoch & Levy (2013) qui requiert des rendements des actifs normalement distribués. La seconde vient de l'hypothèse de Von Neumann et al. (2007), qui demande des fonctions d'utilité quadratiques. Si ces hypothèses sont brisées, les résultats deviennent peu fiables. En outre, la plage stochastique est plus adaptée au risque de moment d'ordre supérieur qu'à l'analyse de l'efficacité. De plus, le test de gain stochastique est justifiable car il est cohérent et asymétriquement exact dans le cas de processus faiblement dépendants. Deux autres avantages importants de cette méthode sont que, premièrement, elle ne fait aucune hypothèse sur la distribution des rendements, et deuxièmement, elle prend en considération tous les portefeuilles possibles, ce qui pourrait aider à surmonter les préoccupations existantes concernant les méthodologies utilisées pour tester les avantages de la diversification des nouveaux actifs.

Dans ce chapitre, le portefeuille traditionnel est construit à partir de quatre classes d'actifs comprenant les actions, les obligations, les liquidités et les devises des marchés du G7. Les deux portefeuilles augmentés sont construits en additionnant les rendements

spot de quatre métaux précieux dans le premier cas, et leurs rendements futurs dans le second. Par cette approche, l'objectif principal de l'étude est de faire la lumière sur la question de savoir si et comment les investisseurs peuvent bénéficier de la diversification en investissant dans les métaux précieux ou leurs instruments financiers. Mon analyse empirique a été menée à la fois sur l'ensemble de la période (de janvier 2005 à septembre 2018) et sur trois sous-périodes liées à la crise financière mondiale de 2008 : avant la crise (de janvier 2005 à août 2007), pendant la crise (de septembre 2007 à décembre 2010) et l'après-crise (de janvier 2011 à septembre 2018), respectivement. Grâce à cela, je peux rechercher des preuves du rôle des métaux précieux en tant que bon diversificateur en temps de crise. En outre, des données quotidiennes sont collectées auprès des pays du G7 en tant que preuves internationales pour clarifier le potentiel de diversification des métaux précieux sur les marchés financiers mondiaux.

J'effectue des analyses en échantillon et hors échantillon pour évaluer les avantages de diversification des métaux précieux pour les actifs traditionnels. Dans le cadre de l'échantillon, je trouve que le portefeuille traditionnel ne couvre pas les portefeuilles augmentés des rendements au comptant et à terme des quatre métaux. Cela signifie que les métaux précieux sont de bons diversificateurs des classes d'actifs traditionnelles. Par conséquent, ce sont des investissements efficaces pour améliorer les avantages de la diversification. Cette conclusion est valable dans un contexte hors échantillon. Notamment, mon analyse hors échantillon montre que les contrats à terme sur les métaux précieux surperforment considérablement leurs spots après la crise financière mondiale de 2008. Ce constat est conforme à l'étude de [Klein & Todorova \(2019\)](#) qui constatent que les contrats à terme sur métaux précieux sont devenus les instruments les plus utilisés pour la gestion des risques, en particulier dans les périodes plus volatiles. Enfin, les tests paramétriques d'évaluation des performances hors échantillon confirment à nouveau les avantages de la

diversification des métaux précieux au comptant et à terme.

Par lequel, ce chapitre apporte plusieurs contributions à la littérature connexe de certaines manières. Tout d'abord, un test de spanning stochastique a été appliqué pour construire des portefeuilles optimaux et comparer leurs performances de manière non paramétrique. Cette méthode semble surpasser les modèles antérieurs liés à la question de la diversification des actifs tels que: les modèles d'évaluation des actifs (Brewer 1981, De Santis et al. 1997), l'inférence bayésienne (Li et al. 2003), l'approche des co-mouvements de marché Christoffersen et al. (2014), Reboredo (2018), ou cadre M-V (Huberman & Kandel 1987, Belousova & Dorfleitner 2012b). Second, to my knowledge, this chapter is the first study into the diversification benefits of precious metals for global portfolios (i.e. the G7 markets), whereas the majority of the previous studies exclusively concentrate on the U.S. market (Conover et al. 2009, Figuerola-Ferretti & McCrorie 2016a). Troisièmement, en menant un examen séparé sur les contributions à la diversification des rendements au comptant et futurs de quatre métaux précieux, ma recherche empirique offre une enquête complète sur les différents types de ces matières premières. Cela peut s'expliquer par un manque d'études approfondies sur les bénéfices de la diversification pour les métaux précieux et leurs dérivés dans la littérature pertinente. Enfin, ce chapitre examine le rôle de diversification des changements des métaux précieux pendant les périodes de stabilité et d'instabilité en se concentrant sur la crise financière mondiale de 2008. Ce faisant, ce chapitre devrait fournir aux investisseurs et aux gestionnaires de portefeuille une référence approfondie lorsqu'ils décident d'investir dans métaux précieux dans le but de diversifier le portefeuille, en particulier pour éviter les risques, en cas de crises financières futures.

Chapitre 4 - **La structure de dépendance de la queue entre les métaux précieux et les marchés boursiers internationaux**, applique à la fois les copules bivariées (copules à paire de vigne) et les copules multivariées (copules archimédiennes

hiérarchiques (HAC)) pour étudier la structure de dépendance extrême entre le stock international et le métal précieux marchés. En effet, ces deux fonctions de copule permettent une modélisation asymétrique pour le modèle de dépendance de queue. Le premier calcule les coefficients de dépendance des queues supérieure et inférieure par paires, tandis que le second estime les coefficients de dépendance des queues multiples supérieures et inférieures.

Dans un environnement turbulent, les métaux précieux qui ont été largement acceptés comme actifs refuges sur les marchés financiers ([Baur & McDermott 2010](#), [Lucey & Li 2015b](#), [Li & Lucey 2017](#), [Bulut & Rizvanoglu 2019](#)), ont attiré beaucoup plus attention. Étonnamment, les mouvements actuels des marchés des métaux précieux semblent être en opposition avec les conclusions académiques alors que ces métaux refuges ont également connu une volatilité forte et imprévisible ainsi que des stocks mondiaux touchés par le coronavirus. En particulier, une seule dernière semaine de février 2020, l'or au comptant a plongé de 3,2% à 1 590,17\$ l'once après avoir atteint le sommet de 7 ans il y a quelques jours, tandis que d'autres métaux précieux, dont l'argent, le platine et le palladium, ont également diminué de 6,6%, 6,1% et 9%, respectivement. Cela peut s'expliquer par diverses opinions. Dans laquelle, selon la majorité des experts, les investisseurs se sont empressés de vendre des métaux précieux pour générer des liquidités afin de couvrir les pertes sur les marchés boursiers et ils s'attendaient à des prix "bien plus élevés" de ces métaux à l'avenir. D'autre part, plusieurs chercheurs trouvent la preuve que la surchauffe de ces marchés des métaux en période de turbulences sur les marchés est capable de réduire la propriété refuge de ces métaux, voire de subir des pertes ([Daskalaki & Skiadopoulos 2011b](#), [Boako et al. 2019](#)).

Parmi les trois rôles largement acceptés des métaux précieux, à savoir : couverture, diversification et valeur refuge, seul le troisième a la propriété spécifique de réduire les

perdes dans des conditions de marché extrêmement défavorables. Selon la définition de [Baur & McDermott \(2010\)](#), les métaux précieux seraient considérés comme une valeur refuge par rapport aux cours des actions si ces métaux n'étaient pas corrélés (valeur refuge faible) ou négativement corrélés (valeur refuge forte) avec les actions en période de mouvements extrêmes du marché. Par conséquent, la structure de dépendance extrême (ou extrême) entre les marchés boursiers et les marchés des métaux précieux nous indique si les métaux précieux sont des valeurs refuges. Cependant, la recherche actuelle a continué à faire face à des défis importants pour mesurer la structure de dépendance extrême entre les actifs financiers. De nombreux travaux antérieurs ont examiné comment déterminer les coefficients de corrélation extrêmes en utilisant une approche appelée théorie des valeurs extrêmes ([Longin & Solnik 2001](#), [Ang & Chen 2002](#), [Ang & Bekaert 2002](#), [Patton 2004](#)). En revanche, plusieurs études utilisent le modèle de régression à seuil pour estimer les effets marginaux ([Baur & McDermott 2010](#), [Wang et al. 2011](#), [Ciner et al. 2013b](#)). Cependant, [Embrechts et al. \(2001\)](#) pensent que la corrélation de dépassement est insuffisante pour rendre compte de la dépendance extrême, en particulier lorsque la distribution conjointe des rendements des actifs n'est pas elliptique. Pendant ce temps, l'application de la régression de seuil est incapable d'expliquer complètement les mouvements extrêmes entre les marchés financiers en même temps ([Sui et al. 2021](#)).

Pour gérer les inconvénients mentionnés ci-dessus, il convient d'appliquer les fonctions de copule pour estimer le coefficient de dépendance de la queue. Le coefficient de dépendance de queue est une mesure commune de la structure de dépendance de queue parmi les variables aléatoires introduites en premier par [Sibuya \(1960\)](#). Il peut être défini comme la probabilité que le pire événement se produise sur un marché étant donné que le pire événement se produise sur un autre marché. En fait, le principal avantage du coefficient de dépendance de queue est qu'il peut conserver son invariance aux modifications des

distributions marginales qui n'exerce aucun effet sur la structure de dépendance (Garcia & Tsafack 2011). Parallèlement à cela, l'approche de la copule offre également des avantages significatifs dans la modélisation de la structure de dépendance lorsque plusieurs fonctions de copule peuvent traiter des distributions de rendement financier non linéaires, lourdes et asymétriques. Les copules traditionnelles ont cependant l'inconvénient de ne pas pouvoir modéliser facilement la structure de dépendance des données multivariées (c'est-à-dire trois variables ou plus). Ce problème peut être surmonté de manière intéressante par les copules archimédiennes hiérarchiques (HAC). Ceci est crucial en raison du fait que la littérature existante sur la dépendance de queue se concentre principalement sur le co-mouvement des rendements extrêmes de deux actifs ou portefeuilles (c'est-à-dire le coefficient de dépendance de queue bivarié) (Garcia & Tsafack 2011, Reboredo 2013, Aloui & Aïssa 2016).

Dans la littérature financière, la dépendance de queue asymétrique (c'est-à-dire que la dépendance de queue inférieure peut être plus grande que la dépendance de queue supérieure ou vice versa) entre les marchés boursiers internationaux a été largement étudiée (Longin & Solnik 2001, Ang & Chen 2002, Patton 2004, Hong et al. 2007, Kocaarslan et al. 2017, Jiang et al. 2018). De plus, la dynamique asymétrique dans le co-mouvement extrême des actions mondiales et d'autres actifs tels que les obligations, les devises étrangères ou les matières premières a fait l'objet d'une attention considérable (Di Iorio & Faff 2000, Yang et al. 2009, Aloui & Mabrouk 2010, Garcia & Tsafack 2011, Nguyen et al. 2015, Bahmani-Oskooee & Saha 2018). Parallèlement aux actions, les métaux précieux se sont également avérés asymétriques à la fois en termes de volatilité (Baur 2012, Todorova 2017) et d'interdépendance (Reboredo & Ugolini 2015, Klein 2017), même dans les mouvements avec d'autres actifs financiers tels que le bitcoin (Mensi et al. 2019) and dollar américain (Miyazaki & Hamori 2016). Cependant, à l'exception de quelques études

démontrant la dépendance asymétrique entre l'or et les actions, l'exploration directe du co-mouvement de queue asymétrique entre les métaux précieux et les actions a reçu très peu d'attention.

Empiriquement, ce chapitre est mené sur les données quotidiennes des marchés boursiers des économies du G7 et des BRICS et des marchés des métaux précieux de janvier 2005 à septembre 2018. Mes résultats empiriques montrent des preuves d'une dépendance extrême significative entre les métaux précieux et les actions internationales. De plus, cette dépendance est variable dans le temps (c'est-à-dire que le niveau et la structure de la queue de dépendance changent sur trois sous-périodes de la crise financière de 2008) et asymétrique à la fois dans les analyses bivariées et multivariées. Dans l'analyse bivariée, les résultats des copules de paires de vignes montrent l'indépendance des queues supérieure et inférieure entre chaque métal précieux et la plupart des marchés boursiers, à l'exception du cas des marchés allemand et italien. Cela signifie que chaque métal précieux peut servir de refuge contre les mouvements extrêmes des actions individuelles sur les marchés du G7. Pendant ce temps, les estimations de la dépendance multivariée de la queue révèlent que chaque métal précieux peut servir de valeur refuge contre les marchés boursiers mondiaux en cas de ralentissement du marché, mais pas en cas de reprise du marché.

Le chapitre 4, par conséquent, apporte un ajout à la littérature actuelle des manières significatives suivantes. Tout d'abord, en sélectionnant les copules de vigne appropriées, je capture le modèle de dépendance de la queue de la manière la plus efficace. Deuxièmement, à ma connaissance, ce chapitre est le premier travail à utiliser des copules archimédiennes hiérarchiques pour estimer la dépendance de queue multivariée efficace entre chaque métal précieux et un total de douze actions des pays du G7 et des BRICS. Mes résultats empiriques sur les copules de vigne et les copules archimédiennes hiérarchiques permettent

de revisiter les propriétés de valeur refuge des métaux précieux face aux mouvements extrêmes des rendements boursiers. À partir de là, il peut donner aux investisseurs des suggestions utiles pour le processus de prise de décision de l'allocation de portefeuille dans des scénarios de marché extrêmes. Troisièmement, les changements dans la structure de dépendance de la queue sur différentes périodes ont été analysés afin de tester les impacts de la crise financière mondiale de 2008 sur les co-mouvements extrêmes entre les métaux précieux et les marchés boursiers.

Enfin, le chapitre 5 se termine par un résumé des principaux résultats et implications de ma thèse. En résumé, ma thèse peut apporter une contribution considérable à la littérature existante sur la finance comportementale, les crises et les futurs marchés des métaux précieux en étudiant l'impact des moteurs macroéconomiques et financiers sur la volatilité à long terme et la corrélation des marchés des métaux précieux à l'échelle mondiale 20 dernières années. En outre, il a confirmé le potentiel de diversification des investissements dans les métaux précieux et le rôle de ces métaux en tant que refuge contre les mouvements extrêmes des marchés boursiers mondiaux.

Contents

List of Tables	33
List of Figures	36
1 GENERAL INTRODUCTION	39
1.1 Context and motivation	41
1.1.1 Global context and the evolution of precious metal markets	41
1.1.2 Measuring the financial role of precious metals in portfolio diversifi- cation	42
1.1.3 The impact of macro-finance drivers on the dynamics of precious metal markets	43
1.1.4 The dynamic relationship between precious metals and other finan- cial assets	44
1.1.5 Motivations of the thesis	48
1.2 Main contributions of the thesis	53
1.3 Thesis structure	55
2 ECONOMIC DRIVERS OF VOLATILITY AND CORRELATION IN PRECIOUS METAL MARKETS	57
2.1 Introduction	58

2.2	Literature review	60
2.3	Methodology	64
2.3.1	GARCH-MIDAS model with economic variables	64
2.3.2	DCC-MIDAS model with economic variables	66
2.4	Empirical applications	68
2.4.1	Data and variables	68
2.4.2	Results and discussions	72
2.5	Conclusion	88
3	DIVERSIFICATION BENEFITS OF PRECIOUS METAL MARKETS: EVIDENCE FROM THE GLOBAL FINANCIAL CRISIS	96
3.1	Introduction	97
3.2	The theoretical framework for assessing diversification benefits	100
3.3	Stochastic spanning methodology	102
3.3.1	Definition	103
3.3.2	Statistical framework and critical values	104
3.4	Data and properties	106
3.4.1	Data	106
3.4.2	Initial statistical analyses	107
3.5	Empirical results	109
3.5.1	In-sample analysis	109
3.5.2	Out-of-sample analysis	111
3.5.3	Out-of-sample performance assessment	114
3.6	Conclusion	118
4	THE TAIL DEPENDENCE STRUCTURE BETWEEN PRECIOUS	

METALS AND INTERNATIONAL STOCK MARKETS	119
4.1 Introduction	120
4.2 Methodology and theoretical design	124
4.2.1 Copulas and multivariate tail dependence coefficients	124
4.2.2 Vine copulas	126
4.2.3 Hierarchical Archimedean copulas	128
4.3 Empirical applications	130
4.3.1 Data and properties	130
4.3.2 Results and discussions	134
4.4 Conclusion	141
5 GENERAL CONCLUSION	146
5.1 Summary of main findings	146
5.2 Practical implications	149

List of Tables

1	Descriptive statistics of spot returns of four precious metals	70
2	Descriptive statistics of future returns of four precious metals	71
3	Parameter estimation results of GARCH, GJR, GARCH-MIDAS-RV and GJR-MIDAS-RV	73
4	Coefficients θ of economics variables of the U.S.	76
5	Coefficients θ of economics variables of China	77
6	Coefficients γ of economic variables of the U.S. and China	78
7	Coefficients θ of economic variables of the U.S. over three sub-periods of the global financial crisis of 2008	80
8	Coefficients θ of economic variables of China over three sub-periods of the global financial crisis of 2008	81
9	Coefficients γ of economic variables of the U.S. over three sub-periods of the global financial crisis of 2008	82
10	Coefficients γ of economic variables of China over three sub-periods of the global financial crisis of 2008	83
11	List of macro-finance variables	90
12	Impact of macroeconomic variables of G7 and BRICS countries on the long-term volatility of precious metals	91

13	Impact of macroeconomic variables of G7 and BRICS countries on the long-term correlations between precious metals	92
14	Impact of macroeconomic variables of G7 and BRICS countries on the long-term volatility and correlations of precious metals	93
15	Impact of financial variables of G7 and BRICS countries on long-term volatility and correlations of precious metals	94
16	Impact of EPU growth of G7 and BRICS countries on the long-term volatility and correlations of precious metals	95
17	Descriptive statistics of precious metals and traditional assets	108
18	Sharpe ratios of traditional assets and precious metals in three periods of the 2008 global financial crisis	110
19	In-sample tests	111
20	Out-of-sample performance: Parametric performance measures	117
21	Descriptive statistics and stationary tests of precious metals and stocks	132
22	Pearson correlation matrix between precious metals and stocks	134
23	Empirical Kendall's tau over the pre-crisis period	134
24	Empirical Kendall's tau over the crisis period	135
25	Empirical Kendall's tau over the post-crisis period	135
26	Vine copulas model selection	136
27	The bivariate lower tail dependence coefficient estimation from C-vine over the pre-crisis period	137
28	The bivariate upper tail dependence coefficient estimation from C-vine over the pre-crisis period	138

29	The bivariate lower tail dependence coefficient estimation from R-vine over the crisis period	139
30	The bivariate upper tail dependence coefficient estimation from R-vine over the crisis period	139
31	The bivariate lower tail coefficient estimation from R-vine over the post-crisis period	140
32	The bivariate upper tail coefficient estimation from R-vine over the post-crisis period	140
33	Multivariate Tail Dependence Coefficients	143
34	Abbreviations	144
35	Considered Bivariate copulas families for Vine copulas	144

List of Figures

1	Precious metals and traditional assets returns of G7 markets over the three periods of the global financial crisis of 2008	45
2	Correlations between precious metals and traditional assets returns of G7 countries	47
3	Daily returns on the spot precious metals and stock indices of G7 and BRICS markets	49
4	Spot returns of four precious metals from Jan 02, 1998, to September 20, 2018	52
5	Future returns of four precious metals from Jan 02, 1998, to September 20, 2018	52
6	Cumulative performance of the traditional optimal portfolio and the two augmented optimal portfolios over the pre-crisis period from Jan 02, 2006 to Jan 31, 2008.	112
7	Cumulative performance of the traditional optimal portfolio and the two augmented optimal portfolios over the crisis period from Feb 01, 2008, to Dec 31, 2010.	113

8	Cumulative performance of the traditional optimal portfolio and the two augmented optimal portfolios over the post-crisis period from Jan 01, 2011, to Sep 20, 2018.	113
9	Samples of selected hierarchical structures for four precious metals and international stock markets (G7 and BRICS)	142
10	C-vine (Tree 1) decomposition for pre-crisis, R-vine (Tree 1) for crisis and post-crisis	145

Chapter 1

GENERAL INTRODUCTION

Precious metals are utilized as important stores of value and monetary assets. In addition, these metals are necessary materials in a variety of industries. In the past, investors typically did not consider precious metals when constructing investment portfolios. Yet precious metals have recently played an increasingly important role as potential alternatives for traditional assets (e.g., stocks, bonds, currencies). These metals are even outperforming traditional assets, especially in such a turbulent environment. Moreover, the introduction of new securities and trading intermediaries related to precious metals (e.g., futures, options, exchange-traded funds), has enhanced the attractiveness of precious metals as investment assets. Participants in these financial markets have expected these metals to become a common asset class, similar to stocks and bonds. However, some argue that investing in precious metals is significantly more risky ([Cao et al. 2010](#), [Daskalaki & Skiadopoulos 2011a](#)). Specifically, both researchers and practitioners doubt that such overheating in the market of precious metals could reduce their diversification benefits. These divergent opinions thus necessitate an analysis of the financial role of precious metals using advanced methods.

Although the contemporary literature has focused on investigating the three widely

accepted roles of precious metals, including hedge, diversifier, and safe haven (Baur & McDermott 2010, Batten et al. 2015, Lucey & Li 2015a), there remains a lack of consensus regarding how, when, and where precious metals are oriented gain or lose investment value according to these roles. Currently, financial markets in general and precious metal markets in particular have become increasingly complex due to booms and crashes with irregular patterns linked to the Covid-19 pandemic. During periods of market turmoil, both risk-taker and risk-averse investors would consider the role of financial assets as diversifiers and safe havens, respectively, in order to build their investment portfolios. In addition, many studies conclude that the dynamic movements of precious metal markets are not only related to supply and demand dynamics but are also associated with changes in economic activities (Anson 2008, Belousova & Dorfleitner 2012a). Therefore, it is vital to clarify this market-oriented role of macroeconomic-financial drivers before going into revisiting the financial roles of precious metal markets.

In addition, in order to investigate the financial role of precious metals accurately, it is required to measure dynamic movements as well as the dynamic relationship between these metals and other financial assets. This measure, however, has still been vigorously challenged because the precious metal markets are highly volatile. Furthermore, the high uncertainty of global financial markets has recently caused the standard methods used in analyzing portfolio diversification (e.g., the M-V model of Markowitz) to reveal some disadvantages. These disadvantages are attributed to the overwhelming evidence of non-normality distribution or “fat-tails” problem (Prakash et al. 2003, Apergis et al. 2014, Fang, Chen, Yu & Xiong 2018), asymmetric and non-linear dependence (Bawa et al. 1979, Campbell et al. 2002), or non-quadratic utility functions (Von Neumann et al. 2007). As a result, dynamic models must be used in addition to static ones to solve these problems and investigate the interactive mechanism of the linkage between global financial markets.

My thesis, thus, provides a comprehensive analysis focusing on discovering the impact of economic activities on the time-varying dynamics of the precious metal markets and accurately positioning the financial role of precious metals in portfolio diversification. In this thesis, global data from highly developed (Group of Seven, G7) and emerging (Brazil, Russia, India, China, South Africa, BRICS) economies were used to provide international evidence for the dynamic relationship of precious metal markets in a multi-factor world. The full sample was divided into three sub-periods, namely the pre-crisis period (01 March 1998—31 August 2007), the crisis period (01 September 2007—31 December 2010), and the post-crisis period (03 January 2011—20 September 2018) in order to study the impact of the 2008 global financial crisis on the financial role of precious metals over time.

1.1 Context and motivation

1.1.1 Global context and the evolution of precious metal markets

From the first quarter of 2020, many countries around the world have faced a range of considerable problems as a result of the ongoing rapid spread of coronavirus as well as earlier global risk factors (e.g., the prolonged US-China trade war, currency fluctuations, long-term interest movements, Brexit). At the end of February 2020, global stock markets suffered the worst week with almost \$6 trillion wiped from their market value¹, since the global financial crisis 2008. Many experts have strongly warned that these extreme events could lead to another global financial crisis.

As a consequence of market shocks, investors prefer to keep safe assets and stay away from risky assets, known as the ‘flight to quality’ phenomenon in financial markets (Bernanke et al. 1994). Accordingly, precious metals have been widely accepted as potential alternatives for traditional assets (e.g., stocks, bonds, currencies), especially in

¹<https://www.cnbc.com/2020/02/28/global-stock-markets-have-lost-6-/trillion-in-value-in-six-days.html>

times of high uncertainty (Hillier et al. 2006a, Baur & Lucey 2010a, Lucey & Li 2015a). As effective investment assets, precious metals have recently become more appealing due to the advent of new instruments and trading intermediaries associated with these markets, such as futures, options, exchange-traded funds, etc. Along with this trend, the financial role of precious metals has constantly been changing. Moreover, the resilience of precious metals to extreme adverse market conditions has also attracted the special attention of scholars and practitioners (Baur & Lucey 2010a, Ciner et al. 2013a, Agyei-Ampomah et al. 2014, Lucey & Li 2015a, Batten et al. 2015).

1.1.2 Measuring the financial role of precious metals in portfolio diversification

The three widely accepted properties of precious metals include hedge, diversified, and safe haven. A hedge is defined as an asset that is uncorrelated (weak hedge) or negatively correlated (strong hedge) with another asset or portfolio on average. In the context of global financial markets mentioned in section 1.1.1, this thesis focuses on the role of precious metals as a diversifier and safe haven.

Precious metals can serve as diversifiers if they are weakly positively correlated with another asset or portfolio on average. In practice, investors might hold a wide range of assets available in the financial markets. The supposed benefits of diversification (i.e., risk reduction for any expected level of return on an investment asset or a portfolio) might suggest that investors should strive to spend money on as many assets as possible. However, this suggestion is not entirely true. Diversification has remained limited (Bodie et al. 1992), as adding more assets could even lead to a reduction in the portfolio performance due to transaction fees or other costs. Therefore, when assessing the diversification role of precious metals, it is mainly based on the M-V framework of (Markowitz 1952). However, the limitation of the M-V approach relies on its two strict assumptions, which require normally distributed returns of assets Hanoch & Levy (2013) and quadratic utility

functions (Von Neumann et al. 2007). If these assumptions are broken, the results become unreliable.

According to the definition of Baur & Lucey (2010b), precious metals would be considered a safe haven against stock prices if these metals uncorrelated (weak safe haven) or negatively correlated (strong safe haven) with stocks in times of extreme market movements. However, current research has faced significant challenges in measuring the extreme co-movements among financial assets, including precious metals. Particularly, when the joint distribution of asset returns is not elliptical as well as the co-movement between asset returns is not symmetric.

To handle all the abovementioned issues, applying the advanced methods that may deal with non-linear, fat-tails, and asymmetric financial return distributions is crucial, especially in the multivariate pattern.

1.1.3 The impact of macro-finance drivers on the dynamics of precious metal markets

A number of previous studies have found that the time-varying dynamics of commodity markets in general and precious metal markets, in particular, are not only related to supply and demand dynamics but also linked to changes in economic activities (Anson 2008, Belousova & Dorfleitner 2012a). However, the relevant research to date has reported conflicting findings about the impact of economic factors on the movements of precious metal markets. It is also generally limited to determining the economic drivers of precious metal markets' conditional volatility and correlation. Tully & Lucey (2007a), Batten et al. (2015), Mo et al. (2018) investigate that macroeconomic and financial variables are key potential drivers of dynamic movements in precious metal markets.

To date, various methods have been applied to measure the impact of economic sources on financial assets' time-varying volatility and correlation, such as modified Generalized

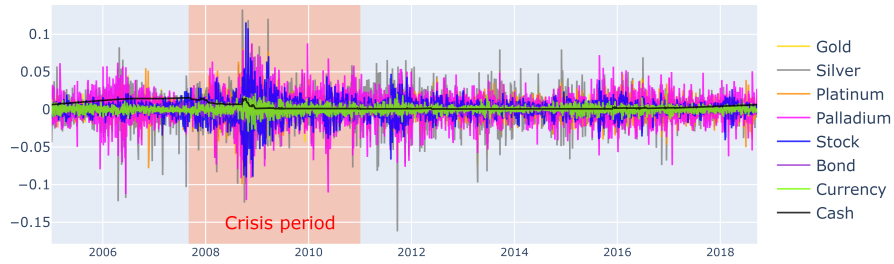
Autoregressive Conditional Heteroskedasticity (GARCH) models ([Hammoudeh et al. 2011b](#), [Pan et al. 2017](#)), popular classes of multiple-equation models including Vector Autoregression- (VAR, [Andersen et al. 2003](#), [Apergis et al. 2014](#)), Vector Error Correction Model-based approaches ([Kucher & McCoskey 2017](#)), and different Dynamic Conditional Correlation (DCC) models ([Fernandez-Diaz & Morley 2019](#)), among others. These studies predominantly investigate only the separated effect of a single driver or focus solely on a small number of given macro-finance variables.² One of the reasons for this may arise from the problem of the low frequency of economic data. Meanwhile, the analyses of time-varying movements of precious metals are mainly based on high-frequency data.

1.1.4 The dynamic relationship between precious metals and other financial assets

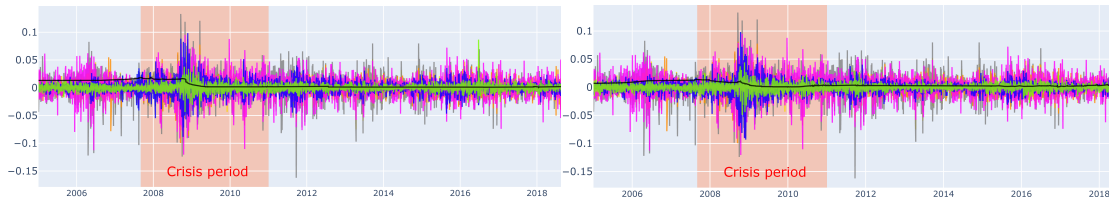
Recently, the dynamic relationship between precious metals and other assets under different market conditions (i.e., tranquil and extreme market scenarios) has attracted much more attention ([Baur & Lucey 2010a](#), [Agyei-Ampomah et al. 2014](#), [Lucey & Li 2015a](#)).

Figure 1 displays the daily return movements of precious metals and traditional assets, including stocks, bonds, cash, and currencies of G7 markets over the three periods of the global financial crisis of 2008. It can be seen that almost all precious metals had considerably higher standard deviations than those of equities, bonds, cash, and currencies. The return series of silver was the most turbulent. Notably, the behavior of precious metals returns during the crisis was not very different from that of the pre-crisis period. However, their returns in the post-crisis period demonstrated a different volatility.

²It is worth noting that some authors propose new techniques for measuring the impact of a large number of predictors jointly, e.g., dynamic factor analysis ([Ludvigson & Ng 2009](#)), quantile regression ([Christiansen et al. 2012](#)), data-rich forecast methodology ([Aslanidis & Christiansen 2014](#)), Bayesian Model Averaging ([Díaz et al. 2021](#)), or component-wise gradient boosting techniques ([Mittnik et al. 2015](#)).

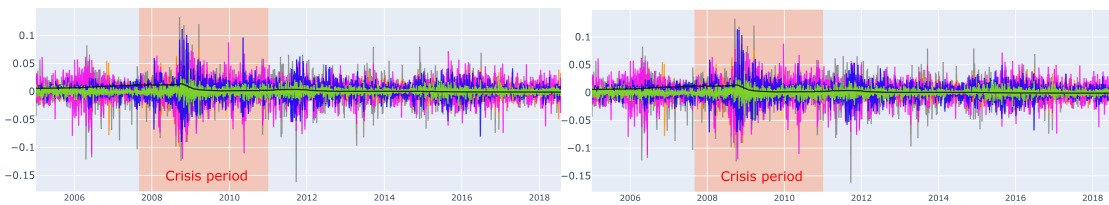


(a) US



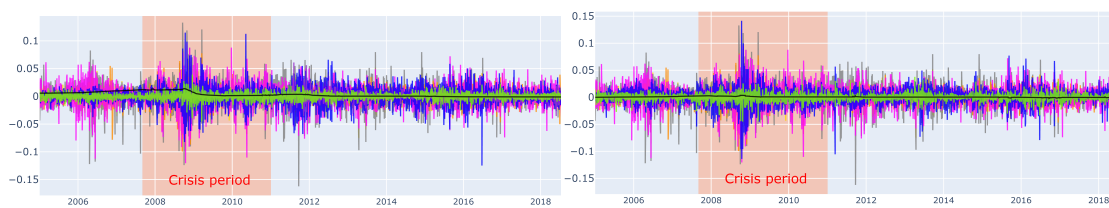
(b) UK

(c) Canada



(d) France

(e) Germany



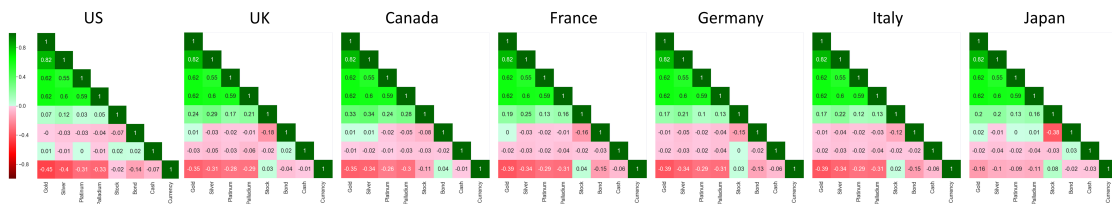
(f) Italy

(g) Japan

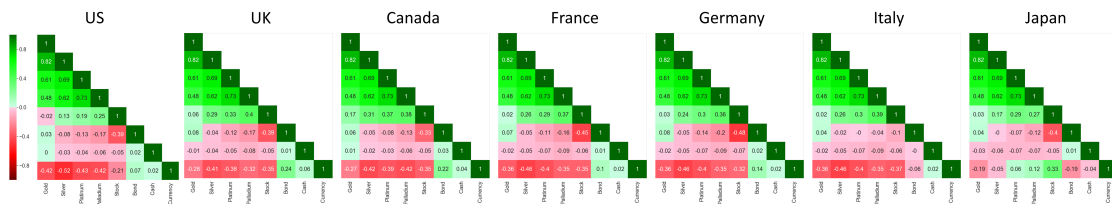
Figure 1: Precious metals and traditional assets returns of G7 markets over the three periods of the global financial crisis of 2008

Figure 2 reports the unconditional correlation coefficients between the individual precious metal and traditional assets of G7 markets. Most precious metals have a very low correlation with traditional assets. The correlation with fixed-income markets (i.e., bonds, cash, and currencies) is negative, whereas the correlation with equity markets is slightly positive. The correlation matrix results repeatedly confirm the findings of [Cao et al. \(2010\)](#), [Delatte & Lopez \(2013\)](#), i.e., that the considerable increase in capital inflows into precious metals markets can reduce their diversification benefits because of the higher correlation between precious metals markets and stock and bond markets. As seen in Figure 2c in comparison with figure 2a and figure 2b, the correlation between precious metals returns and stocks, bonds, cash, and currencies in the post-crisis period was higher than during the crisis or pre-crisis. The increased correlation between assets after the crisis can be explained by the fact that when there is a significant increase in uncertainty in the global financial system, the role of precious metals becomes more essential and can be a part of a well-diversified portfolio ([Białkowski et al. 2015a](#), [Balcilar et al. 2015](#)). The increased significance of precious metals results in over-investment in these markets during the crisis. Thus, the correlation between precious metals and traditional assets increased in the subsequent period.

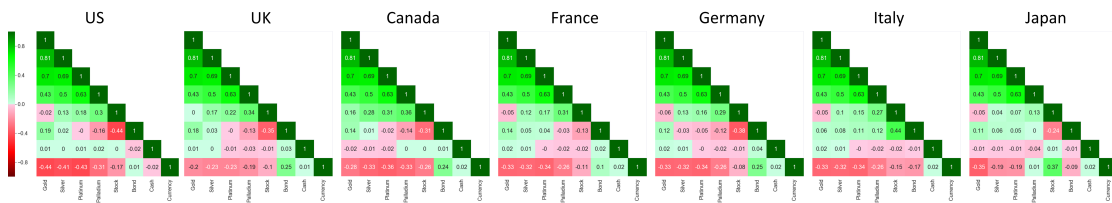
In the finance literature, the movement between precious metals and international stocks has received special attention from both investors and scholars. However, current movements seem to be in opposition to academic findings when these safe-haven metals also experienced a sharp and unpredictable fluctuation along with coronavirus-afflicted global stocks. Particularly, in only one final week of February 2020, spots of gold plunged 3.2% to \$1,590.17 per ounce after surging to a 7-year top a few days ago, while other precious metals, including silver, platinum, and palladium also declined 6,6%, 6,1% and



(a) Before crisis



(b) During crisis



(c) After crisis

Figure 2: Correlations between precious metals and traditional assets returns of G7 countries

9%, respectively³. This situation can be explained by various opinions. According to the majority of experts, investors hurried to sell precious metals to generate cash in order to cover losses in the stock markets, and they expected "far higher" these metal prices in the future. On the other hand, several researchers find evidence that overheating in these metals markets during times of market turmoil is able to reduce the safe haven property of these metals, even incur loss (Daskalaki & Skiadopoulos 2011*b*, Boako et al. 2019).

Figure 3 exhibits log returns of all four precious metals and twelve series of G7 and BRICS stock markets. Consistent trends can be observed, all asset returns had the highest volatility during times of the 2008 global financial crisis and precious metal markets seem to be more volatile than stock markets over the entire sample period.

1.1.5 Motivations of the thesis

The emerging financialization of precious metal markets over the last few decades has caused an intense public and scientific debate on precious metals investment and their diversification benefits. Many studies, including Jaffe (1989*b*), Chua et al. (1990*b*), and Hillier et al. (2006*b*), present strong evidence that adding precious metals improves the overall performance of stock and bond portfolios. (Hillier et al. 2006*b*), (Conover et al. 2009), (Baur & Lucey 2010*a*) and (Jain & Biswal 2016*b*) demonstrate that precious metals all have low correlations with stock and bond returns during turbulent periods and financial crises, which enables these metals to be a part of a well-diversified portfolio. Using M-V spanning tests, Belousova & Dorfleitner (2012*b*) also find that compared to other commodities, precious metals provide the highest performance improvement for traditional portfolios. Several other studies, however, argue against such diversification benefits (Cao et al. 2010, Daskalaki & Skiadopoulos 2011*a*). These studies argue that the current over-financialization of precious metal markets and the considerable rise of

³<https://www.cnbc.com/2020/02/28/gold-markets-coronavirus-in-focus.html>

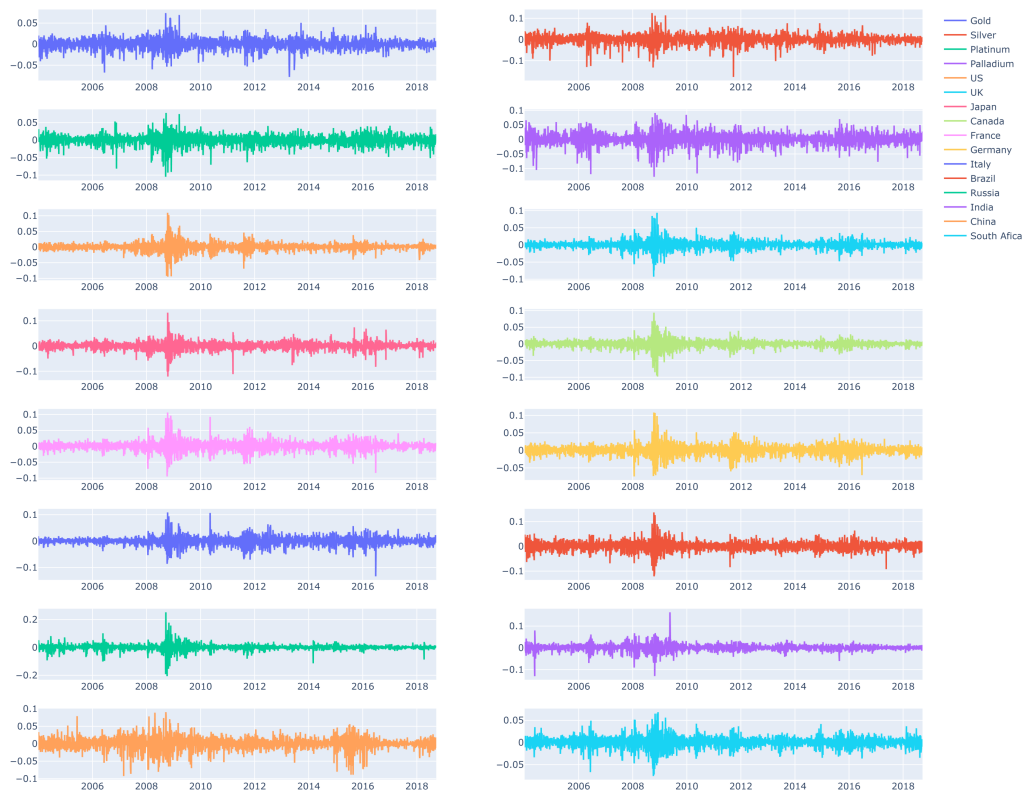


Figure 3: Daily returns on the spot precious metals and stock indices of G7 and BRICS markets

capital inflows into these markets may cause an increased correlation between precious metal markets and traditional markets, reducing their diversification contribution. This debate gives me a strong motivation to revisit the financial role of precious metals.

Despite being a controversial issue to date, it is undoubtedly true that the financial role of precious metals has constantly been changing. When there is a significant increase in the level of uncertainty in the global financial system, this role becomes more vital (Morales & Andreosso-O'Callaghan 2011a, Białkowski et al. 2015a). A growing body of research demonstrates that the uncertain shocks related to financial crises are a significant source of precious metal markets dynamic (Morales & Andreosso-O'Callaghan 2011a, Hammoudeh et al. 2011a). However, it is surprising that there is a limitation in in-depth research regarding the impact of financial crises on the financial role of precious metals (Białkowski et al. 2015a, Balcilar et al. 2015). This is because measuring the financial role of precious metals under different market conditions has still been challenging. It requires accurate modeling of multi-asset dependency patterns. Therefore, this thesis explicitly investigates the financial role of gold, silver, platinum, and palladium across the three financial period scenarios of the global financial crisis 2008: the pre-crisis, the crisis, and the post-crisis periods.

In the global economy, the trade war between the U.S. and China, the two largest economies in the world, has been becoming more complicated, triggering fears of a global economic slowdown. Many experts are concerned that the escalating tension between the U.S. and China after 2018 and its subsequent persistent headwind for all financial markets. Due to the fact that between 2014 and 2017, around 80% of the precious metals used by the U.S. were imported from China, precious metals played a crucial role in the trade war between these two countries. In addition to the U.S. and China, other G7 (i.e., the UK, Canada, Japan, Germany, France, and Italy) and BRICS countries (Brazil, Russia, India,

and South Africa) are also top-ranked in precious metal exchanges. However, until now, most of the academic literature on the financial roles of precious metals has only focused on U.S. markets, which seems to ignore other important markets such as Russia or India, and South Africa, which already accounts for around 30% of the total world in importing gold bar and coin (World Gold Council, 2016), etc. Because of these reasons, I decided to choose the highly developed (Group of Seven, G7) and emerging (Brazil, Russia, India, China, South Africa, BRICS) economies for the research sample of the thesis on precious metal markets.

Furthermore, it is clear that white metals, including silver, platinum, and palladium, are generally overshadowed by gold in the volume of academic literature. In certain circumstances, they even outperform gold, although both serve the same purpose as significant investment vehicles. In particular, [Lucey & Li \(2015b\)](#) concluded that these white metals act as a safe haven when gold does not this role. Accordingly, it is necessary to study all four precious metals, including gold, silver, platinum, and palladium, in dynamic relationships with other asset classes.

Has the increased financialization of precious metal markets over the past few decades benefited global financial markets? For many years, this has been a contentious question in both academia and practice, while there has been a lack of holistic research on the role of precious metals and their derivatives up to now. [Figures 4 and 5](#) show the dynamic movements of precious metal spot and their future returns from 1998 to 2018. For this reason, my thesis provides a broad investigation into two various types of these metals, by testing separately and comparing the performance of spot returns (i.e., gold spot return, silver spot return, platinum spot return, palladium spot return) and future 1-month returns (gold future 1M return, silver future 1M return, platinum future 1M return, palladium future 1M return).

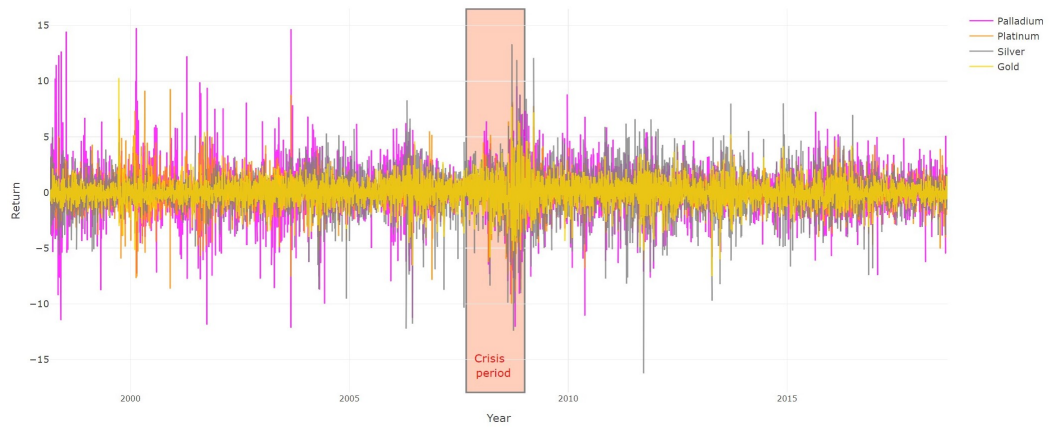


Figure 4: Spot returns of four precious metals from Jan 02, 1998, to September 20, 2018

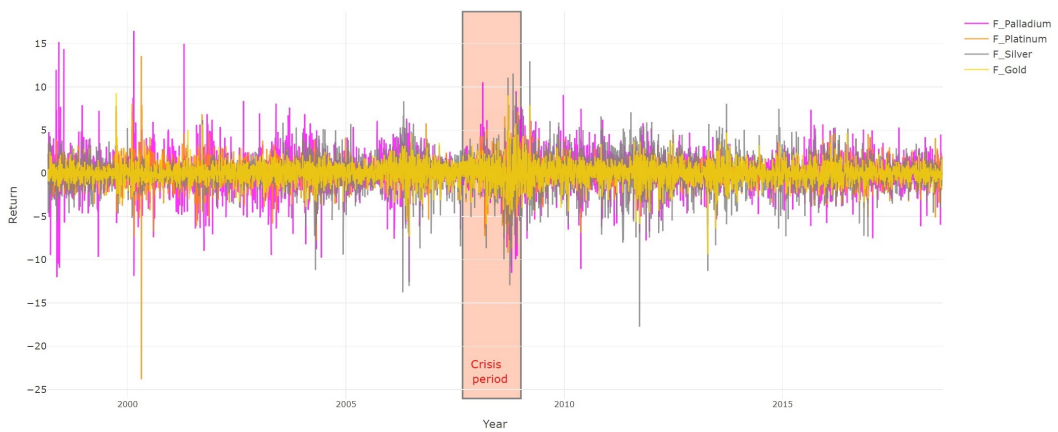


Figure 5: Future returns of four precious metals from Jan 02, 1998, to September 20, 2018

1.2 Main contributions of the thesis

This section outlines the main objectives and contributions of each empirical chapter in the thesis. **Chapter 2 - Economic Drivers of Volatility and Correlation in Precious Metal Markets** with the primary objective is to analyze the individual impact of the most important economic and financial drivers on the time-varying volatility and correlation of precious metal markets, which makes several contributions to the existing literature. Firstly, to the best of my knowledge, this chapter analyses macroeconomic and financial drivers of the dynamic correlation within the precious metal markets for the first time. Although many previous studies have investigated the determinants of dynamic correlations between precious metals and other assets, such as stocks ([Mensi et al. 2013](#), [Jain & Biswal 2016a](#), [Klein & Walther 2022](#)), oil ([Šimáková 2011](#)), exchange rates ([Pal et al. 2014](#), [Apergis 2014](#)), or cryptocurrencies ([Klein et al. 2018](#)), there are a few papers that analyze the time-varying correlation between the precious metals themselves ([Sensoy 2013](#), [Klein 2017](#)) without considering their drivers. Secondly, in this chapter, the entire sample was divided into three sub-periods related to the 2008 global financial crisis (i.e., pre-crisis, the crisis, and the post-crisis), in order to determine whether the influence of economic drivers on the dynamic volatility and correlation of precious metal markets changes between calm and turbulent times. As a result, it may provide policymakers, investors, and portfolio managers with helpful recommendations for managing future global financial crises. Thirdly, this chapter may make considerable contributions to the existing literature by investigating the different impacts of a set of nineteen economic and financial variables from twelve countries (G7 and BRICS) on the volatility and correlation of precious metals. Most of the aforementioned studies have only focused on U.S.-based determinants ([Batten et al. 2015](#)).

Chapter 3 - The Global Financial Crisis of 2008 and Diversification Benefits

of Precious Metal Markets aims to assess the role of using precious metals to gain diversification benefits. This chapter makes several contributions to the related literature in certain ways. First, a stochastic spanning test has been applied to construct optimal portfolios and compare their performance in a non-parametric way. This method seems to outperform the prior models related to the issue of asset diversification such as asset pricing models (Brewer 1981, De Santis & Gerard 1997), Bayesian inference (Li et al. 2003), market co-movement approach (Christoffersen et al. 2014, Reboredo 2018), or M-V framework (Huberman & Kandel 1987, Belousova & Dorfleitner 2012b). Second, to my knowledge, this chapter is the first study into the diversification benefits of precious metals for global portfolios (i.e. the G7 markets), whereas the majority of the previous studies exclusively concentrate on the U.S. market (Conover et al. 2009, Figuerola-Ferretti & McCrorie 2016b). Third, by conducting a separate examination of the diversification contributions of spot and future returns of four precious metals, my empirical research offers a complete investigation into the different types of these commodities. This can be explained by a lack of thorough studies on the benefits of diversification for precious metals and their derivatives in the relevant literature. Finally, this chapter examines the diversifier role of precious metals changes during periods of stability and instability by focusing on the global financial crisis of 2008. By doing this, this chapter is expected to provide investors and portfolio managers an extensive reference when deciding to invest in precious metals with the purpose of portfolio diversification, especially for risk averters, in the case of future financial crises.

Chapter 4 - The Tail Dependence Structure between Precious Metals and International Stock Markets computes the bivariate and multivariate tail dependence coefficients between stocks of G7 and BRICS markets and precious metal markets across various phases of the global crisis of 2008 by applying copula functions. This chapter

makes an addition to the current literature in the following significant ways. First, by selecting suitable vine copulas, I capture the tail dependence pattern in the most effective way. Second, to the best of my knowledge, this chapter is the first work to use hierarchical Archimedean copulas to estimate the multivariate tail dependence coefficients between each precious metal and a total of twelve stocks from the G7 and BRICS countries. The empirical results from vine copulas and hierarchical Archimedean copulas help to revisit the safe-haven properties of precious metals against the extreme movements of stock returns. This finding may give investors helpful suggestions for the making-decision process of portfolio allocation under extreme market scenarios. Third, the changes in the tail dependence structure across various periods have been analyzed in order to test the impacts of the global financial crisis of 2008 on the extreme co-movements between precious metals and stock markets.

1.3 Thesis structure

The rest of the thesis is organized as follows. Chapter 2 investigates the time-varying dynamics of the precious metal markets. By employing a mixed data sampling technique, this chapter identifies the impact of macroeconomic and financial drivers from G7 and BRICS countries on the daily volatility and pairwise correlation of gold, silver, platinum, and palladium. Chapter 3 revisits the role of precious metals as good diversifiers for a traditional portfolio of stocks, bonds, cash, and currencies, as well as the impact of the global financial crisis of 2008 on that contribution. In this chapter, a stochastic spanning methodology ([Arvanitis et al. 2019](#)) has been applied to test whether the traditional portfolio spans the portfolio augmented with all four precious metals in the G7 countries. Next, a study on the tail dependence structure between precious metals and stock markets of G7 and BRICS countries by applying both bivariate copulas (pair-vine copulas) and multivariate copulas (hierarchical Archimedean copulas) has been conducted in Chapter

4. Finally, Chapter 5 concludes with a summary of the main findings and implications of the thesis.

Chapter 2

ECONOMIC DRIVERS OF VOLATILITY AND CORRELATION IN PRECIOUS METAL MARKETS

In addition to market supply and demand, economic activities affect considerably the dynamic movements of the precious metal markets. This chapter aims to investigate the time-varying dynamics of the precious metal markets. A mixed data sampling technique was employed to identify the impact of macroeconomic and financial drivers from G7 and BRICS countries on the daily volatility and pairwise correlation of gold, silver, platinum, and palladium. The empirical results reveal that the U.S. and Chinese economies, in particular, influence the precious metal markets, but in opposite directions. The stock markets and trade balance of both G7 and BRICS countries, as well as the consumer confidence of G7 countries, are the key drivers for the volatility of precious metals. The

most influential drivers for correlation are stock markets, money supply, and the inflation rate. Surprisingly, the economic policy uncertainty does not affect the dynamics as much as expected. Lastly, the global financial crisis of 2008 affected the direction of most macroeconomic and financial drivers. These findings could suggest both investors and portfolio managers in making optimal decisions based on forecasting changes in macro-finance activities.

2.1 Introduction

The precious metal markets are highly volatile and difficult to predict. Therefore, the proper modeling of the volatility and correlation dynamics is crucial in these markets. Investors and portfolio managers can make better investment decisions if they are provided with a more accurate depiction of the dynamics, including the volatility as well as the correlation, of precious metals markets. Many studies reveal that in addition to being influenced by supply and demand dynamics, the volatility and correlation of markets for precious metals, are also linked to changes in economic activity ([Anson 2008](#), [Belousova & Dorfleitner 2012a](#)). In particular, macroeconomic and financial variables are well-known as the key potential drivers of dynamic movements in precious metal markets ([Tully & Lucey 2007a](#), [Batten et al. 2015](#), [Mo et al. 2018](#)). Another important economic variable linked to high volatility markets like precious metals is Economic Policy Uncertainty (EPU), which has also attracted considerable attention ([Li & Lucey 2017](#), [Huynh 2020](#)). However, up to now, the frequency mismatching problem between economics and precious metal data has caused the fact that the prior studies predominantly focus on only a single driver or a small number of given macro-finance variables.

There are a few papers that analyze the time-varying correlation between the precious metals themselves ([Sensoy 2013](#), [Klein 2017](#)). However, the problem of inter-connectedness between precious metal markets is still somehow unexplored in academic literature.

Accordingly, many prior works have considered the drivers of dynamic correlations between precious metals and traditional assets (Mensi et al. 2013, Šimáková 2011, Apergis 2014, Jain & Biswal 2016a, Klein et al. 2018) but so far there is no study that mentions to the drivers of correlations between precious metals together.

This chapter can effectively solve the frequency mismatch problem by applying the generalized autoregressive conditional heteroskedasticity mixed data sampling model (GARCH-MIDAS, Engle et al. 2013) and the dynamic conditional correlation mixed data sampling model (DCC-MIDAS, Colacito et al. 2011). The main advantage of the GARCH-MIDAS and DCC-MIDAS models is that they separate the volatility and correlation, respectively, into the long-term and short-term components. In addition, the advancements in GARCH- and DCC-MIDAS models allow for considering the impact of exogenous variables on the respective long-term component (Conrad et al. 2014, Asgharian et al. 2015). In the context of this chapter, the monthly data of economic variables from G7 and BRICS countries are used as the data sources of exogenous variables, while daily data of four precious metals with both spot and future returns are collected to compute volatility and correlation. This dataset covers a long period from 1998 to 2018 and it is divided into three sub-periods related to the 2008 global financial crisis: the pre-crisis period (March 1998—August 2007), the crisis period (September 2007—December 2010) and the period following the crisis (January 2011—September 2018), respectively, to study the impact the global financial crisis on the macro-finance drivers of precious metal markets.

The primary objective of this chapter is to analyze the impact of the most important economic and financial drivers on the time-varying volatility and correlation of precious metal markets. The results indicate the inverse impact of economic drivers from G7 and BRICS countries, most notably between the U.S. and China. Among the considered eco-

conomic and financial factors, stock market returns, interest rates, and consumer confidence are identified as the most helpful predictors for modeling volatility and correlation. In addition, the trade balance growth is the most important variable in driving dynamic volatility, whereas money supply and inflation rate are important determinants of long-term correlation between precious metals. Notably, the global financial crisis of 2008 had a significant impact on the influence of economic and financial drivers on the dynamics of the precious metal markets, as many drivers changed the direction of their impact after the crisis.

The rest of this chapter is organized as follows. Section 2.2 gives an overview of the existing literature. Section 2.3 describes the methodology. The data and the results will be explained in section 2.4. Section 2.5 concludes and discusses the implications of this research.

2.2 Literature review

The issue of what determines precious metal prices has been addressed in various studies, especially after the global financial crisis of 2008 (Radetzki 1989, Kucher & McCoskey 2017). However, the factors determining the volatility of the market for precious metals are less well-known. In addition, a study on the determinants of pair-wise correlation within precious metal markets is lacking.

Among the existing literature, the first strand focuses on the role of macroeconomic fundamentals in the dynamic movements of the volatility and correlation of precious metal markets. Batten et al. (2015) investigates the monthly price volatility of precious metals based on macroeconomic determinants, including the business cycle, monetary environment, and financial market sentiment. They conclude that whereas monetary variables can explain the volatility of gold, they cannot explain the volatility of silver. Moreover, the same macroeconomic factors do not jointly influence the price series of all

four precious metals. The impact of macroeconomic fundamentals seems much stronger on palladium than on other precious metals.

In addition, [Mo et al. \(2018\)](#) finds that the economic activities and the monetary environment (GDP, Inflation Rate, and M2) show a significant and positive relation with precious metals in China and India. Moreover, the authors show that the volatility of macroeconomic variables causes an increase in the volatility of precious metal futures.

Contrary to the two above-mentioned studies, [Fang, Yu & Xiao \(2018\)](#) solely pay attention to identifying the economic drivers of the long-term volatility of the gold futures market in the U.S. by employing the GARCH-MIDAS method. The results show that the macroeconomic variables have a significant impact on gold volatility during and after the GFC of 2008. More specifically, Economic Policy Uncertainty, Employment Rate, and Inflation Rate have a positive effect on the long-run volatility of gold futures, while the effects of Capacity Utilization, Diffusion Index, New Consumer Goods and Materials Orders, and Consumer Confidence are negative and significant.

Similarly, [Nguyen & Walther \(2020\)](#) also applies the GARCH-MIDAS approach to investigate the time-varying volatility patterns of some major commodities, including gold, silver, and platinum. The authors find that the long-term volatility is significantly affected by the level of Global Real Economic Activity, as well as changes in Consumer Sentiment, Industrial Production, and Economic Policy Uncertainty. Moreover, they find that Industrial Production has a negative impact on the long-term volatility of gold and silver.

The rest of the related studies pay more attention to studying the impact of a specific aspect of macroeconomics on precious metal markets, such as GDP ([Radetzki 1989](#)), Money Supply ([Bailey 1988](#)), Business Cycle ([Kucher & McCoskey 2017](#)), Macroeconomic News ([Smales 2017](#)), Industrial Production ([Tully & Lucey 2007b](#)), Inflation ([Gorton](#)

& Rouwenhorst 2006b), Private Inventories (Radetzki 1989), Capacity Utilization and Unemployment Rates (Apergis et al. 2014).

The second strand of literature focuses on the impact of financial variables on the dynamic movements of the volatility and correlation of precious metal markets. Among the financial factors, the short-term interest rate, which is an important tool of monetary policy, affects precious metal returns and volatility through multiple channels (Hammoudeh & Yuan 2008). Therefore, a strong relationship between precious metals and interest rates has been reported in the literature (Fortune 1987, Cai et al. 2001, Hammoudeh & Yuan 2008). In general, most studies conclude that high-interest rates reduce the demand for storing precious metals (Hammoudeh et al. 2015) and have calming effects on the volatility of precious metal markets (Hammoudeh & Yuan 2008, Cai et al. 2001).

In terms of the relationship between exchange rates and precious metals, Ghosh et al. (2004) and Akram (2009) show that commodity prices can be attributed to the influence of changes in exchange rates, especially with respect to the U.S. dollar. Sari et al. (2010) study the relationship between information transmission among the spot prices of precious metals and the U.S. dollar/euro exchange rate. The authors find evidence of a weak long-term equilibrium relationship but strong co-movement in the short run.

Another line of research focuses more specifically on the impact of stock markets on the dynamics of precious metals, but the related literature provides inconclusive findings. Tully & Lucey (2007b) and Creti et al. (2013) find that stock returns negatively affect gold returns and that this impact becomes slower with a decline in equity prices over time. In contrast, Boako et al. (2019) finds a positive association between stock prices and gold.

With the aim of investigating the effects of multiple economic and financial factors on metals price movements, Liberda et al. (2017) uses mixed data sampling methodology to simultaneously study eight possible macroeconomic and financial drivers with various

frequencies in a single model. The results show that the financial variables including Interest Rate, Exchange Rate, Stock Returns, and Crude Oil Returns affect precious metal markets more than macroeconomic variables, such as GDP growth, Inflation, and Industrial Production. Among the financial variables, the equity index has the most significant negative impact on the metals' returns. In addition, the financial variables are better at explaining the movement of the prices of platinum and palladium than that of gold and silver.

A third strand of literature is concerned with the relationship between the time-varying volatility and correlation of the precious metals market with Economic Policy Uncertainty. Due to the fact that precious metals can act as a hedge or safe-haven for stock investment (Baur & Lucey 2010a), precious metals become a key investment possibility when the degree of policy uncertainty in global financial markets rise (Białkowski et al. 2015b, Balcilar et al. 2016). In particular, Fang, Chen, Yu & Qian (2018) and Nguyen & Walther (2020) find that GEPU (i.e., Global Economics Policy Uncertainty) positively affects the volatility of precious metals. More specifically, Nguyen & Walther (2020) show that the changes in GEPU positively affect the long-term volatility of gold and platinum, but not silver. Similarly, Prokopczuk et al. (2019) finds a strong co-movement between commodity market volatility and economic uncertainty, especially during recession periods.

Zhou et al. (2018) also uses DCC-MIDAS, based on the mixed data sampling technique, combining the threshold VAR model in order to provide international evidence on the impact of macroeconomic policy uncertainty on the correlation between gold and the U.S. dollar. The authors conclude that the gold-dollar relationship has not remained constant over time and greatly depends on unpredictable political or economic uncertainty. Moreover, due to the different sources of economic uncertainty, the impact is varied. The results also show that both gold and the dollar, in return, can influence the economic

uncertainty of the U.S. Europe, Russia, and China.

As a very limited literature that provides international evidence on the impact of extreme events such as the 9/11 terrorist attack, the 2008 global financial crisis, the European Debt crisis, and the Brexit vote on the inter-correlation among precious metals, the contributions of [Klein \(2017\)](#) and [Klein & Walther \(2022\)](#) are noteworthy. The authors point out the significant differences in correlation structures between the pair gold/silver and the pair palladium/platinum in connection to market shocks. This study also concludes that gold and silver act as safe havens. However, this result does not hold after 2013. Especially platinum seems to serve as a temporal surrogate safe haven during periods of market turmoil.

2.3 Methodology

In this section, the two-step methodology is presented. The first step relates to the heteroskedasticity process of the return series with the GARCH-MIDAS model ([Engle et al. 2013](#)) and its extended models for assessing the impact of the economic drivers of the conditional volatility of precious metals. The next section gives an overview of the DCC-MIDAS model ([Colacito et al. 2011](#)) and its modifications for analyzing the effect of economic determinants on the dynamic correlations between precious metals themselves.

2.3.1 GARCH-MIDAS model with economic variables

In this section, the GARCH-MIDAS model is employed in order to analyze the volatility drivers. This model disentangles the volatility into a short-term (daily) and a long-term (monthly) component. The variable $r_{i,t}$ is considered the (logarithmic) return, where i and t denote short- and long-run indexes, respectively, e.g., i for day and t for

month, quarter, or half-year. The mean equation of this return is as follows

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}} \varepsilon_{i,t} \quad \forall i = 1, \dots, N_t, \quad (2.1)$$

in which N_t is the number of trading days in the period t and $\varepsilon_{i,t} | \Phi_{i-1,t} \sim \mathcal{N}(0, 1)$ with $\Phi_{i-1,t}$ is the information set up to day $(i - 1)$ of period t . The factors τ_t and $g_{i,t}$ are the long- and short-run variance components, respectively. According to [Engle & Rangell \(2008\)](#), $g_{i,t}$ follows a standard GARCH(1,1) model with unit variance

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t}, \quad (2.2)$$

with non-negativity and stationary conditions $\alpha, \beta \geq 0$ and $\alpha + \beta < 1$.

Compared to the original GARCH model, which has a constant baseline variance, the GARCH-MIDAS model allows the baseline variance to change slowly over time. Following [Engle et al. \(2013\)](#) and model the long-term component τ_t as a slowly varying function of an exogenous variable X_t ,

$$\log(\tau_t) = m + \theta \sum_{k=1}^K \varphi_k(\omega_1, \omega_2) X_{t-k}, \quad (2.3)$$

which is denoted as GARCH-MIDAS-X. Here, K is the number of lags, and m is an intercept of a long-term trend. Notably, the sign and magnitude of coefficient θ denote the direction and size of the impact of an exogenous variable on the long-term volatility of precious metal markets.

The Beta-weighting scheme φ_k is determined by a beta lag polynomial ([Ghysels et al. 2007](#)) as follows

$$\varphi_k(\omega_1, \omega_2) = \frac{(k/K)^{\omega_1-1} (1 - k/K)^{\omega_2-1}}{\sum_{j=1}^K (j/K)^{\omega_1-1} (1 - j/K)^{\omega_2-1}}, \quad (2.4)$$

depending on the parameters $\omega_1, \omega_2 > 1$, the Beta scheme can depict increasing, decreasing, or hump-shaped weights, which sum up to unity. Eventually, the parameters are estimated by Quasi-Maximum-Likelihood-Estimation (QMLE, [Engle et al. 2013](#)).

2.3.2 DCC-MIDAS model with economic variables

The DCC-MIDAS model proposed by [Colacito et al. \(2011\)](#) is a natural extension and combination of the DCC model ([Engle 2002](#)) and the GARCH-MIDAS model that allows us to decompose the short- and long-run correlation components by the mixed data sampling approach.

Assuming that the n -dimensional vector of returns r_t follows the process

$$\begin{aligned} r_t &\stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(\mu, C_t), \\ C_t &= D_t \Omega_t D_t, \end{aligned} \tag{2.5}$$

where μ is the vector of unconditional means, C_t is the conditional covariance matrix, D_t denotes a diagonal matrix with standard deviations on the diagonal, and Ω_t represents the conditional correlation matrix of returns on time $(t - 1)$ information:

$$\begin{aligned} \Omega_t &= E_{t-1}[\eta_t \eta_t^i], \\ \eta_t &= D_t^{-1}(r_t - \mu), \end{aligned} \tag{2.6}$$

where η_t is the standardized residuals. Hence, $r_t = \mu + C_t^{1/2} \eta_t$ with $\eta_t \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, I_n)$.

Equation 2.5 suggests a two-step model specification strategy. It means that D_t is first specified by estimating the GARCH-MIDAS model as in equation 2.2. The standardized residuals then $\eta_{i,t}$ are extracted. After that, the DCC-MIDAS parameters are estimated. To be more specific, I initially calculate the conditional statistics, which are denoted as $q_{ij,t}$ (i.e. the short-run correlation between asset i and asset j at time t). The $q_{ij,t}$ are

the elements of the $(n \times n)$ -dimensional quasi-correlation matrix Q_t

$$q_{ij,t} = \bar{\rho}_{ij,t}(1 - a - b) + a\eta_{i,t-1}\eta_{j,t-1} + bq_{ij,t-1}, \quad (2.7)$$

where $\bar{\rho}_{ij,t}$ is the slowly moving long-term correlation between asset i and asset j . Here, following [Conrad et al. \(2014\)](#) and model the long-term correlation using a Fisher- z transformation:

$$\bar{\rho}_{ij,t} = \frac{\exp(2z_{ij,t}) - 1}{\exp(2z_{ij,t}) + 1}, \quad (2.8)$$

where $z_{ij,t}$ is driven by an exogenous variable X_t . This study does not present the formula from the realized correlation framework of [Colacito et al. \(2011\)](#) here, as it focuses on the effects of macroeconomic and financial drivers on the dynamic correlation only,

$$z_{ij,t} = c + \gamma \sum_{k=1}^K \varphi_k(\omega_1, \omega_2) X_{t-k}. \quad (2.9)$$

The weighting scheme $\varphi_k(\omega_1, \omega_2)$ is defined as the equation 2.4 of section 2.3.1. The parameter γ measures the effect of the exogenous variables on the long-run correlations between the precious metals. In particular, the sign of γ reveals whether a rise in the relevant economic factors can lead to an upward or downward trend in the long-term correlation among precious metal markets.

Finally, the conditional correlation matrix is given as

$$\Omega_t = \text{Diag}(Q_t)^{-1/2} Q_t \text{Diag}(Q_t)^{-1/2}. \quad (2.10)$$

This chapter also follows [Colacito et al. \(2011\)](#) and [Conrad et al. \(2014\)](#) in terms of estimation and uses the QMLE to estimate the coefficients of the dynamic correlation model.

2.4 Empirical applications

2.4.1 Data and variables

The data consists of daily spot and futures (one month) price series of gold, silver, platinum, and palladium, which are obtained from Thomson Reuters Datastream. Both spot and futures prices are used to account for their different dynamics (Pindyck 2001).

Tables 1 and 2 summarize the descriptive statistics for the daily spot and futures returns, respectively. These two tables include the statistics for the full sample period and the financial crisis-related sub-periods. The results show that the mean and standard deviation values of the spot returns of each precious metal are similar to those of their futures returns. The mean is small and positive for most return series in both full samples and sub-samples, with the exception of platinum and palladium during the 2008 global financial crisis. Interestingly, gold returns exhibit the highest mean but the lowest volatility during the crisis, reflecting the safe-haven role (Baur & Lucey 2010a). Tables 1 and 2 also report the results of skewness and kurtosis. The skewness is negative, while the kurtosis values are above three for the majority of return series, indicating a non-normally, leptokurtic distribution, which is also confirmed by a Jarque-Bera statistical test.

In addition to the descriptive statistics, the p -values of Ljung-Box (LB) statistics of order 15 for the returns series show the existence of auto-correlation in most of them. For the squared returns series, however, p -values of LB are highly significant, which reveals a long-range serial dependence. This result is confirmed by the results of the ARCH test, hence motivating my decision to use the GARCH model to filter the daily returns.

Following the literature review in the section 2.2, a set of exogenous variables is selected with respect to data availability. These exogenous variables are divided into three categories: Macroeconomic variables, Financial variables, and Economics Policy Uncertainty (see Table 11 in the Appendix). However, the distinction between economic

and financial variables is not mutually exclusive as some of the financial variables can also be regarded as economic variables and vice versa (e.g., the EPU or the exchange rates). The monthly data for the macroeconomic and financial variables are retrieved for twelve countries (i.e., G7 and BRICS) from March 1998 to August 2018 from Thomson Reuters Datastream, the FRED database at the Federal Reserve Bank of St. Louis, the OECD database, and the World Bank database. Additionally, monthly data of EPU indices are collected from <https://www.policyuncertainty.com>. In order to ensure consistency between countries and to remove the potential adverse impact of different currencies, the macroeconomic variables used in this chapter are index variables calculated according to the same formula or transformed in terms of growth variables.

Table 1: Descriptive statistics of spot returns of four precious metals

	Mean	Stdev	Skewness	Kurtosis	J.B.	Q(15)	Q ² (15)	ARCH(15)
Panel A: Spot return								
<i>Full sample</i>								
gold	0.032	1.073	0.085	6.226	0.000	0.010	0.000	0.000
silver	0.032	1.803	-0.523	6.573	0.000	0.012	0.000	0.000
platinum	0.023	1.406	-0.296	4.950	0.000	0.035	0.000	0.000
palladium	0.049	2.092	0.016	5.091	0.000	0.000	0.000	0.000
<i>pre-crisis</i>								
gold	0.038	0.985	0.183	7.786	0.000	0.009	0.000	0.000
silver	0.038	1.568	-0.907	6.443	0.000	0.041	0.000	0.000
platinum	0.058	1.379	-0.004	6.009	0.000	0.010	0.000	0.000
palladium	0.040	2.264	0.295	5.934	0.000	0.001	0.000	0.000
<i>crisis</i>								
gold	0.091	1.793	0.300	2.099	0.000	0.129	0.000	0.000
silver	0.028	2.839	-0.147	3.878	0.000	0.441	0.005	0.000
platinum	-0.057	2.316	-0.795	2.347	0.000	0.209	0.000	0.000
palladium	-0.120	2.641	-0.532	3.004	0.000	0.319	0.022	0.000
<i>post-crisis</i>								
gold	0.018	1.023	-0.227	4.872	0.000	0.006	0.000	0.000
silver	0.026	1.835	-0.416	5.523	0.000	0.030	0.000	0.000
platinum	0.001	1.257	-0.138	1.810	0.000	0.058	0.000	0.000
palladium	0.081	1.809	-0.235	2.252	0.000	0.057	0.000	0.000

Note: The table shows the descriptive statistics for the daily returns series of four precious metal spots over the whole sample period (Mar 02, 1998, to Aug 31, 2018) and three sub-sample periods, including pre-crisis (Mar 02, 1998, to Aug 31, 2007), crisis (Sept 03, 2007, to Dec 31, 2010) and post-crisis (Jan 03, 2011, to Aug 31, 2018), respectively. J.B. refers P-value of the Jarque-Bera test for normality. Q(15) and Q²(15) denote the Ljung-Box Q-test statistics for auto-correlation in the return and squared return series, respectively, up to 15 lag. Furthermore, ARCH(15) is the Engle (1982) LM test for ARCH effects up to 15 lags.

Table 2: Descriptive statistics of future returns of four precious metals

	Mean	Stdev	Skewness	Kurtosis	J.B.	Q(15)	Q ² (15)	ARCH(15)
Panel B: Futures one month return								
<i>Full sample</i>								
goldF	0.032	1.088	0.049	6.815	0.000	0.004	0.000	0.000
silverF	0.033	1.867	-0.628	6.919	0.000	0.235	0.000	0.000
platinumF	0.024	1.458	-0.957	7.542	0.000	0.004	0.000	0.000
palladiumF	0.049	2.085	-0.014	5.383	0.000	0.000	0.000	0.000
<i>pre-crisis</i>								
goldF	0.038	0.999	0.336	7.839	0.000	0.040	0.000	0.000
silverF	0.039	1.625	-0.882	7.711	0.000	0.058	0.000	0.000
platinumF	0.059	1.441	-1.665	5.283	0.000	0.000	0.000	0.000
palladiumF	0.040	2.232	0.185	6.607	0.000	0.001	0.000	0.000
<i>crisis</i>								
goldF	0.090	1.733	0.297	2.631	0.000	0.049	0.000	0.002
silverF	0.027	2.863	-0.311	3.432	0.000	0.239	0.000	0.000
platinumF	-0.058	2.363	-0.591	1.964	0.000	0.294	0.000	0.000
palladiumF	-0.122	2.635	-0.339	3.347	0.000	0.204	0.000	0.000
<i>post-crisis</i>								
goldF	0.018	1.056	-0.385	6.198	0.000	0.015	0.000	0.000
silverF	0.028	1.914	-0.558	6.095	0.000	0.077	0.000	0.000
platinumF	0.001	1.301	-0.100	1.669	0.000	0.013	0.000	0.000
palladiumF	0.082	1.835	-0.183	2.211	0.000	0.217	0.000	0.000

Note: See Table 1. goldF, silverF, platinumF, and palladiumF denote gold future 1M return, silver future 1M return, platinum future 1M return, and palladium future 1M return, respectively.

2.4.2 Results and discussions

This section first tests the impact of various macroeconomic and financial drivers on the conditional volatility of each precious metal and six pairs of correlations of four major precious metals¹ in our sample by employing the GARCH-MIDAS-X model and DCC-MIDAS-X model, respectively.

In the first step, standard and asymmetric GARCH and GARCH-MIDAS variants are estimated in order to check whether a decomposition in short- and long-term volatility components is actually useful. For all metals, the GARCH-MIDAS model using monthly realized volatility as a driver of long-term volatility outperforms the other variants in terms of the Bayesian Information Criterion (BIC). For platinum only, the GJR-MIDAS-RV has a slightly better BIC. All the comparison results are reported in Table 3. Additionally, $K = 36$ (i.e. three years of monthly observations) is determined as the optimal lag length for the MIDAS component with regard to the BIC.

In the following sub-sections, the impact of the various macroeconomic and financial variables on the dynamic volatility and correlation of precious metals is analyzed. This part focuses on the statistical significance of coefficients θ in equation 2.3 and γ in equation 2.9, which determine the size and direction of the impact of an exogenous variable on the long-term volatility and inter-correlation of precious metals, respectively. Accordingly, the signs of θ and γ reveal whether an upside or downside trend in the long-term volatility and correlation can be caused by an increase in the respective economic variables.²

Macro-finance drivers of precious metals volatility and correlation - opposite evidence between the U.S. and China

Due to the escalating tension between the U.S. and China after 2018 and its subsequent

¹gold-silver (G-S), gold-platinum (G-Pl), gold-palladium (G-Pa), silver-platinum (S-Pl), silver-palladium (S-Pa) and platinum-palladium (Pl-Pa).

²An alternative approach is presented by [Walther et al. \(2019\)](#) for the case of cryptocurrencies. Instead of statistical inference, the authors focus solely on the predictive accuracy of volatility drivers.

Table 3: Parameter estimation results of GARCH, GJR, GARCH-MIDAS-RV and GJR-MIDAS-RV

Asset	Model	μ	α	β	m	LL	BIC
gold	GARCH	0.0158	0.0508***	0.9366***	0.1970	-6624.20	13282.13
	GJR	0.0249*	0.0678***	0.9392***	0.2277	-6612.13	13266.40
	GARCH-MIDAS-RV	0.0201	0.0288***	0.9664***	0.1212	-5576.00	<i>11209.67</i>
	GJR-MIDAS-RV	0.0280*	0.0405**	0.9604***	0.0376	-5909.39	11263.80
silver	GARCH	0.0034	0.0408***	0.9531***	1.1818***	-8973.04	17979.80
	GJR	0.0130	0.0552***	0.9510***	1.2803***	-8966.31	17974.76
	GARCH-MIDAS-RV	0.3387***	0.0899***	0.9101***	-0.0440***	-8565.24	<i>17188.16</i>
	GJR-MIDAS-RV	0.0322	0.0864***	0.8613***	0.6445***	-8669.08	17208.46
platinum	GARCH	0.0153	0.0718***	0.9101***	0.7567***	-7811.90	15657.51
	GJR	0.0221	0.0843***	0.9092***	0.7828***	-7809.45	15661.06
	GARCH-MIDAS-RV	0.0143	0.0946***	0.8457***	0.1896*	-6315.86	<i>12689.40</i>
	GJR-MIDAS-RV	0.0158	0.0982***	0.8500***	0.1981*	-6315.69	12697.29
palladium	GARCH	0.0764***	0.0778***	0.9100***	1.6448***	-9565.36	19164.44
	GJR	0.0740***	0.0757***	0.9095***	1.6384***	-9565.23	19172.62
	GARCH-MIDAS-RV	0.0601***	0.0279***	0.9155***	1.2577***	-8084.97	<i>16227.63</i>
	GJR-MIDAS-RV	0.0465*	0.0703***	0.9183***	1.2206*	-8384.70	16822.96
goldF	GARCH	0.0199	0.0456***	0.9407***	0.2060	-6720.80	13475.34
	GJR	0.0258*	0.0571***	0.9410***	0.2307	-6716.34	13474.83
	GARCH-MIDAS-RV	0.0260*	0.0406***	0.9459***	0.3078*	-5664.93	<i>11387.54</i>
	GJR-MIDAS-RV	0.0278*	0.0392***	0.9605***	0.3870*	6011.17	12072.15
silverF	GARCH	0.0114	0.0385***	0.9540***	1.2137***	-9149.26	18332.24
	GJR	0.0198	0.0506***	0.9529***	1.2944***	-9143.54	18329.23
	GARCH-MIDAS-RV	0.0387*	0.0727***	0.8404***	0.7658***	-7782.28	<i>15622.23</i>
	GJR-MIDAS-RV	0.0375*	0.0802***	0.8713***	0.7274***	-8207.01	16487.18
platinumF	GARCH	0.0183	0.0589***	0.9262***	0.7318***	-7887.02	15807.76
	GJR	0.0225	0.0660***	0.9254***	0.7519***	-7883.11	15804.38
	GARCH-MIDAS-RV	0.0151	0.0569***	0.9237***	0.4255***	-6447.86	<i>12953.41</i>
	GJR-MIDAS-RV	0.0159	0.0585***	0.9237***	0.4310**	-6447.82	12961.56
palladiumF	GARCH	0.0759***	0.0778***	0.9060***	1.6166***	-9634.40	19302.53
	GJR	0.0774***	0.0791***	0.9061***	1.6193***	-9634.36	19310.87
	GARCH-MIDAS-RV	0.0692**	0.0759***	0.8892***	0.9678***	-7816.59	<i>15690.86</i>
	GJR-MIDAS-RV	0.0788**	0.0798***	0.9070***	0.1064*	-8464.81	16918.54

Note: This table presents the estimates of GARCH(1,1), GJR(1,1,1), GARCH(1,1)-MIDAS-RV and GJR(1,1,1)-MIDAS-RV general coefficients, respectively for both spot returns and future 1-month returns of four precious metals. The full sample covers the period from 1998 to 2018. The symbols ***, **, and * denote statistical significance at the levels of 1%, 5% and 10%, respectively. LL is the Log-Likelihood and BIC is the Bayesian Information Criterion. Numbers in italics and bold show the model with the best goodness-of-fit (i.e. lowest BIC) and best statistical fit (i.e. highest LL), respectively.

persistent headwind for all financial markets, this section starts with a focus on these two countries.

In general, the results in Tables 4, 5 and 6 show that Chinese economic drivers have less impact on volatility and correlation among precious metals pairs than their U.S. counterparts. In addition, the long-term volatility of gold and long-term correlations of the gold-silver and platinum-palladium pairs appear to be the most affected by economic variables. This finding is consistent with that of Klein (2017), which represents significant differences in correlation structures for two groups of precious metals: (1) gold and silver as investment assets and (2) palladium and platinum as mainly industrial metals.

Interestingly, the results reveal a totally contrary scenario between the U.S. and China in terms of the impact of almost all macro and financial drivers on the precious metals return volatility and their pairwise correlations. A few exceptions have a similar directional impact for volatility: EPU growth (positive impact), Exchange rate (negative impact), and gold & Foreign Reserves growth (positive impact); and on correlation: import growth.

Table 4 shows that the effect of Consumer Confidence on both volatility and correlation can be observed more clearly. This U.S. indicator has a negative impact on long-term volatility and a positive one on the inter-correlation of most precious metals. Meanwhile, the figure for China from Table 5 shows no effect on any precious metals volatility or correlation. China's Composite Leading Indicator (CLI) seems to have been an important determinant of precious metals volatility except for gold, but the U.S. CLI does not indicate any statistically significant effect. Additionally, the long-run volatility of precious metals is significantly affected by the foreign trade of both countries. However, Chinese export growth has more influence on volatility than that of the U.S., whereas the import growth of China has less impact on volatility than that of the U.S. This result can be

explained by China's dominance in exporting rare metals. This country produced around 90% of the world's rare earth metals in 2019.³ Meanwhile, the U.S. remains one of the world's top importers of precious metals, although the U.S. has recently made it a priority to diversify its sources of rare metals in order to reduce its dependence on China.⁴

Notably, all four precious metals in both spot and future returns react significantly and negatively to the U.S. stock market returns. In contrast, only the long-term volatility of spot precious metal returns has a significantly positive response to the stock returns in China. This result indicates that, in the long term, an upward trend of stock returns in the U.S. would help to stabilize precious metal markets. However, this is not true for the Chinese stock market because almost all θ coefficients of the Chinese stock returns are insignificant. Concerning correlation, Table 6 reveals that the U.S. stock market returns are positively associated with almost all correlation pairs between precious metals spot returns. Meanwhile, their Chinese counterparts do not appear to affect any conditional correlation. These findings are similar to the conclusion of Uddin et al. (2020) regarding the key role of the largest stock market (i.e. the U.S. market, which has over 5000 listed firms) in driving the precious metal markets. In contrast, the Chinese stock market shows poor long-run performance. It has not been as prominent as the banking sector in financing firms and promoting economic growth in China and globally. In addition, many companies, especially mining companies, are publicly listed, but none are listed in the domestic market. Finally, several other factors also show an opposite impact between the U.S. and China on the dynamic correlation levels among precious metal returns (e.g. M1, M2, and inflation).

The global financial crisis of 2008 and macro-finance drivers of precious metals volatility and correlation

³<https://www.investopedia.com/insight/chinese-mining-companies/>

⁴<https://www.visualcapitalist.com/chinas-dominance-in-rare-earth-metals/>

Table 4: Coefficients θ of economics variables of the U.S.

Assets	gold	goldF	silver	silverF	platinum	platinumF	palladium	palladiumF
<i>Macroeconomic variables</i>								
M1 Growth		-0.1345**	-0.9366**	-0.8870**		0.1692*		
M2 Growth	0.4923**	0.6750*	0.2682**	0.3155**			0.2331*	
Inflation Rate	0.4079*	0.2641*				0.0989*		0.1749*
Unemployment Rate	0.0974*	0.0858**			0.0663*		-0.1251*	-0.1251*
Saving Ratio	-0.1909**		-0.2569**		-0.0796***	0.0658*		
Capacity Utilisation	-0.0512*						-0.0881*	-0.0881*
Industrial Production	-0.0494**	-0.0411**		-0.1195**	-0.1718***		-0.0710***	-0.0645***
Consumer Confidence	-0.2731***		-0.2762***	-0.3054***	-0.1691**	-0.1754**	-0.2116***	
Composite Leading Indicator							-0.1630*	
Export Growth	0.4668*	-0.0548*			-0.1999**	-0.0762***	-0.1011**	
Import Growth	0.4283*		0.7013*	0.8101*	-0.2011**		0.1029**	
gold&Foreign Reserves	0.1813**	0.1813**	0.4138**	0.5142**		0.0749**	0.2495**	0.2495**
<i>Financial variables</i>								
Stock market	-0.0775**	-0.0652***		-0.0569**	-0.3542***	-0.2593**	-0.0395***	-0.5079***
Bond market							0.0802*	0.2028**
Interest Rates		0.1978*						
Interbank 3M Rates	0.1677**			-0.3911***			0.1647***	0.1475***
T-bill 3M Rates					0.0923*		0.1685***	
Exchange Rates	-0.0313**	-0.0304**	-0.0492***	-0.0527***			0.0158***	
<i>FPU</i>					0.2242***			

Note: The table reports estimated results for parameters θ of macroeconomic and financial variables of the U.S. from the GARCH(1,1)-MIDAS-X model. The symbols ***, **, and * denote statistical significance at the levels of 1%, 5%, and 10%, respectively. Otherwise, the field is left blank.

Table 5: Coefficients θ of economics variables of China

Assets	gold	goldF	silver	silverF	platinum	platinumF	palladium	palladiumF
Macroeconomic variables								
M1 Growth		0.3164*		-0.0730**		0.3275***		0.1788***
M2 Growth	0.6364**						3.7941***	
Inflation Rate	0.1505***		0.2840***	0.1989**				
Unemployment Rate	1.2893**	1.6245***	2.1366***	2.1216***			2.5641***	2.2086**
Saving Ratio								
Capacity Utilisation								
Industrial Production								
Consumer Confidence								
Composite Leading Indicator			-0.1976***	-0.2054***	-0.1848**	-0.1635*	-0.2376***	-0.1906***
Export Growth	0.2379***	0.2070***	0.4766*	0.5682*	0.0495**			0.0199***
Import Growth			0.6376***	0.6859***				
gold&Foreign Reserves	0.1892*	0.0638**		0.0897***	0.9346*		-0.0714**	
Financial variables								
Stock market	-0.0230*		0.2049*		0.1382***	0.1567***	-0.0953**	
Bond market								
Interest Rates	0.5162***			-4.0609**		0.2120*		
Interbank 3M Rates								
T-bill 3M Rates								
Exchange Rates	-0.0252***	-0.0219***	-0.0201***					
EPU					0.0489***			

Note: Note: The table reports estimated results for parameters θ of macroeconomic and financial variables of China from the GARCH(1,1)-MIDAS-X model. The symbols ***, **, and * denote statistical significance at the levels of 1%, 5%, and 10%, respectively. Otherwise, the field is left blank.

Table 6: Coefficients γ of economic variables of the U.S. and China

Pairs of Assets	gold-silver		gold-platinum		gold-palladium		silver-platinum		silver-palladium		platinum-palladium	
	US	China	US	China	US	China	US	China	US	China	US	China
Macroeconomic variables												
M1 Growth	0.3568**		0.6277***	-1.0963**			0.5191***				0.4717**	
M2 Growth	0.9507*	-1.1396***		-1.1596***	-1.1347*			-0.1537***			-0.6549***	
Inflation Rate	-0.1382**	0.8183***	-1.2895***				-0.2543**	0.1238**		0.1377***		
Unemployment Rate							0.8990***	0.9423***				
Saving Ratio												
Capacity Utilisation	0.1139*		0.3390*								0.3466*	
Industrial Production			0.3386**									
Consumer Confidence	1.5113**		1.9844***		1.7165**		1.4700*		1.7635*		2.7214**	-2.7959**
Composite Leading Indicator			1.5281*	1.7337*								1.2851*
Export Growth	-0.1739*				0.1772**							
Import Growth	-0.1969**	-1.0317***						-0.1161**	0.1812**			
gold&Foreign Reserves		-0.1214**		-0.2788***							0.11599*	0.5301***
Financial variables												
Stock market	0.1486*		0.1774**		0.0996***				0.0854**		0.1019***	1.1359***
Bond market			0.9956***									
Interest Rates	-0.0745**		-0.1362***		-0.1007*							
Interbank 3M Rates		-0.0700**						-0.1059**	-0.5612***			-0.2331***
T-bill 3M Rates								-0.1102**				
Exchange Rates												0.4757**
EPU												-0.0138***

Note: The table shows estimation results γ of macro-finance drivers of the U.S. and China from the DCC-MIDAS-X model. The asterisks ***, **, and * denote significance at 1%, 5%, and 10%, respectively. Otherwise, the field is left blank.

The safe-haven ability of precious metals against market shocks, such as the 2008 global financial crisis, is proven in many prior works (Baur & Lucey 2010a, Batten et al. 2015). Furthermore, Morales & Andreosso-O'Callaghan (2011b) suggests that the precious metal markets are less influenced by times of market stress than other financial markets. Therefore, this section uses a sub-period analysis, still focusing on the U.S. and China, to investigate any change in the role of economic drivers of precious metals across the various phases of the global financial crisis of 2008. Tables 7 and 8 report the estimated results of the potential drivers from the U.S. and China of volatility in precious metal futures over three periods of the 2008 crisis, while Tables 9 and 10 for correlation. This selection arises as future contracts on precious metals have become the most widely used instruments for risk management in more volatile periods. The U.S. and China have played an important role in global derivatives trading for metals (Klein & Todorova 2021).

Generally, the period after the 2008 global financial crisis witnessed a greater number of economic determinants in China affecting the long-term volatility of all four precious metals as well as their correlation compared to other periods (i.e. there are more significant coefficients of θ and γ). In addition, the opposite trend can be seen between the signs of significant coefficients θ and γ of several drivers in China during the crisis and after the crisis. More specifically, some economic drivers of China make pair-correlations turn from positive to negative (e.g., M1 on the goldF-platinumF and goldF-palladiumF) or the reverse (e.g., M2 on platinumF-palladiumF). These findings align with the conclusion of Agyei-Ampomah et al. (2014), who find that the prominent role of precious metals is to protect investors' wealth against shocks in the U.S. financial market. One possible explanation is that the demand for precious metals has increased in emerging countries like China, which have not been strongly affected by the financial crisis. This evidence

Table 8: Coefficients θ of economic variables of China over three sub-periods of the global financial crisis of 2008

Assets	goldF		silverF		platinumF		palladiumF		
	Pre.	Post.	Pre.	Post.	Pre.	Post.	Pre.	Post.	
<i>Macroeconomic variables</i>									
M1 Growth	-0.9797**	-0.7815***			5.0030**	-0.6633**	2.8881**	0.4993**	0.0482**
M2 Growth	-1.0026***				5.0078***	4.4239**			
Inflation Rate	0.2282***	0.3384*	-0.3139**	-0.2140**	-0.1072**	0.3529***			
Unemployment Rate	0.1085***	0.5031***	1.1528***		0.1099**		-0.7097**		
Saving Ratio									
Capacity Utilisation									
Industrial Production									
Consumer Confidence		-0.3606**			-0.1051**			-0.1001***	
Composite Leading Indicator	-0.1041***	-0.3842***		-0.5557***	-0.2022*	-0.9907***		-0.1001***	-1.4815*
Export Growth	0.5091**	0.5005***	0.5141**	0.0990*				-0.0674**	
Import Growth		-0.4602***			-0.1579***	-0.1079*	0.6196***	0.5030***	
gold&Foreign Reserves	0.1145***	0.1370***	0.2192**	0.5627***	0.1955***	0.4796***	0.4398***	1.0010***	0.9180***
<i>Financial variables</i>									
Stock market returns	0.0955*	0.1510***		0.3050***		-1.6245***	0.3307***	-0.3608***	-0.0518*
Bond market returns		-0.6495**		-1.0820***		0.1132***			-0.7091***
Interest Rates		0.5539***				0.0884***	-0.4786**	1.4465**	0.1397*
Interbank 3M Rates									
T-bill 3M Rates									
Exchange Rates	-0.1039***	-0.0368***	-0.1413***						
<i>EPU</i>	-0.0070**	-0.0979***	-0.0015**		0.0106***	-0.0979*	-0.0050***	-0.0113**	-0.1001***

Note:

Table 9: Coefficients γ of economic variables of the U.S. over three sub-periods of the global financial crisis of 2008

Pairs of Assets Periods	goldF-silverF		goldF-palladiumF		goldF-platinumF		silverF-palladiumF		silverF-platinumF		palladiumF-platinumF			
	Pre.	crisis	Post.	Pre.	crisis	Post.	Pre.	crisis	Post.	Pre.	crisis	Post.		
Macroeconomic variables														
M1 Growth	-0.5358	0.7505	-0.3771	-1.7955	1.7138	1.6702	1.1398	1.0211	1.1721	1.1312	0.5250	-0.5866	1.2181	
M2 Growth	-2.7528					-0.0953	1.1712		-0.8140			0.8350		
Inflation Rate					0.9332	-1.0377	-0.1336					0.2356	0.4387	
Unemployment Rate														
Saving Ratio								0.9640						
Capacity Utilisation	1.7927		1.5556		1.3446	-0.1372	1.4774	-0.0963	0.7210		-0.2685	0.9914	0.0193	
Industrial Production	0.4717		1.8865		1.4699		0.3422		0.8095			0.6883	1.6340	
Consumer Confidence			-0.5650		1.3006		1.9444		1.7336			1.0868		
Composite Leading Indicator	48.4845	1.4141	0.5378	0.9870	1.9899	0.4509	0.7966	-0.7738	0.3750	0.0386		3.2115	0.7872	
Export Growth		0.1252	0.3972	1.1659	0.4960	1.3114		0.4645	0.4336		0.4464	1.5078		
Import Growth	0.2478	5.6445	0.2018	0.7123	1.3338	0.6336	1.5653		0.6044					
gold&Foreign Reserves		0.2192	1.0438				0.6474	-0.0931	1.3503		-0.2093			
Financial variables														
Stock market														
Bond market														
Interest Rates	-12.446		1.0907	0.7091	-27.307		1.9066		3.5705		-0.1527	0.1988	-0.1480	
Interbank 3M Rates	0.4258		1.8672		-0.2132	0.0470	-0.3100		-0.1865		-2.8012		-0.1279	
T-bill 3M Rates	7.9615	1.6404	-9.2773	0.8577	-23.022	1.3426	-0.3578		-0.2084	0.3164	0.0860	1.2322		
Exchange Rates			-0.2061	-1.1922	0.5773	-0.9044	1.9272				-0.7224			
<i>FPI</i>	-0.6191		0.0912	-0.2343				0.6190	-0.0055		-0.0063	-0.1557	-0.9037	-0.1054

Note: The table reports estimated results for parameters γ of macroeconomic and financial variables of the U.S. over three sub-periods of the 2008 global financial crisis from the DCC-MIDAS-X model. Three periods include pre-crisis (Mar 1998 to Aug 2007), crisis (Sep 2007 to Dec 2010), and post-crisis (Jan 2011 to Aug 2018). GoldF, silverF, platinumF, and palladiumF denote gold future IM return, silver future IM return, platinum future IM return, and palladium future IM return. The value is given if the parameter γ is statistically significant (i.e., the critical value at the significance level is 10%). Otherwise, the field is left blank.

Table 10: Coefficients γ of economic variables of China over three sub-periods of the global financial crisis of 2008

Pairs of Assets Periods	goldF-silverF		goldF-palladiumF		goldF-platinumF		silverF-palladiumF		silverF-platinumF		palladiumF-platinumF	
	Pre.	Post.	Pre.	Post.	Pre.	Post.	Pre.	Post.	Pre.	Post.	Pre.	Post.
Macroeconomic variables												
M1 Growth	-2.6774	-1.2394	0.6738	-0.0987	0.7189	-0.0860	0.2851				1.2647	-0.1537
M2 Growth			1.4732					0.3078	0.3078		-0.3109	0.2315
Inflation Rate		0.2654		0.2592				0.2215			0.1844	
Unemployment Rate		0.7609		0.6690								
Saving Ratio												
Capacity Utilisation												
Industrial Production												
Consumer Confidence		0.6557	-1.4576		-1.5888				-0.4440	-0.1048	-0.2537	
Composite Leading Indicator	0.9995	1.1891	1.0021		1.9121	1.0008	0.6243		-0.0879	0.6952		0.6286
Export Growth								1.0538		0.4659		0.3466
Import Growth		0.1003	-0.1685	0.8596	-0.1730						1.6200	-0.1466
gold&Foreign Reserves	1.7590	-0.3707	0.6474		1.5735	0.7948						-2.7245
Financial variables												
Stock market		1.2630			-0.5088	0.8928	0.0376		-0.0258		0.0329	1.0091
Bond market								0.9922				-0.1691
Interest Rates			0.3312		0.9830							-1.1517
Interbank 3M Rates												0.9544
T-bill 3M Rates												
Exchange Rates		-0.2724	-0.3934	1.4551	-0.0223		-0.2085			-1.5215		
EPU	-0.0642	-0.8463				-0.0358				-0.1518	-0.1042	
												-1.8683
												-0.0614

Note: The table reports estimated results for parameters γ of macroeconomic and financial variables of China over three sub-periods of the 2008 global financial crisis from the DCC-MIDAS-X model. Three periods include pre-crisis (Mar 1998 to Aug 2007), crisis (Sep 2007 to Dec 2010), and post-crisis (Jan 2011 to Aug 2018). GoldF, silverF, platinumF, and palladiumF denote gold future 1M return, silver future 1M return, platinum future 1M return, and palladium future 1M return. The value is given if the parameter γ is statistically significant (i.e., the critical value at the significance level is 10%). Otherwise, the field is left blank.

denotes the growing influence of China on the global financial market in general and the precious metals market in particular after the financial crisis of 2008.

For the case of the U.S., the signs of the coefficients θ and γ of the macro-finance factors of this country show the most significant change between the pre-crisis and crisis periods compared to other periods. In detail, several drivers of the U.S. turn from negative to positive (e.g., signs of θ of the Export, gold & Foreign Reserves growth or Stock on the long-term volatility of goldF and palladiumF and signs of γ of M1 on goldF-silverF, Exchange Rates on goldF-platinumF and goldF-palladiumF, T-Bill 3M on goldF-platinumF, the Interest rate on palladiumF-platinumF). This result confirms the significant impact on the U.S. economy during the global financial crisis of 2008.

Finally, the long-term volatility of silver futures and the long-term correlations of silver and other metals are the least responsive to any changes in economic variables during the crisis period. Because only the Capacity Utilization and Exchange rate of the U.S. and the gold & Foreign Reserves growth of China influence the volatility of silver futures 1-month, and only the M1 growth of the U.S. impact the correlation of the silver-palladium futures pair, in comparison with non-crisis periods. On the contrary, the volatility of palladium futures is the most strongly influenced by the global crisis of 2008. A similar tendency can be found in platinum volatility under the impact of the economic drivers of China in the case of M2, Inflation, Stock, and Interest rate, apart from gold and silver futures volatility.

Extensive estimation results for other G7 and BRICS countries

This part extends the analysis to other G7⁵ and BRICS⁶ countries, which are top-ranked in precious metal exchanges. Tables 12 to 16 in the Appendix present the estimates of statistically significant θ and γ signs for each macroeconomic and financial variable of

⁵United Kingdom, Canada, Japan, Germany, France, and Italy

⁶Brazil, Russia, India, and South Africa

the ten countries in the entire sample from 1998 to 2018.

Tables 12 and 13 focus on the macroeconomic factors in other G7 and BRICS countries. These tables indicate that neither the export nor the import growth of G7 and BRICS countries affects the correlations between precious metals to a large extent, despite acting as essential drivers of the volatility of precious metals. Here, the influence of the export growth of almost all G7 and BRICS nations on long-term volatility is negative or positive, respectively. More precious metals are affected by the export of BRICS than that of G7 countries. The export growth of Russia is considered the most vital determinant of the long-term volatility of all precious metals in both spot and future returns, followed by the export growth of South Africa, the United Kingdom, and France. With respect to the impact of import growth on precious metals volatility, the strongest positive effect is from India and South Africa. For G7 countries, a varying impact of countries' import growth on volatility is observed, with mostly negative effects.

The Gold & Foreign Reserves Growth of G7 and BRICS appear to be important drivers for long-term volatility but are not applicable for long-term correlations. In particular, table 12 illustrates that the Gold & Foreign Reserves Growth of BRICS has considerably more impact on the volatility of precious metal markets than G7's Gold & Foreign Reserves Growth. This finding is in accordance with the fact that approximately two-thirds of global gold and foreign currency reserves are held by emerging and developing economies⁷. Additionally, the positive figures for most of the statistically significant coefficients of this variable reveal that the rise in gold and foreign currency reserves of countries, especially BRICS, may contribute to the increase in the volatility of the global precious metals market.

Tables 12 and 13 also show that the impacts of the Composite Leading Indicator

⁷https://www.ecb.europa.eu/pub/economic-bulletin/articles/2019/html/ecb.ebart201907_01~c2ae75e217.en.html

(CLI), Consumer Confidence (CC), and Industrial Production (IP) of both G7 and BRICS on volatility are negative, but CLI and CC increase the correlation between precious metals. CLI represents the future expectation of the business cycle. Therefore, the results mean that an increase in the future expectations of real economic activity leads to a decrease in volatility and an increase in correlation. Moreover, the CLI of the United Kingdom and India appears to be more important than the CLI of other countries. The results also suggest that the impacts of CC and the IP of G7 countries on volatility and correlation are much stronger than in BRICS countries. Apart from the positive effects of Russia and Brazil's CC on the long-term volatility of gold, the negative signs of all θ and γ coefficients of CC can be observed. This implies that the increase in consumer confidence, along with the decrease in the volatility and correlation between precious metals returns, may raise diversification benefits among them.

Regarding the variables of the monetary environment (i.e. M1, M2, INF), the results of Table 14 reveal that these variables have a stronger influence on the long-term correlation between precious metals than on their volatility. In addition, the empirical results illustrate that the impact of the money supply growth is much more influential on gold volatility than on any other precious metals, which is reasonable since gold is still regarded as surrogate money. Moreover, according to the money supply, the positive sign of θ of M2 and the negative one of its γ in almost all cases indicate that precious metal prices are more volatile and more closely linked during the recession period (i.e. because an increase in M2 reflects the recession of the economy). Although gold and silver are known as a hedge against inflation (Ghosh et al. 2004), my empirical results show that higher inflation rates in both G7 and BRICS countries explain the rise in the volatility of all four precious metals (except for Japan). Meanwhile, G7 (BRICS) inflation rates have a negative (positive) association with correlation.

In terms of financial variables, the results from Table 15 show the influence of equity market returns on both precious metals volatility and correlation is more considerable than any other financial variables. Notably, the volatility of all the precious metals is negatively linked to the stock market returns of both G7 and BRICS countries. In contrast, the correlations among these metals respond positively to equity market returns⁸. In addition, a mainly positive impact from the government bond returns of the G7 and BRICS countries on volatility as well as on correlation among precious metal markets can be found. With respect to interest rates, it can be seen clearly that while there are varying effects across countries on volatility, the impact on long-term correlations is consistently negative. This could illustrate the decline in correlations between precious metals during periods of high-interest rates. In regard to the impact of the exchange rate, my major finding is a significant but negative effect of the exchange rate of each country on precious metals volatility, while there is a minor impact on correlation.

Finally, Table 16 shows the influence of the EPU growth of each country in the sample on the long-term volatility and correlation of precious metals markets. This analysis reveals that the EPU growth of G7 and BRICS cannot explain the dynamic correlations. In contrast, EPU growth is associated with the volatility of precious metals. Except for the negative impact of the EPU growth of Japan on the volatility of gold, the EPU of all other countries increases the volatility of precious metals. This result aligns with the findings of Fang, Yu & Xiao (2018) and Nguyen & Walther (2020), which point out that EPU positively affects the long-run volatility of precious metals. Notably, the EPU growth of G7 countries seems to have a more substantial effect on volatility than the EPU growth of BRICS. This finding strongly confirms the leading role of the G7 group in shaping the stability of the global financial market in general and the precious metal

⁸This finding is in line with Aroui et al. (2015) and Mishra et al. (2010)

markets in particular.

In regard to the long-term correlations' reaction to the EPU of the two groups, the positive response of gold-platinum, gold-palladium, and silver-palladium to the change of the EPU of Russia can be seen, while other pairs are all negatively related to EPU with significant coefficients. This means an increase in EPU growth would lead to a decrease in the long-run correlations between precious metals markets. Hence, I find a decoupling of precious metal markets in times of higher economic uncertainty.

2.5 Conclusion

This chapter sheds light on the understanding of precious metal market dynamics by investigating how the time-varying volatility and inter-correlation of four precious metals are influenced by macroeconomic variables, financial variables, and economic policy uncertainty in twelve countries belonging to G7 and BRICS over the last 20 years. Using the GARCH-MIDAS-X and DCC-MIDAS-X models, the study found that the stock market returns of G7 and BRICS countries play the most crucial role in determining both the long-term volatility and correlations among precious metals. In particular, stock market returns negatively impact the long-term volatility of four precious metals while positively affecting the long-run correlation of these metals. Besides stock market returns, other variables, including M1, M2, inflation rate, and the short-term interest rate of considered countries, are also helpful predictors of both volatility and correlations, albeit with mixed effects.

Additionally, economic drivers cause a more substantial effect on the volatility than on the correlation. Specifically, the EPU growth of G7 countries has a significantly positive influence on the volatility of precious metals; however, no effect caused by this driver can be seen on the long-term correlations between precious metals to a similar extent. Therefore, in periods of policy instability, it is recommended that investors hold these

metals to reduce risks. Similarly, the volatility of precious metals is closely linked to the growth of import, export, gold & foreign reserves, and exchange rates. Still, there is no such association in the case of correlations between precious metals.

There are considerable differences in the impact of drivers between G7 and BRICS, especially in terms of consumer confidence. In detail, consumer confidence in G7 countries makes the volatility of precious metals follow a negative direction but drives the pairwise correlation positively. On the contrary, consumer confidence in BRICS countries has almost no effect on either volatility or correlation. As a result, the more consumer confidence is improved in G7 nations, the better the portfolio hedging benefits precious metals offer. Similarly, this trend can be investigated in the influence of industrial production on both volatility and correlation, bond return on volatility, or short-term interest rate on correlation.

Notably, this chapter also shows that the 2008 global financial crisis played a vital role in the change of the impact of determinants on precious metals markets, as the signs of many determinants are reversed for this crisis. Palladium is the most strongly influenced by the global crisis of 2008, while silver is the least responsive to this crisis.

Finally, the return volatility of gold markets and the correlation between gold and silver have the closest relationship to the changes in the economic drivers of both the G7 and BRICS countries.

Appendix

Table 11: List of macro-finance variables

Variable name	Acronym	Description	Data sources
<i>Macroeconomic variables</i>			
Export Growth	EX	The % annual growth rate of exports of goods and services, is used to assess the progress of an economy because exports boost economic output.	Thomson Reuters Datastream
Import Growth	IM	The % annual growth rate of imports of goods and services. Imports make a country dependent on other countries' political and economic power.	Thomson Reuters Datastream
Capacity Utilisation	CU	Measure the manufacturing and production capabilities that are being utilized by a nation at any given time. It is a useful indicator of the strength of demand.	Thomson Reuters Datastream
gold&Foreign Reserves	GFR	The % annual growth rate of total reserve of gold and U.S dollars.	Thomson Reuters Datastream
Consumer Confidence	CC	Measure the degree of optimism that consumers feel about the state of the economy. Its increase may signal a strong consumer demand and, thus, a growing economy.	OECD
Industrial Production	IP	Measure the real output of the industrial sector. It covers manufacturing, mining, electric, and gas industries, relative to a base year.	OECD
Composite Leading Indicator	CLI	Provide early signals of turning points in business cycles.	OECD
M1 Growth	M1	The % annual growth rate of the narrow measure of the money supply that includes physical currency, demand deposits, traveler's checks, and other checkable deposits.	Thomson Reuters Datastream
M2 Growth	M2	The % annual growth rate of a broader measure of the money supply than M1 (includes cash and checking deposits). This variable reflects future inflation.	Thomson Reuters Datastream
Inflation Rate	INF	Computed as the percentage change of consumer price index for all urban consumers of all items. This price variable is related to consumers consumption decisions and their real wealth.	Thomson Reuters Datastream
Unemployment Rate	UNP	Calculated as the ratio of the employed to the working age population. Employment rates are sensitive to the economic cycle.	Thomson Reuters Datastream
<i>Financial variables</i>			
Stock Market Return	Stock	Calculated from national stock market indices including SP500 of US, FTSE 100 of UK, SP/TSX Composite Index of Canada, NIKKEI 225 of Japan, CAC 40 of France, DAX of Germany and FTSE MIB of Italy.	Thomson Reuters Datastream
Bond Market Return	Bond	Calculated from 10-year government bond indices of each country in sample.	Thomson Reuters Datastream
Short-term Interest Rate	IR	Interest rate charged on a short-term borrowings which are effected between financial institutions or the rate at which short-term government paper is issued or traded in the market. Short-term interest rates are generally averages of daily rates, measured as a percentage.	Thomson Reuters Datastream
Real Effective Exchange Rate	ExR	The weighted average of a country's currency in relation to an index or basket of other major currencies. The weights are determined by comparing the relative trade balance of a country's currency against each country within the index.	Thomson Reuters Datastream
<i>Economic Policy Uncertainty</i>	EPU	Measure the contribution of government policymakers to the uncertainty regarding fiscal, regulatory, or monetary policy.	https://www.policyuncertainty.com

Table 12: Impact of macroeconomic variables of G7 and BRICS countries on the long-term volatility of precious metals

	US	UK	Canada	Japan	Germany	France	Italy	Brazil	Russia	India	China	South Africa
Export Growth												
gold	0.4668*		-0.0238**			-0.1464**			0.0988*	0.2046**	0.2379***	0.1153*
goldF	-0.0548*					-0.1686**		-0.0619*	0.0967*	0.2211**	0.2070***	0.0088*
silver		0.2218**		0.6540*		-0.1875***	0.7427*	0.4429*	0.4318**		0.4766*	
silverF		0.7227**		0.6710*		-0.1915***		0.4986*	0.3138***	0.2350**	0.5682*	-0.4694*
platinum		0.0512**	0.1530***	-0.2883***	-0.0148**		0.1569***		-0.1215**	0.0503*	0.0495**	0.1942***
platinumF	-0.0855***		0.1375***				0.1181**		-0.4809***	0.0394**		0.1394*
palladium	-0.1011**	0.2425*	-0.0267***	-0.0249*		-0.0353***	-0.0951**		0.0966*			
palladiumF		0.1723*									0.0199***	
Import Growth												
gold	0.4283*			-0.0451**		0.2374**	0.1628*	0.2263**		0.2487***		0.2317**
goldF			-0.0155*	-0.1244**						0.2509***		0.2108***
silver	0.7013*	0.3077*	-0.0885*	-0.1210**					0.2860*		0.6376***	
silverF	0.8101*								0.4051**	0.2858***	0.6859***	0.1119**
platinum	-0.2011**		0.1440***	-0.2539***	-0.0129**	-0.3025**	0.0057*	0.0746*				
platinumF			0.1246***			0.1181**		-0.0738**		0.0969*		0.1848**
palladium		0.2907***	-0.0280***	-0.2991**		-0.0951*						
palladiumF		-0.0290*					-0.0266**	-0.0385***	0.0207**	0.2154*		-0.1538**
gold&Foreign Reserves												
gold	0.1813*	-0.0386***	0.5165**		-0.0597***		-0.0474***	0.0517**	0.3566*	0.0650*	0.1892*	0.2964***
goldF	0.1813**		0.5073**		-0.0517***	0.0459***	-0.0432***	0.2797***		0.0616*	0.0638**	0.1077*
silver	0.4138**		-0.1015**					0.3342***		0.1094***		0.0583*
silverF	0.5142**					0.2188**	-0.0490***	0.2017**		0.0897***	0.0897***	0.1913***
platinum			0.3667**	0.0884**	0.1279*		0.2039***	0.2061**		0.0345*	0.9346*	0.0870*
platinumF				-0.1378***	0.1051*		0.1912*		0.0358**			-0.2977**
palladium	0.3077**			0.1588*	0.3145***		0.3316***	0.1375*		-0.0714**	-0.0714**	0.0471***
palladiumF	0.2495**						0.3517***	0.1873**				
Consumer Confidence												
gold	-0.2731***	-0.2215**	-0.0484**	-0.2031**	-0.1289*		-0.2100**	0.2109**	0.1350***	-0.1373**		
goldF		-0.2358***	-0.0391**	-0.1949*		-0.3923**		0.2128**	0.1256***	-0.1310**		
silver	-0.2762***	-0.2919***	-0.0949**		-0.3519**							
silverF	-0.3054***		-0.0774*	-0.2493**	-0.4052**		-0.3284**			-0.2869***		
platinum	-0.1691**	-0.1905**	-0.0578***	-0.2653***					-0.0820**	-0.2292***		
platinumF	-0.1754**	-0.1819**		-0.1911**								
palladium		-0.1856**	-0.0574***	-0.4122***	-0.2452***	-0.2733**						
palladiumF	-0.2157***	-0.1736**	-0.0481***		-0.2209***			-0.1007*				
Composite Leading Indicator												
gold		-0.1425**						0.2373*				-0.1848*
goldF		-0.1974**										-0.2100*
silver		-0.1376*		-0.3088*					-0.1095*	-0.3397**	-0.1976***	
silverF		-0.1466*	-0.2366*	-0.3250*	-0.2202**			-0.0348**		-0.3629**	-0.2054***	
platinum		-0.2342***		-0.2762**		0.2393*					-0.1848**	
platinumF		-0.2243***								-0.2004***	-0.1635*	
palladium		-0.2623***	-0.2776**							0.2145*	-0.2376***	-0.2464***
palladiumF	-0.1611*	-0.2431***	-0.2474***		-0.1448*					0.2485*	-0.1906***	
Industrial Production												
gold	-0.0494**		-0.0595**		-0.0326***		0.0187*					-0.0336*
goldF	-0.0411**		-0.0607**		0.0262*							-0.0277**
silver		-0.1975***	-0.0918**	-0.0579**			-0.0969***	-0.0635*				
silverF	-0.1195**	-0.2074***	-0.1004*	-0.0652**			-0.1011***	-0.0709***				
platinum												
platinumF				0.0626*								
palladium	-0.0728***		-0.0478*		-0.0352**		0.0184***					
palladiumF	-0.0645***		-0.0365**									

Note: Estimation results θ of Trade Balance Growth, gold and Foreign Reserves Rate, Consumer Confidence, Composite Leading Indicator and Industrial Production of other G7 and BRICS nations from GARCH(1,1)-MIDAS-X. The asterisks ***, **, and * denote significance at 1%, 5%, and 10%, respectively. Otherwise, the field is left blank. The results of the U.S. and China in gray format are for reference.

Table 13: Impact of macroeconomic variables of G7 and BRICS countries on the long-term correlations between precious metals

Countries	US	UK	Canada	Japan	Germany	France	Italy	Brazil	Russia	India	China	South Africa
Export Growth												
gold-silver	-0.1739*	-0.1351*		-0.1694*				-0.1004**		-1.3839*		-0.1201*
gold-platinum		-0.0208**						1.5306***				-0.3845***
gold-palladium	0.1772***											
silver-platinum								0.7893***			-0.1161**	-0.3358***
silver-palladium	0.1812**											
platinum-palladium											1.0045***	
goldF-silverF	-0.1923*			-0.1654*		-0.2870*	-0.2735*	-0.1136**				-0.0940*
platinumF-palladiumF			-1.5145***			0.3484*	-0.8478*					
Import Growth												
gold-silver	-0.1969**		1.0339***	-0.1149**			-0.2362***				-1.0317***	0.6697***
gold-platinum							-0.2562***					-0.2654***
gold-palladium												
silver-platinum							-0.2661***			-1.4910***		
silver-palladium							-0.2105*			-1.4740***		-0.2202***
platinum-palladium										-0.0190***		
goldF-silverF	-0.2198**					-0.2735*			1.5273***		-0.1927**	
platinumF-palladiumF						-0.8478*						
gold& Foreign Reserves												
gold-silver					-1.4564*	-0.0554***			-0.0783***	-0.1214**	-0.0254**	
gold-platinum			-0.1751**	-0.2371***						-0.5718***	-0.2788***	-1.0827***
gold-palladium								0.3947***				
silver-platinum				-0.4336**								
silver-palladium				1.6086***				1.9438***				
platinum-palladium	0.1599*		1.0297*							1.0314***	0.5301***	
goldF-silverF				-0.1952***		-0.0545***		0.8992***		0.9938***	0.2998***	-0.0574***
platinumF-palladiumF								1.0287***		-0.6687***	-0.2644***	
Consumer Confidence												
gold-silver	1.5113**			0.9181*								
gold-platinum	1.9844***			1.3277**								
gold-palladium	1.7165***				1.2177*							
silver-platinum	1.4700*				0.8710*							
silver-palladium	1.7635*											
platinum-palladium	2.7214**		0.2822**		1.7999***							
goldF-silverF	1.6091***			0.9118*		2.1157***	1.0325**				0.3571**	
platinumF-palladiumF			0.5039*									
Composite Leading Indicator												
gold-silver		-1.7928*			-1.0897*		-1.6025*					
gold-platinum	1.5281*	1.9337*	0.6183**								1.7337*	1.2760*
gold-palladium												
silver-platinum												
silver-palladium												
platinum-palladium		1.2289**		1.4314*	1.0245*				0.5204*		1.2851*	
goldF-silverF			-1.1972***					0.6066***				
platinumF-palladiumF												
Industrial Production												
gold-silver		-0.3194*		-0.1963**	-0.2301	-0.3334*	-0.2532					
gold-platinum	0.3386**											
gold-palladium				0.4761*				-1.0032***				
silver-platinum												
silver-palladium												
platinum-palladium		-1.3522***				-1.7507**						
goldF-silverF		-0.3170		-0.1946*		-0.2302*	-0.2680*					
platinumF-palladiumF							-1.4254***					

Note: Estimation results γ of Export Growth, Import Growth, gold and Foreign Reserves, Consumer Confidence, Composite Leading Indicator and Industrial Production of other G7 and BRICS nations from DCC-MIDAS-X. The asterisks ***, **, and * denote significance at 1%, 5%, and 10%, respectively. Otherwise, the field is left blank. The results of the U.S. and China in gray format are for reference.

Table 14: Impact of macroeconomic variables of G7 and BRICS countries on the long-term volatility and correlations of precious metals

	US	UK	Canada	Japan	Germany	France	Italy	Brazil	Russia	India	China	South Africa
Panel A: Long-term volatility												
<i>M1 Growth</i>												
gold				-0.1222***		-0.5119***	-0.6396**	-0.0350*	0.1423**	0.6701**		0.8812*
goldF	-0.1345**		-0.4013*	-0.1188*	0.0886***	-0.4449*	-0.7019***				0.3164*	
silver	-0.9366**			-1.2088***	-0.4155**	-0.2401*			-0.0938**	1.1034***		0.3100*
silverF	-0.8870**									0.8483***	-0.0730**	0.4788**
platinum		-0.5808*	0.7389*	0.2325*				0.2790**				0.4741**
platinumF	0.1692*	0.1934***	0.2451***	-0.2535*				0.2606*			0.3275***	0.3843*
palladium		0.1849**	-0.1676**	-0.0616**			0.1092***		0.0842*	0.3241*		0.2911**
palladiumF										0.3883*	0.1788***	0.3065*
<i>M2 Growth</i>												
gold	0.4923**	1.4255*		-1.4092***		-1.3128**	0.4357*	0.2004***				0.7124**
goldF	0.6750*	1.1178*	1.0012**	-3.7169**	0.6718**	-1.1919*		0.2066***			0.6364**	0.5385**
silver	0.2682**		0.7192***		1.7430*	-1.1935**	-0.1394*			0.8198**		
silverF	0.3155**		0.4262*	0.2505*		-1.1816**				0.3845***	1.0820***	
platinum	1.2215***		1.1187***	1.5943**	1.5663***	1.5550**	-0.4514**				0.7887**	
platinumF					1.5598***	1.5424**		0.5624***				
palladium	0.2331*	-0.5053***	0.9162*			-0.1733**		0.5905**	-0.0490**	0.3156*	3.7941***	0.0554*
palladiumF		0.9777***	1.0379**					0.6782***		0.3685*		-0.3157*
<i>Unemployment Rate</i>												
gold	0.0974*	0.1633***		0.2210**	0.1659***	-0.2351**	-0.1442***		0.1460**		1.2893**	
goldF	0.0858**	0.1811***	-0.1309**		0.1482**	-0.2085**	-0.1356***		0.1288*		1.6245***	-0.1830**
silver				-1.2091**	-0.6962***	-0.8011*	-0.4145*	-0.3236***	-0.6840*	-2.1264**	2.1366***	
silverF				-1.2157***	-0.6186***		-0.5021**	-0.3374***			2.1216***	-0.2324**
platinum						0.2941**				-0.5543**		-0.1378**
platinumF						-0.2940*			0.1145*	-1.0268*		-0.1085*
palladium	0.1374*			0.3907**				0.0794*	0.1238*		2.5641***	0.1327*
palladiumF	-0.1251*		0.2704*		-0.3595***				0.2653***		2.2086**	
<i>Inflation Rate</i>												
gold	0.4079*	0.2742**	0.1817**	-0.1739***		0.2342*	0.2128*	0.0629**	0.0518***	0.0744***	0.1505***	
goldF	0.2641*	0.2641*			0.4219**			0.0581**	0.0465**	0.0813***		-0.0870*
silver		0.1861***						-0.1352***	-0.0366***		0.2840***	-0.0975**
silverF									-0.1172**	0.1378*	0.1989**	
platinum			0.3644***			-0.2551**			-0.0716**			0.1122***
platinumF	0.0989*								-0.0341**			
palladium			0.5363*	-0.1426***		0.2626*	0.2062**	0.1277***	0.0709**			0.0727**
palladiumF	0.1749*		0.5444*			0.2600*			0.0669**			
Panel B: Long-term correlations												
<i>M1 Growth</i>												
gold-silver	0.3568**				0.2647***		-0.3399*		-0.1640***			
gold-platinum	0.6277***	-0.6311**			1.0452***			-0.4540***	-0.2377***		-1.0963**	-0.6187*
gold-palladium				-0.3368***								
silver-platinum	0.5191***	-0.5603**			0.8958***	1.4759**		-0.3759**	-0.2134***			-2.2312**
silver-palladium										0.8599***		
platinum-palladium	0.4717**		1.1272**	-0.4952***	0.7579***		-0.5357*					
goldF-silverF	0.6579**	-0.4341*							0.9985***		0.9528*	-1.7688***
platinumF-palladiumF					1.3945**							
<i>M2 Growth</i>												
gold-silver	0.9507*	-1.0383***	0.5668*		1.0401***				-0.1565***			-1.1396***
gold-platinum		-1.1931***	0.3490*	1.1883**			-0.6773**		-0.2290***			-1.1596***
gold-palladium	-1.1347*							0.3156*				
silver-platinum		-1.0857***		1.9932*	0.9188*	-0.7040*			-0.2116***			-0.1537***
silver-palladium												-0.4269***
platinum-palladium	-0.6549***	-0.9149**	1.1455**	1.7706*		-0.6501*		-1.2196**				
goldF-silverF	1.9460*	-0.9547***	0.5307*		0.7638***							-1.3834***
platinumF-palladiumF	-2.0365***							0.5200**				
<i>Unemployment Rate</i>												
gold-silver						0.9212***		0.9011***				
gold-platinum		-0.7587***		1.2883***	0.9923***	0.9998***			-0.1398***			
gold-palladium				1.2967***								
silver-platinum								0.9980***		1.0033***	0.8990***	
silver-palladium	0.9423***											
platinum-palladium										1.2633***		
goldF-silverF			0.9970***			0.1299***	0.8321***			-0.4168*		
platinumF-palladiumF												
<i>Inflation Rate</i>												
gold-silver	-0.1382**		-0.2470***					0.8183***		0.8990***	0.1387***	
gold-platinum	-1.2895***	-0.2777***		-1.3283*		-0.1957*	-0.1831**		0.9969***			
gold-palladium			1.5626***				0.6755***			0.0365*		
silver-platinum	-0.2543**	-0.2355**									0.1238**	
silver-palladium										0.7981***	0.1377***	
platinum-palladium												
goldF-silverF	-0.2769**		-0.2423***			-0.1305*	0.7169***			0.8990***		
platinumF-palladiumF		0.6665***										

Note: Estimation results in θ and γ of Money Supply (M1, M2 Growth), Unemployment Rate, and Inflation Rate of other G7 and BRICS nations from GARCH-MIDAS-X and DCC-MIDAS-X, respectively. The asterisks ***, **, and * denote significance at 1%, 5%, and 10%, respectively. Otherwise, the field is left blank. The results of the U.S. and China in gray format are for reference.

Table 15: Impact of financial variables of G7 and BRICS countries on long-term volatility and correlations of precious metals

	US	UK	Canada	Japan	Germany	France	Italy	Brazil	Russia	India	China	South Africa
Panel A: Long-term volatility												
<i>Stock Market Returns</i>												
gold	-0.0775**	0.0438***	-0.1332***		-0.0713***		-0.1213***	-0.0473*	-0.0691**	-0.0590*	-0.0230*	0.3294***
goldF	-0.0652***	-0.1026***	-0.1294***		-0.0594***					0.0903**		0.2845**
silver		-0.1070***	0.0979*		-0.0533**		-0.1016**	-0.0562***	-0.0347***	-0.0360***	0.2049*	
silverF		-0.1014***	-0.0945***		-0.0479**							
platinum	-0.0569**									0.0260**		
platinumF	-0.3542***	-0.0886***	-0.3749***	-0.2118***	-0.2170***	-0.2785***	-0.2678***				0.1382***	0.1283*
palladium	-0.2593**		-0.3002***		-0.3504*						0.1567***	-0.2657***
palladiumF	-0.6221***	-0.6200***		-0.2973***	-0.0333***	-0.4602***	-0.4310***	0.0322**	0.0286***	-0.0289*	-0.0953**	-0.1793**
	-0.5079***						-0.1129**			0.0923*		
<i>Bond Markets Returns</i>												
gold		0.3220***	0.1562**	0.7560***	0.1720**	0.1914***	0.2654***					
goldF		0.1593*			0.1375**	0.1456***	0.1517**			0.2479**		-0.2818**
silver		0.2791***		0.5234**								-0.5378*
silverF		-0.1737	-0.5924***									-0.7090***
platinum				0.4937*						0.1692***		
platinumF										0.1469**		
palladium		0.2585**			0.1531*					-0.3194***		0.3017***
palladiumF	0.2028**		0.1747**		0.1591**	-0.4547**				-0.2726***		
<i>Interest Rate</i>												
gold		0.0864**	0.1996**		0.2351***	0.1244**	0.2351***			0.1837**	0.5162***	
goldF	0.1978*	0.0940*	0.1703*			0.1849**	0.1849**			0.1971**		
silver				-2.5648**			-0.6129***	1.3216**	1.1509***		-4.0609**	-0.3187**
silverF		-0.5317***		1.3974*						-0.1983***		-0.2284**
platinum				1.9709***							0.2120*	0.0952*
platinumF												0.0955***
palladium	0.1691**		0.4122***	-1.6181**	0.2074***	0.2074**	0.2074**	0.7550*		-0.1630***		0.0850***
palladiumF		0.0963*	0.3380***		0.1823***	0.1823**	0.1823***					
<i>Exchange Rate</i>												
gold	-0.0313**	-0.0908***	0.0355***	0.0150***			0.0357**				-0.0252***	0.0332***
goldF	-0.0304**	-0.0963***	0.0353***			0.0454***				-0.0462***	-0.0219***	0.0285***
silver	-0.0492***	-0.1074***	-0.0291*	-0.0811***		-0.0536***	-0.0534***				-0.0201***	-0.0332**
silverF	-0.0527***		-0.0383*	-0.0784***	-0.0696**	-0.0685***	-0.0685**		-0.0310**			0.0342***
platinum							-0.0048*	-0.0322*				
platinumF				-0.0148*								
palladium					0.0265*							-0.0197**
palladiumF					0.0407**		0.0407**		-0.0256**			0.0302**
Panel B: Long-term correlations												
<i>Stock Market Returns</i>												
gold-silver	0.1486*			0.0508***	0.0440***	-1.9030***			-0.1074***			
gold-platinum	0.1774**	0.0906***			0.0539*	0.0648*			0.1270***	0.0371**		0.8430***
gold-palladium	0.0996***	0.1065***	0.1703*	0.6992*	0.0921***	0.0848***		0.0716***		0.0368***		
silver-palladium	0.0854**	0.0936**	0.0864***		0.0708*	0.0702**				0.0346***		
silver-platinum												
platinum-palladium	0.1019***		0.0831***		1.5640***				0.0012***		1.1359***	
goldF-silverF	0.0585***			0.0445***	0.0457***				-0.0898***	0.1215***		0.0726***
platinumF-palladiumF	0.1584**	0.1786**			0.1261***	0.1240**				1.0985***	0.0833*	0.6562***
<i>Bond Market Returns</i>												
gold-silver			-0.1452***			-0.1249**	0.8990***					
gold-platinum	0.9956*			-0.3998*						0.9949***		0.9993***
gold-palladium												
silver-platinum		1.5151***	-0.1653***									
silver-palladium		1.4057***	0.7895***	-1.8601***								
platinum-palladium												
goldF-silverF			1.2006***	0.2446*						0.9981***		0.9998***
platinumF-palladiumF	0.4587***											
<i>Interest Rate</i>												
gold-silver	-0.0745**		-0.0995**	-0.2773*	-0.7846***	-0.1119***	-0.1154***					0.8868***
gold-platinum	-0.1362***		0.8990***	-0.6451**			-0.1707***	-0.6857***				
gold-palladium	-0.1007*	0.5390***			-0.1357*							
silver-platinum	-0.5612***		-0.1472***			-0.1393***	-0.3212***					
silver-palladium	-0.1059**		0.3590***		-0.1417*		-0.5487*					
platinum-palladium	-0.2331***			-0.4514*								
goldF-silverF	-0.0612**		1.8169***	-0.2444*	-0.3406***	0.0237***	-0.0710***	-0.5578***				
platinumF-palladiumF	0.2012***											
<i>Exchange Rate</i>												
gold-silver		-1.0225***			-0.2714*	-0.2714*	-0.2714*			-0.3862**		
gold-platinum												0.2615**
gold-palladium				0.1688*				0.2436***	0.3130*			
silver-platinum				0.1693*				0.2696**				
silver-palladium				0.1996**				0.2595**	-0.3870*			
platinum-palladium								0.1268**				
goldF-silverF	0.2544*	0.3824***								-0.3050**	0.4757*	
platinumF-palladiumF											0.3204*	

Note: Estimation results in θ and γ of Stock Market Returns, Bond Market Returns, Interest Rate, and Exchange Rate of G7 and BRICS nations from GARCH-MIDAS-X and DCC-MIDAS-X, respectively. The asterisks ***, **, and * denote significance at 1%, 5%, and 10%, respectively. Otherwise, the field is left blank. The results of the U.S. and China in gray format are for reference.

Table 16: Impact of EPU growth of G7 and BRICS countries on the long-term volatility and correlations of precious metals

	US	UK	Canada	Japan	Germany	France	Italy	Brazil	Russia	India	China	South Africa
Panel A: Long-term volatility												
gold				-0.0939**		0.0297**						
goldF				-0.0868**		0.0232**						
silver			0.1668**									
silverF												
platinum	0.2242***	0.1154***		0.2585***	0.2035***		0.0295*	0.0505**			0.0489***	
platinumF			0.1783***	0.2575***	0.2146***		0.0886*		0.0622*			
palladium					0.1341**		0.2026***					
palladiumF	0.1415**	0.0912**	0.1702**	0.1458*	0.1361***		0.1656**					
Panel B: Long-term correlations												
gold-silver	-0.0138***		-0.0286**	-0.0344***	-0.0229*	-0.0230***						
gold-platinum								0.6119**				
gold-palladium					-0.0279**	0.7576***		0.9982**				
silver-platinum											-0.3046***	
silver-palladium				-0.0552***			0.0912**	0.9982***				
platinum-palladium					0.7598***	0.9618*						
goldF-silverF	-0.0112***		-0.0311**	-0.0328***	0.0358*	-0.0200***						
platinumF-palladiumF		-0.9983***	-0.1782*	-0.1379**	-0.1997**	-0.4019***						

Note: Estimation results in θ and γ of EPU of G7 and BRICS nations from GARCH-MIDAS-X and DCC-MIDAS-X, respectively. The asterisks ***, **, and * denote significance at 1%, 5%, and 10%, respectively. Otherwise, the field is left blank. The results of the U.S. and China in gray format are for reference.

Chapter 3

DIVERSIFICATION BENEFITS OF PRECIOUS METAL MARKETS: EVIDENCE FROM THE GLOBAL FINANCIAL CRISIS

Can precious metals provide diversification for traditional assets (e.g., stocks, bonds, currencies)? If so, which precious metals or their derivatives better perform this role? Or does the financial crisis change the role of precious metals as good diversifiers? In order to answer these questions, chapter 3 investigates the diversification contribution of four precious metals (i.e., gold, silver, platinum, and palladium) to a traditional portfolio of stocks, bonds, cash, and currencies over various periods of the global financial crisis of 2008 on that contribution. In this chapter, a stochastic spanning methodology ([Arvanitis et al. 2019](#)) was employed to test whether the traditional portfolio spans the portfolio augmented with all four precious metals in the G7 countries over three periods: before, during, and

after the global financial crisis of 2008. Both in-sample and out-of-sample analyses of stochastic spanning tests were conducted. The results confirm the diversification benefits of precious metals for traditional assets in both spot and futures returns. These findings hold over three sub-periods of the global financial crisis of 2008. Notably, precious metal futures significantly outperform precious metal spots in the aftermath of the 2008 crisis. Investors should therefore favor precious metal futures in post-crisis periods to improve their investment diversification.

3.1 Introduction

The financial roles of precious metals provide tremendous incentives for researchers and practitioners to learn more about their complex behaviors. Most studies suggest the favorable benefits of precious metals for investment, such as a safe-haven investment target, a hedging tool against various risks and inflation, or a high liquidity investment, etc (Jaffe 1989a, Baur & McDermott 2010, Jain & Biswal 2016a). The authors further emphasize that during turbulent times, precious metals all have low correlation (Baur & McDermott 2010) or no correlation (Hillier et al. 2006a) with other assets, indicating that these metals may provide diversification benefits. Nonetheless, some studies argue against such benefits Reboredo (2013), Lucey & Li (2015b). (Reboredo 2013), for example, provides empirical evidence for weekly data from January 2000 to September 2011 and concludes that there is a positive and significant average dependence between gold and oil price. This means that gold cannot give diversification benefits for oil returns.

To the best of my knowledge, there are a large number of studies that evaluate portfolio's diversification benefits from investing in commodities in general (Gorton & Rouwenhorst 2006a, Chong & Miffre 2010, Belousova & Dorflleitner 2012b, Gao & Nardari 2018, Bessler & Wolff 2015, Daskalaki et al. 2017a) or gold in particular (Johnson & Soenen 1997, Ratner & Klein 2008, Bedoui et al. 2018b). Among these, the study of

[Daskalaki et al. \(2017a\)](#) applied for the first time a stochastic dominance efficiency (SDE) approach to analyze the diversification benefit of commodities. This research shows that commodities provide diversification benefits in both in-sample and out-of-sample settings. In addition, the authors found that commodity markets are segmented from the stock and bond markets. Prior to this study, [Van Hoang et al. \(2016\)](#) used the stochastic dominance (SD) method to evaluate the contribution of gold quoted in Paris to portfolio diversification from 1949 to 2012. The research pointed out that stock portfolios augmented with gold would dominate significantly those without gold in the second and third orders. However, these results are not true for bond and free-risk portfolios. In the robustness test, they conducted a stochastic dominance analysis of a mixed portfolio (50% stocks, 30% bonds, and 20% free-risk assets). This analysis also provides results similar to a portfolio with stocks only, except for the period 1971-1983. Meanwhile, other precious metals, including silver, platinum, and palladium which probably outperform gold in a turbulent environment ([McCown & Shaw 2017](#), [Baur & Lucey 2010a](#)) seem to have been ignored.

In addition, the financialization of precious metal markets has recently sparked a heated debate on the diversification benefits of investing in these markets. Despite the fact that it has been a contentious topic up to now, the role of precious metals as a diversifier has clearly evolved, especially in times of extreme markets ([Białkowski et al. 2015a](#), [Balcilar et al. 2015](#)). In particular, the more uncertain the global financial system, the more the role of precious metals is reinforced ([Białkowski et al. 2015a](#), [Balcilar et al. 2015](#)). Accordingly, there is burgeoning literature demonstrating that financial crisis-related uncertainty shocks have a significant impact on precious metal market dynamics ([Morales & Andreosso-O'Callaghan 2011a](#), [Hammoudeh et al. 2011a](#)). Surprisingly, there is so little in-depth research on the impact of financial crises on the role of precious metals as good

diversifiers.

Therefore, by employing stochastic spanning methodology ([Arvanitis et al. 2019](#)), which focuses on the second-order stochastic dominance (SSD), this chapter aims to assess effectively and accurately the role of using precious metals spot and precious metals futures to gain diversification benefits for investors. This choice of methodology matches the economic application of the expected utility theory and the dual theory of risk ([Yaari 1987](#)), which is associated with risk-averse investors. In this chapter, the traditional portfolio is constructed from four asset classes, including stocks, bonds, cash, and currencies of G7 markets. Two augmented portfolios are constructed by adding, in the first case, the spot returns of four precious metals and, in the second case, their future returns. By this approach, the main goal of the study is to shed light on the question of whether and how investors can benefit from diversification through investing in precious metals or their financial instruments. The empirical analysis has been conducted in three sub-periods: before the financial crisis of 2008 (from January 2005 to August 2007), during the crisis (from September 2007 to December 2010), and after the crisis (from January 2011 to September 2018). In addition, daily data is collected from the G7 countries as international evidence to clarify the diversification potential of precious metals in global financial markets.

This chapter includes both in-sample and out-of-sample analyses to assess the diversification benefits of precious metals for traditional assets. Under the in-sample analysis, the traditional portfolio does not span augmented portfolios of both spots and futures returns of all four metals, meaning that precious metals are good diversifiers of traditional asset classes and effective investments for enhancing diversification benefits. This finding is confirmed in an out-of-sample analysis. Notably, our out-of-sample analysis shows that futures contracts on precious metals significantly outperform precious metals spots

after the 2008 global financial crisis. This finding is in line with the study of [Klein & Todorova \(2019\)](#), which finds that the future contracts of precious metals have become the most widely-used instruments for risk management, particularly in more volatile periods. Finally, parametric tests of out-of-sample performance assessment reconfirm the diversification benefits of both precious metals' spots and futures.

The rest of the chapter is organized as follows. Section [3.2](#) gives a theoretical background explanation for using stochastic spanning methodology in testing the diversification benefits of precious metals. Section [3.3](#) describes the mathematical perspective of the stochastic spanning methodology. The data and its properties are reported in section [3.4](#). Section [3.5](#) summarizes the empirical results in both in-sample and out-of-sample analyses. Section [3.6](#) concludes and discusses implications.

3.2 The theoretical framework for assessing diversification benefits

According to the portfolio investment strategies, investors might hold a wide range of assets available in the financial markets. The supposed benefits of diversification (i.e., risk reduction for any expected level of return on an investment asset or a portfolio) might suggest that investors should strive to spend money on as many assets as possible. However, this suggestion is not entirely true. Diversification has remained limited ([Bodie et al. 1992](#)), as adding more assets could even lead to a reduction in the portfolio performance due to transaction fees or other costs. This limitation raises the question of whether introducing a new set of risky assets may improve the traditional portfolio ([Kan & Zhou 2012](#)) by bringing diversification benefits. The concept of spanning is helpful for addressing the issue of limited diversification. Spanning occurs if introducing new assets or relaxing investment constraints does not improve the investment possibility set for a given class of investors ([Arvanitis et al. 2019](#)). The concept of spanning is firmly linked to the diversification benefits of new assets. Diversification benefits arise if adding new

assets into the original portfolio leads to the efficient frontier shifting leftward significantly (Bekaert & Urias 1996).

Huberman & Kandel (1987) first introduced the mean-variance spanning test (hereinafter called “M-V spanning”). M-V spanning is based on the M-V framework of Markowitz (1952) in order to assess the effect of adding more risky assets into a portfolio. This test is specifically designed to evaluate the statistical significance of improving the augmented efficient frontier over the initial frontier of benchmark assets. Spanning happens when the augmented portfolio produces an efficient frontier that coincides with that of the initial portfolio. However, the limitation of the M-V spanning approach is rooted in two strict assumptions. The first corresponds with the study of Hanoch & Levy (2013), which requires normally distributed returns of assets. The second comes from Von Neumann et al. (2007) assumption, which demands quadratic utility functions. If these assumptions are broken, the results become unreliable.

In order to remedy the weakness of the M-V spanning test, Daskalaki & Skiadopoulos (2011a) applies the spanning test for non-M-V utility functions (i.e., not in the form of a quadratic function). This test uses stochastic discount factors (SDF) to analyze spanning, and Newey and West’s method (Newey & West 1987) to adjust the standard errors of coefficients. Meanwhile, Belousova & Dorfleitner (2012c) states that the assumption of normally distributed returns would not be a problem if conditional homoskedasticity were satisfied, driving them to propose applying GMM-based spanning test (Ferson et al. 1993, De Santis et al. 1997). This test is reinforced by Kan & Zhou (2008), which confirms its efficacy with a regression approach.

Despite the progress in dealing with the drawbacks of the M-V approach, the above-mentioned methods have not fully sorted out the issues of normally distributed returns and higher-order moment risk. To deal with these issues, Arvanitis et al. (2019) introduced

stochastic spanning, a non-regression alternative to M-V spanning. The stochastic spanning test is conducted on a stochastic dominance (SD) platform. According to the portfolio selection theory, SD compares two investment portfolios and determines which is dominant. The framework for SD criteria were developed from the first studies of [Quirk & Saposnik \(1962\)](#), [Hadar & Russell \(1969\)](#), [Rothschild & Stiglitz \(1970\)](#), and [Bawa \(1975\)](#). Furthermore, the stochastic dominance rule is based on the expected utility paradigm and provides a uniform ordering of prospects that is independent of specific utility functions ([Whang 2019](#)). To define criteria for dominance, SD frequently applies two settings. First-order stochastic dominance is suitable for both risk-averse investors and risk lovers. Second-order stochastic dominance is applied to risk averters, who are represented by concave utility functions.

Nevertheless, the main weakness of SD rules is that they can only classify two specific portfolios. It is, therefore, impossible to verify whether one portfolio dominates all others. To tackle this problem, [Post \(2003\)](#), [Scaillet & Topaloglou \(2010\)](#), and [Daskalaki et al. \(2017b\)](#) developed a statistical test of stochastic dominance efficiency (SDE) to determine the most efficient asset or portfolio out of a set of given assets or portfolios. [Arvanitis et al. \(2019\)](#) argued that the spanning test is appropriate for dealing with higher-order moment risk rather than SDE. The stochastic spanning test is justifiable since it is consistent and asymmetrically exact in the case of weakly dependent processes. Two other essential advantages of this method are that it does not assume the distribution of returns and that it considers all feasible portfolios. These advantages can help overcome the current concerns about methodologies used for testing the diversification benefits of new assets.

3.3 Stochastic spanning methodology

3.3.1 Definition

According to [Arvanitis et al. \(2019\)](#), portfolio set Λ is second-order stochastically spanned by subset $K \subset \Lambda$ if all portfolios $\lambda \in \Lambda$ are weakly second-order stochastically dominated by some portfolios $\kappa \in K$

$$\forall \lambda \in \Lambda, \exists \kappa \in K : \forall x \in X : G(x, \kappa, \lambda; F) \leq 0 \quad (3.1)$$

$$G(x, \kappa, \lambda; F) := F^2(x, \kappa) - F^2(x, \lambda), \quad (3.2)$$

in which, $\Lambda := \{\lambda \in \mathbb{R}_+^N : \mathbf{1}_N^T \lambda = \mathbf{1}\}$ denotes the investment opportunity set, which is based on convex combinations of N base assets. The random vector $X := (x_1, \dots, x_N)$ represents the returns of the base assets, with support bounded by $\mathcal{X}^N := [\underline{x}, \bar{x}]^N$, $-\infty < \underline{x} < \bar{x} < +\infty$. The function F refers to the continuous joint cumulative distribution function of X . Furthermore, let $F(y, \lambda) := \int \mathbf{1}(X^T \lambda \leq y) dF(X)$ denotes the marginal cumulative distribution function for portfolio $\lambda \in \Lambda$. As a consequence, the integrated cumulative distribution function is computed by

$$F^2(x, \lambda) := \int_{-\infty}^x F(y, \lambda) dy = \int_{-\infty}^x (x - y) dF(y, \lambda). \quad (3.3)$$

[Arvanitis et al. \(2019\)](#) provides a measurement for deviation by spanning stochastic that is based on the scalar-valued functional of the population cumulative distribution function(c.d.f) F as follows

$$\eta(F) := \sup_{\lambda \in \Lambda} \inf_{\kappa \in K} \sup_{x \in X} G(x, \kappa, \lambda; F). \quad (3.4)$$

The value of $\eta(F)$ is used to identify the likelihood of spanning. If $\eta(F) = 0$, it means no portfolio from Λ is not weakly dominated by a portfolio from K . In case $\eta(F) > 0$, stochastic spanning does not take place. [Arvanitis et al. \(2019\)](#) also suggest a transformation to

estimate $\eta(F)$ by using expected utility functions as below

$$\eta(F) = \sup_{\lambda \in \Lambda; u \in \mathcal{U}_2} \inf_{\kappa \in K} \mathbb{E}_F \left[u \left(X^T \lambda - u \left(X^T \kappa \right) \right) \right], \quad (3.5)$$

in which, \mathcal{U}_2 is a set of normalized, increasing, and concave functions that are designed from the convex combination of elementary [Russell & Seo \(1989\)](#) ramp function $r(y; x), x \in X$

$$\mathcal{U}_2 := \left\{ u \in \mathcal{C}^0 : u(y) = \int_x^{\bar{x}} \omega(x) r(y; x) dx ; \omega \in \mathcal{W} \right\}, \quad (3.6)$$

$$r(y; x) := (y - x) \mathbf{1}(y \leq x), (x, y) \in \mathcal{X}^2. \quad (3.7)$$

Stochastic spanning occurs ($\eta(F) = 0$) in case no risk averters ($u \in \mathcal{U}_2$) take advantage of the enlargement $(\Lambda - K)$.

3.3.2 Statistical framework and critical values

In theory, the c.d.f. F is covert; in practice, financial analysts have data, a discrete-time series of realized returns $(X_t)_{t=1}^T$, in which $X_t \in \mathcal{X}$. To solve this problem, [Arvanitis et al. \(2019\)](#) proposed using the empirical c.d.f. to calculate the test statistic for the null hypothesis of stochastic spanning ($H_0 : \eta(F) = 0$, which represents the existence of stochastic spanning) as follows

$$\eta_T := \sqrt{T} \sup_{\lambda \in \Lambda} \inf_{\kappa \in K} \sup_{x \in X} G(x, \kappa, \lambda; F_T)$$

The null hypothesis H_0 is rejected if $\eta_T > q(\eta_\infty; 1 - \alpha)$. In empirical applications, computing the test statistic η_T is a challenging global optimization problem estimated through a quasi-Monte Carlo and an embedded Linear Programming problem. The critical value corresponds with the $1 - \alpha$ quantile of the distribution regarding the relevant weak limit. However, the critical value is computed based on c.d.f. F , and c.d.f. F is

a latent function in practice. Therefore, the basic decision rule is to reject H_0 against H_1 only if $\eta_T > q(\eta_\infty; 1 - \alpha)$ is infeasible. To make it become feasible, [Arvanitis et al. \(2019\)](#) employed a subsampling procedure and then conducted a regression to correct the estimation for the critical value. Notably, the subsampling procedure began by creating $(T - b_T + 1)$, which makes subsamples $(X_s)_{s=t}^{t+b_T-1}$, $t = 1, \dots, T - b_T + 1$ maximally overlapped. Then, test scores for each subsample are computed from the empirical joint c.d.f. of $(X_s)_{s=t}^{t+b_T-1}$ given by $\eta_{b_T;T,t} = \sqrt{b_T}\eta(F_{b_T;T,t})$, from which the empirical distribution and the quantile function are presented by

$$s_{T,b_T}(y) := \frac{1}{T - b_T + 1} \sum_{t=1}^{T-b_T+1} \mathbf{1}(\eta_{b_T;T,t} \leq y), \quad (3.8)$$

$$q_{T,b_T}(1 - \alpha) := \inf_y \{y : s_{T,b_T}(y) \geq 1 - \alpha\}. \quad (3.9)$$

The decision rule for rejecting the null hypothesis of spanning now at the given significant level is $\eta_T > q_{T,b_T}(1 - \alpha)$. This sub-sampling procedure is asymptotic exact and reasonable if consistent assumptions about the length of the sub-sample and significance level are always held. However, in practice, two problems may arise. Firstly, the quantile estimators $q_{T,b_T}(1 - \alpha)$ tend to be biased corresponding to the small sub-sample size b_T . Second, the choice of b_T can be quite sensitive. A regression-based method has been proposed to correct the bias ([Anyfantaki & Topaloglou 2018](#), [Chalamandaris et al. 2018](#), [Arvanitis et al. 2019](#)). More precisely, the quantile values $q_{T,b_T}(1 - \alpha)$ are calculated for a rational range of the sub-sample size b_T . From this calculation, OLS regression can be estimated using the following equation

$$q_{T,b_T}(1 - \alpha) = \beta_{0;T,1-\alpha} + \beta_{1;T,1-\alpha}(b_T)^{-1} + \epsilon_{T;1-\alpha,b_T}. \quad (3.10)$$

Finally, the bias-corrected quantile (at given significance level α) is estimated based on the estimators of intercept and slope of the above regression, which are the OLS predicted values in the case $b_T = T$

$$q_T^{BC}(1 - \alpha) := \hat{\beta}_{0;T,1-\alpha} + \hat{\beta}_{1;T,1-\alpha}(T)^{-1}.$$

3.4 Data and properties

This section introduces the dataset used to perform stochastic spanning tests. Initial statistical analyses are given, including information about the descriptive statistics and Sharpe ratios of all considered assets and correlations between these assets over the three various periods of the 2008 global financial crisis.

3.4.1 Data

The dataset consists of daily returns of traditional and augmented portfolios of seven countries belonging to the G7 group, which is the world's largest consumer of precious metals. All data is retrieved from Thomson Reuters DataStream. It covers three periods corresponding to three phases of the global financial crisis of 2008: pre-crisis (from January 03rd, 2005 to August 31st, 2007), crisis (from September 03rd, 2007 to December 31st, 2010), and post-crisis (from January 03rd, 2011 to September 20th, 2018), respectively. In this study, the traditional portfolio comprises four types of traditional assets: shares, bonds, cash, and currencies. Notably, we use national stock market indices as proxies for stock assets ¹; 10-year government bond indices as proxies for bond assets; one-month Libor interest rates as proxies for cash in each country ²; and finally, exchange rates as proxies for currencies. We use each country's one-month Libor interest rate as the

¹S&P500 of US, FTSE 100 of UK, S&P/TSX Composite Index of Canada, NIKKEI 225 of Japan, CAC 40 of France, DAX of Germany and FTSE MIB of Italy

²1 month US Dollar USD Libor interest rate, 1-month British pound sterling GBP Libor interest rate, Canadian dollar Libor rates, 1-month Japanese yen JPY Libor interest rate, 1-month euro Libor interest rate

risk-free rate for its markets. As for precious metals, the study looks at two forms of these assets: spot and one-month futures.

3.4.2 Initial statistical analyses

Table 17 reports the descriptive statistics for the various asset classes, including the spot and futures return of all four precious metals and four traditional asset returns of G7 countries. The results show that the mean and standard deviation values of the spot returns of each precious metal are similar to those of their futures returns. Table 17 reports the mean is positive for all return series. Interestingly, precious metals return exhibit a higher standard deviation than traditional assets. Table 17 also summarizes the results of skewness and kurtosis. The skewness is not equal to zero and the kurtosis values are above three for most return series, indicating a non-normal distribution, which is also confirmed by a Jarque-Bera statistical test.

In addition to the descriptive statistics, the p -values of Ljung-Box (LB) statistics of the order 15 for the return series show the existence of auto-correlation in most of them. For the squared return series, however, the p -values of LB are highly significant, which reveals a long-range serial dependence. This result is confirmed by the results of the ARCH test, thus motivating our decision to use the GARCH model to filter the daily returns.

A Sharpe ratio (developed by William F. Sharpe) can be calculated for each asset in both the traditional and augmented portfolios by using the one-month Libor rate as a proxy for the risk-free rate. This ratio is often used to analyze the change in overall risk-return trade-off when a new asset or asset class is added to a portfolio. Generally, the greater the value of the Sharpe ratio, the more attractive the risk-adjusted return becomes. Table 18 shows the Sharpe ratio of each asset in each country, revealing that the Sharpe ratio of all four precious metals in the pre-crisis and crisis periods was positive and higher

Table 17: Descriptive statistics of precious metals and traditional assets

		Mean	Stdev	Skewness	Kurtosis	J.B.	Q(15)	Q ² (15)	ARCH(15)
Panel A: Precious metals									
Spot	gold	0.0347	1.1306	-0.1043	4.9659	0.0000	0.0162	0.0000	0.0000
	silver	0.0402	1.9716	-0.5029	6.1362	0.0000	0.4430	0.0000	0.0000
	platinum	0.0085	1.3693	-0.5466	4.4916	0.0000	0.1165	0.0000	0.0000
	palladium	0.0668	1.9143	-0.3899	3.2659	0.0000	0.4144	0.0000	0.0000
Future	gold	0.0349	1.1518	-0.2159	5.6863	0.0000	0.0027	0.0000	0.0000
	silver	0.0416	2.0447	-0.6362	6.2910	0.0000	0.1058	0.0000	0.0000
	platinum	0.0090	1.4090	-0.3905	3.7328	0.0000	0.6019	0.0000	0.0000
	palladium	0.0677	1.9335	-0.3282	3.4138	0.0000	0.0696	0.0000	0.0000
Panel B: Traditional assets of G7									
Stock	US	0.0313	1.1543	-0.1284	12.9188	0.0000	0.0000	0.0000	0.0000
	UK	0.0182	1.1196	0.0277	9.1011	0.0000	0.0000	0.0000	0.0000
	Japan	0.0308	1.4526	-0.3019	8.9664	0.0000	0.3950	0.0000	0.0000
	Canada	0.0213	1.0577	-0.5047	12.0736	0.0000	0.0000	0.0000	0.0000
	France	0.0191	1.3524	0.1477	7.5651	0.0000	0.0000	0.0000	0.0000
	Germany	0.0383	1.3144	0.1357	7.2767	0.0000	0.0552	0.0000	0.0000
	Italy	0.0016	1.5388	-0.0603	5.8304	0.0000	0.0012	0.0000	0.0000
Bond	US	0.0044	0.4620	0.1286	3.6511	0.0000	0.0032	0.0000	0.0000
	UK	0.0105	0.3985	0.1730	2.3668	0.0000	0.0027	0.0000	0.0000
	Japan	0.0067	0.1922	-0.1717	3.1283	0.0000	0.0251	0.0000	0.0000
	Canada	0.0068	0.3583	-0.0268	1.1791	0.0	0.3885	0.0000	0.0000
	France	0.0115	0.3448	-0.1659	2.6902	0.0000	0.0002	0.0000	0.0000
	Germany	0.0114	0.3515	-0.0973	2.1413	0.0000	0.0002	0.0000	0.0000
	Italy	0.0081	0.4985	0.5897	16.4242	0.0000	0.0000	0.0000	0.0000
Cash	US	0.4301	0.4935	1.1081	-0.3111	0.0000	0.0000	0.0000	0.0000
	UK	0.5160	0.5750	0.9985	-0.8541	0.0000	0.0000	0.0000	0.0000
	Japan	0.0396	0.0814	1.2103	2.5917	0.0000	0.0000	0.0000	0.0000
	Canada	0.4691	0.3636	1.0843	-0.2436	0.0000	0.0000	0.0000	0.0000
	France	0.3045	0.4348	0.9686	-0.4250	0.0000	0.0000	0.0000	0.0000
	Germany	0.3045	0.4348	0.9686	-0.4250	0.0000	0.0000	0.0000	0.0000
	Italy	0.3045	0.4348	0.9686	-0.4250	0.0000	0.0000	0.0000	0.0000
Currency	US	0.0043	0.4557	-0.2841	4.4938	0.0000	0.2807	0.0000	0.0000
	UK	0.0123	0.6193	0.8453	14.3510	0.0000	0.0000	0.0000	0.0000
	Japan	0.0047	0.6452	-0.2178	4.3681	0.0000	0.1234	0.0000	0.0000
	Canada	0.0040	0.6140	-0.0565	5.0183	0.0000	0.0319	0.0000	0.0000
	France	0.0059	0.6011	-0.0914	3.2534	0.0000	0.4008	0.0000	0.0000
	Germany	0.0059	0.6011	-0.0914	3.2534	0.0000	0.4008	0.0000	0.0000
	Italy	0.0059	0.6011	-0.0914	3.2534	0.0000	0.4008	0.0000	0.0000

Note: The table shows the descriptive statistics for the daily returns series of four precious metals and four traditional assets of G7 countries over the full sample period (Jan 03, 2005, to Sep 20, 2018). J.B. refers P-value of the Jarque-Bera test for normality. Q(15) and Q²(15) denote the Ljung-Box Q-test statistics for auto-correlation in the return and squared return series, respectively, up to 15 lag. Furthermore, ARCH(15) is the (Engle 1982), LM test for ARCH effects up to 15 lags.

than that of stocks, bonds, and currencies in all seven countries. In contrast, this ratio of traditional markets in all G7 members was negative during the crisis and pre-crisis times, except for several stock markets in the pre-crisis period (Canada, Japan, France, Germany, and Italy). This negative ratio suggests that incorporating precious metals into an original portfolio of stocks, bonds, cash, and currencies could provide diversification benefits before and during the global financial crisis of 2008. However, it seems that the Sharpe ratio of traditional assets in the post-crisis era followed the opposite trend. More specifically, excepting palladium, the Sharpe ratio of precious metals post-crisis was negative and lower than that of traditional assets. This finding is consistent with the studies of [Cao et al. \(2010\)](#), [Delatte & Lopez \(2013\)](#), which suggest that the rapid financialization of the precious metals markets and the sharp rise in investment capital flow in these markets after the 2008 global crisis may have caused a higher correlation between precious metals and traditional assets, hence, reducing their diversification contribution.

3.5 Empirical results

This section investigates whether the portfolios augmented with precious metals spot and precious metals futures are spanned by a traditional portfolio. Subsection [3.5.1](#) presents an in-sample analysis that tests the spanning hypothesis by estimating the critical value and comparing it with the test statistic value. Subsection [3.5.2](#) then tests whether the inclusion of the spot returns or future returns of four precious metals provides diversification benefits in an out-of-sample setting. The section closes by carrying out parametric tests that assess the out-of-sample performance in subsection [3.5.3](#).

3.5.1 In-sample analysis

This subsection interrogates in-sample the null hypothesis that the traditional portfolio spans the augmented portfolios. In this analysis, is constructed from four asset classes of

Table 18: Sharpe ratios of traditional assets and precious metals in three periods of the 2008 global financial crisis

	United States	United Kingdom	Canada	Japan	France	Germany	Italy
A. Before global crisis, 03/01/2005 - 31/08/2007							
Stock	-0.0147	-0.0043	0.0338	0.0535	0.0393	0.0689	0.0186
Bond	-0.1448	-0.1897	-0.1229	-0.0044	-0.1220	-0.1231	-0.1289
Cash	-	-	-	-	-	-	-
Currency	-0.1170	-0.1047	-0.1007	0.0321	-0.0533	-0.0533	-0.0533
Gold	0.0247	0.0209	0.0319	0.0607	0.0383	0.0383	0.0383
Silver	0.0311	0.0290	0.0352	0.0512	0.0387	0.0387	0.0387
Platinum	0.0191	0.0153	0.0262	0.0544	0.0324	0.0324	0.0324
Palladium	0.0319	0.0297	0.0362	0.0529	0.0398	0.0398	0.0398
B. During global crisis, 03/09/2007 - 31/12/2010							
Stock	-0.0087	-0.0105	-0.0026	-0.0202	-0.0254	-0.0088	-0.0421
Bond	0.0023	-0.0125	-0.0040	0.0238	-0.0184	-0.0101	-0.0440
Cash	-	-	-	-	-	-	-
Currency	-0.0313	0.0109	-0.0226	-0.0510	-0.0191	-0.0191	-0.0191
Gold	0.0568	0.0502	0.0550	0.0637	0.0531	0.0531	0.0531
Silver	0.0512	0.0472	0.0501	0.0554	0.0490	0.0490	0.0490
Platinum	0.0223	0.0172	0.0210	0.0278	0.0195	0.0195	0.0195
Palladium	0.0482	0.0443	0.0472	0.0524	0.0461	0.0461	0.0461
C. After global crisis, 03/01/2011 - 20/09/2018							
Stock	0.0418	0.0066	0.0039	0.0316	0.0208	0.0293	0.0038
Bond	-0.0151	0.0084	-0.0101	-0.0120	0.0468	0.0426	0.0093
Cash	-	-	-	-	-	-	-
Currency	0.0039	0.0012	0.0101	0.0148	0.0145	0.0135	-0.0019
Gold	-0.0129	-0.0129	-0.0129	-0.0129	-0.0035	-0.0041	-0.0129
Silver	-0.0180	-0.0180	-0.0180	-0.0180	-0.0128	-0.0131	-0.0180
Platinum	-0.0329	-0.0329	-0.0329	-0.0329	-0.0253	-0.0258	-0.0329
Palladium	0.0110	0.0110	0.0110	0.0110	0.0165	0.0161	0.0110

Note: The table shows the Sharpe ratio of traditional assets in the G7 markets and precious metals across three phases of the 2008 financial crisis. One-month Libor rate is used to proxy the risk-free rate.

the G7 group, including stocks, bonds, cash, and currencies. Two augmented portfolios are constructed by adding, in the first case, the spot returns of four precious metals and, in the second case, their future returns, into the traditional portfolio. In order to reduce the sensitivity to the choice of b_T in finite samples of realistic time series and cross-sectional dimensions, the bias correction proposed by [Arvanitis et al. \(2019\)](#) was applied for the quantile estimates q_{T,b_T} . Accordingly, subsample size $b_T \in [T^{0.6}, T^{0.7}, T^{0.8}, T^{0.9}]$ was chosen to obtain the subsampling distribution of the test statistic. After that, OLS regression was used on the empirical quantiles q_{T,b_T} with the significance level $\alpha = 0.05$ in order to estimate the critical value q_T^{BC} . Spanning was rejected if the test statistic η_T^* is higher than the regression estimate q_T^{BC} .

Table 19 reports the results of the test statistic η_T^* and the regression estimate q_T^{BC} . In both augmentation cases (i.e., the portfolio augmented with the spot or future of

precious metals) and any period relevant to the global financial crisis of 2008, the optimal traditional portfolio cannot span any of its optimal augmented ones. These results indicate that augmenting the traditional portfolio with the spot or futures of four precious metals can improve its investment performance. Risk-averse investors might therefore be better off by performing such augmentations.

Table 19: In-sample tests

Periods	Variables	Test statistic η_T^*	Reg. Estimates q_T^{BC}	Results
Full period	Spots	0.2680	0.2435	<i>Reject Spanning</i>
	Futures	0.3210	0.2651	<i>Reject Spanning</i>
pre-crisis	Spots	0.3609	0.2820	<i>Reject Spanning</i>
	Futures	0.3412	0.2430	<i>Reject Spanning</i>
crisis	Spots	0.1684	0.1567	<i>Reject Spanning</i>
	Futures	0.1743	0.1458	<i>Reject Spanning</i>
post-crisis	Spots	0.2645	0.1935	<i>Reject Spanning</i>
	Futures	0.2815	0.2012	<i>Reject Spanning</i>

Note: The table reports the results of the test statistic η_T^* and the regression estimate q_T^{BC} for two augmentation cases (i.e., precious metals spot and future returns) over the whole sample period (Jan 2005 to Sep 2018) and three sub-sample periods, including pre-crisis (Jan 2005 to Aug 2007), crisis (Sept 2007 to Dec 2010), and post-crisis (Jan 2011 to Sep 2018), respectively. We reject spanning if the test statistic η_T^* is higher than the regression estimate q_T^{BC} .

3.5.2 Out-of-sample analysis

Next, this subsection conducts an out-of-sample setting to examine whether the augmented portfolios outperform the traditional ones.

Three optimal portfolios were built separately from various asset universes. The first portfolio includes only traditional asset classes (i.e., stocks, bonds, cash, and currencies). The second one is the traditional portfolio augmented with precious metal spots, and the last is the traditional portfolio augmented with precious metal futures. The out-of-sample analysis covers the period from 03 Jan 2005 to 20 Sep 2018. The data from the first year was used as the first training set for each day to calibrate the procedure. Thus, the out-of-sample period began from 02 Jan 2006 to 20 Sep 2018. The optimization problem

was solved for the stochastic spanning test and the optimal weights were then recorded for both traditional and augmented portfolios.

Figures 6 to 8 exhibit the cumulative performance of the optimal traditional and augmented portfolios. The analysis was carried out for three sub-periods. These figures reveal that the augmented portfolios significantly outperformed the traditional portfolio in any case and period. This conclusion confirms the findings about the diversification benefits of precious metals from the in-sample analysis. Notably, figure 8 shows that, in the aftermath of the 2008 financial crisis, precious metal futures offered more diversification benefits than precious metals spots. This finding agrees with those of [Kang et al. \(2017\)](#), [Mensi et al. \(2021\)](#), which point out that the future contracts of precious metals have become the most widely used instruments for risk management in more volatile periods and suggests that investors can hold precious metal futures to improve their portfolio more than by investing in these metals spots.

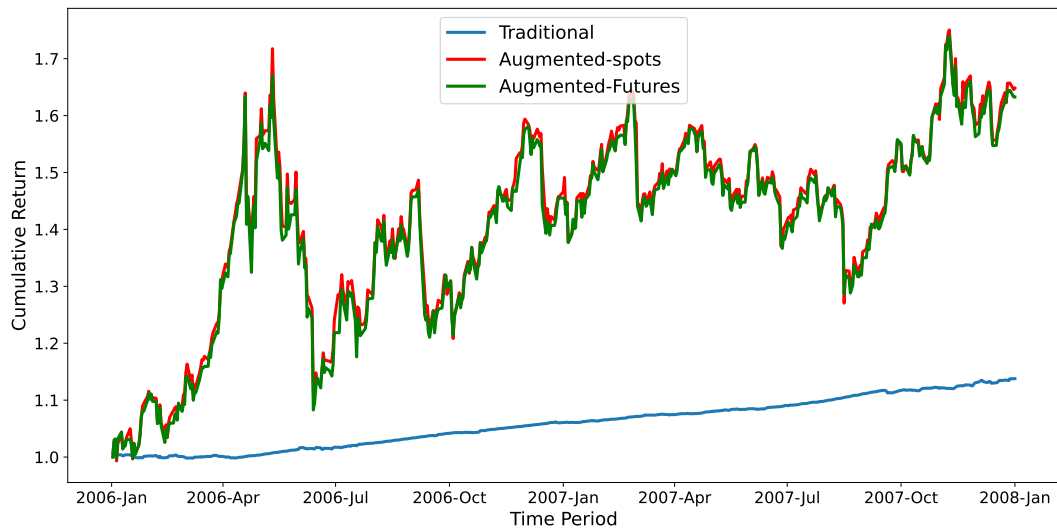


Figure 6: Cumulative performance of the traditional optimal portfolio and the two augmented optimal portfolios over the pre-crisis period from Jan 02, 2006 to Jan 31, 2008.

3.5.3 Out-of-sample performance assessment

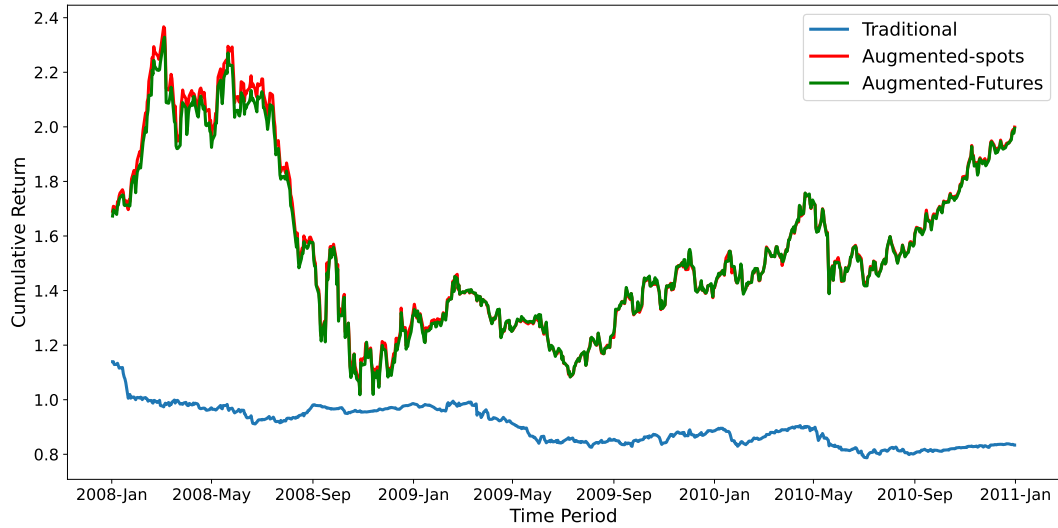


Figure 7: Cumulative performance of the traditional optimal portfolio and the two augmented optimal portfolios over the crisis period from Feb 01, 2008, to Dec 31, 2010.

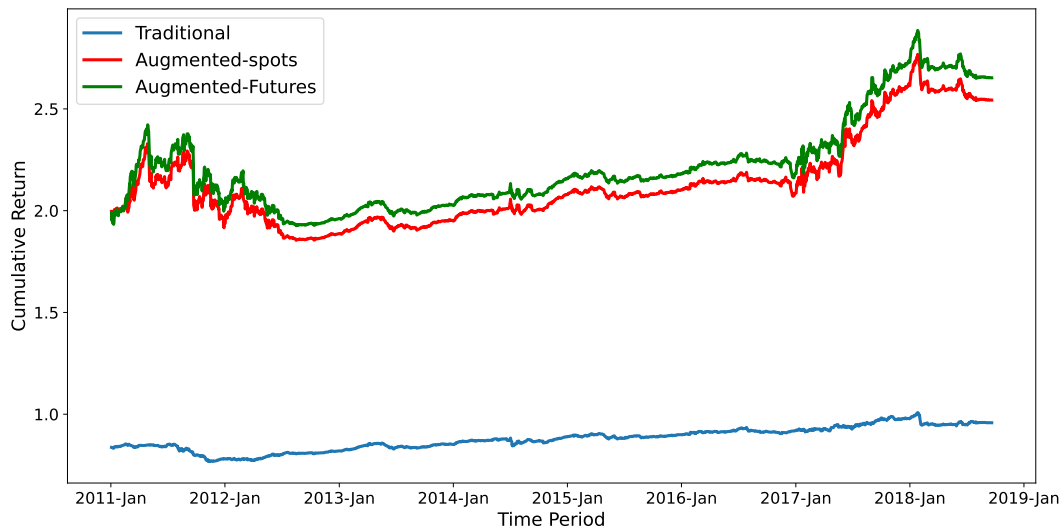


Figure 8: Cumulative performance of the traditional optimal portfolio and the two augmented optimal portfolios over the post-crisis period from Jan 01, 2011, to Sep 20, 2018.

This subsection computes and compares the out-of-sample performance between the optimal augmented and the optimal traditional portfolios by using parametric tests. Several ratios suggested by [Anyfantaki & Topaloglou \(2018\)](#), were calculated, including the Sharpe ratio, the downside Sharpe ratio of [Ziemba \(2005\)](#), the upside potential and downside risk (UP) ratio of [Sortino & Van Der Meer \(1991\)](#), the opportunity cost, the portfolio turnover, and a measure of the portfolio risk-adjusted returns net of transaction costs. These ratios can cover the impact of the higher order moments and transaction costs on performance evaluation.

The downside Sharpe is considered a more appropriate performance measure than the typical Sharpe ratio, given the asymmetric return distribution of precious metals ([Baur 2012](#), [Todorova 2017](#)).

The downside Sharpe ratio of Ziemba (2005)

$$S_P = \frac{\bar{R}_p - \bar{R}_f}{\sqrt{2}\sigma_{P-}},$$

\bar{R}_p is the average back-testing period return of portfolio P and \bar{R}_f is the average risk-free rate. σ_{P-} is the downside standard deviation.

The next ratio is *the portfolio turnover (PT)*

$$PT = \frac{1}{T} \sum_{t=1}^T \sum_{i=1}^N \left(\left| \omega_{P,i,t+1} - \omega_{P,i,t} \right| \right),$$

where $\omega_{P,i,t+1}$ and $\omega_{P,i,t}$ are the optimal weights of asset i under strategy P (traditional or augmented) at time t and $t + 1$, respectively, over T rebalancing points in time and across the N available assets.

From PT , [DeMiguel et al. \(2007\)](#) proposed the new ratio, named the proportional transaction cost (PTC), as a risk-adjusted returns measure. $R_{P,t+1}$ is the realized return

of portfolio P at time $t + 1$. The change in the net transaction cost wealth (NW_P) is calculated as follows

$$NW_{P,t+1} = NW_{P,t} \left(1 + R_{P,t+1} \right) \left[1 - PTC \cdot \sum_{i=1}^N \left(\left| \omega_{P,i,t+1} - \omega_{P,i,t} \right| \right) \right]$$

Net transaction costs (NTC) are then determined as

$$NTC_{P,t+1} = \frac{NW_{P,t+1}}{NW_{P,t}} - 1$$

Let μ_0 , σ_0 , and μ_1 , σ_1 be the out-of-sample mean and standard deviation of daily NTC with the traditional and augmented opportunity set, respectively, from which the return loss is defined as

$$ReturnLoss = \frac{\mu_1}{\sigma_1} \sigma_0 - \mu_0$$

Finally, *the opportunity cost* θ is the return of a new asset that needs to be added to the traditional portfolio if the investor is indifferent between two different investment opportunity sets [Simaan \(1993\)](#). In other words, the opportunity cost measure is defined (functions, works, is used, is treated) as the return trade-off of choosing the traditional portfolio over the augmented portfolio and is defined as

$$\mathbb{E} \left[U \left(1 + R_0 + \theta \right) \right] = \mathbb{E} \left[U \left(1 + R_1 \right) \right]$$

,

where R_0 and R_1 are the returns of the optimal portfolio for the traditional and augmented asset classes, respectively. $\theta > 0$ (< 0) indicates that the investors are better (worse) off when adding new assets to their investment opportunity set.

The opportunity cost takes into account the higher order moments rather than just the first and second moment in the case of the Sharpe ratio because it covers the entire probability density function of asset returns. Thus, the opportunity cost can be used reasonably to assess investment strategies even when the asset returns do not distribute normally.

Table 20 reports the results of the parametric performance measures and the opportunity costs for the traditional and augmented portfolios in the entire period of the financial crisis, as well as the three sub-periods mentioned above. In general, the higher values of these measures correspond with a greater number of diversification benefits for investing in precious metals. The results show that the augmented portfolios' Sharpe and downside Sharpe ratios outperform those of the traditional portfolios. These results complement the conclusion of the in-sample and out-of-sample analyses, i.e., that adding precious metals into the traditional portfolio significantly improves its performance.

In all cases, the traditional portfolio had a higher portfolio turnover than the augmented portfolios. This result indicates that the augmented portfolios require less frequent re-balancing and have lower cumulative transaction costs. Table 20 also shows that the return-loss measure, which accounts for transaction costs, was positive in both augmentation cases as well as in different periods.

The opportunity costs were calculated to consider higher-order moments rather than only the first and second moments. The opportunity costs were positive in all cases of augmentation, which hold for the exponential and power utility functions under the different degrees of absolute risk aversion (i.e., $ARA = 2, 4, 6$) and relative risk aversion (i.e., $RRA = 2, 4, 6$). These results showed that investors are better off by adding either spot or future returns of all four precious metals into their traditional portfolio.

The parametric performance measures thus demonstrate that the investment universe

of the augmented portfolios outperforms the traditional portfolio of stocks, bonds, cash, and currencies, resulting in benefits of diversity and greater investment opportunities. It is noteworthy that after the global financial crisis of 2008, precious metal futures were better than spot returns. This finding strongly reconfirms our conclusion about the hedging role of precious metal futures stated in section 3.5.2, and it also explains the emerging financialization of precious metal markets over the last few decades.

Table 20: Out-of-sample performance: Parametric performance measures

	Whole period			pre-crisis			crisis			post-crisis		
	Trad.	Augm. Spot	Augm. Futures	Trad.	Augm. Spot	Augm. Future	Trad.	Augm. Spot	Augm. Future	Trad.	Augm. Spot	Augm. Future
Performance Measures												
Sharpe Ratio	-0.0018	0.0295	0.0287	0.0515	0.0559	0.0535	-0.0616	0.0216	0.0221	0.0293	0.0358	0.0337
Downside Sharpe Ratio	-0.0023	0.0400	0.0389	0.0708	0.0729	0.0706	-0.0762	0.0302	0.0307	0.0384	0.0484	0.0447
Portfolio Turnover	0.2680	0.1681	0.1681	0.3202	0.0129	0.0129	0.3259	0.1320	0.1320	0.2618	0.2224	0.2224
Return Loss (vs Trad. portfolio)		0.0002	0.0002		0.0040	0.0040		0.0035	0.0034		0.0012	0.0012
Opportunity Cost												
<i>Exponential Utility</i>												
ARA = 2		0.0740	0.0731		0.1185	0.1149		0.1310	0.1350		0.0254	0.0237
ARA = 4		0.0557	0.0554		0.0921	0.0887		0.0830	0.0881		0.0227	0.0210
ARA = 6		0.0403	0.0407		0.0724	0.0692		0.0468	0.0525		0.0208	0.0190
<i>Power Utility</i>												
RRA = 2		0.0745	0.0738		0.1189	0.1152		0.1211	0.1255		0.0259	0.0239
RRA = 4		0.0517	0.0521		0.0901	0.0867		0.0624	0.0682		0.0246	0.0222
RRA = 6		0.0276	0.0294		0.0668	0.0638		0.0194	0.0259		0.0247	0.0220

Note: This table reports the various performance measures for the traditional portfolio and the portfolios augmented with precious metals spot or precious metals futures. The results for the opportunity costs are reported for different degrees of absolute risk aversion ($ARA = 2, 4, 6$) and different degrees of relative risk aversion ($RRA = 2, 4, 6$). The dataset covers the out-of-sample period from Jan 03, 2005, to Sep 20, 2018.

3.6 Conclusion

This chapter explores whether investors may be better off by augmenting their traditional portfolio of stocks, bonds, cash, and currencies with spots or futures of precious metals. The study focuses on the financial markets of G7 countries. It also pays special attention to the behavior of the spot and future returns of all four metals in and around the global financial crisis of 2008. This work contributes to the existing literature on behavior finance, crises, and the future markets of precious metals, showing that precious metals can offer diversification benefits for an international investment portfolio of equities, bonds, cash, and currencies. Additionally, the out-of-sample analysis compares diversification benefit potential between spot and future returns of precious metals. Precious metal futures outperformed their spots after the 2008 global crisis. This finding explains the increasing prevalence of precious metal futures over the last few decades. This study provides strong evidence for introducing and developing new financial innovations (e.g., futures, options, ETFs).

This chapter strongly supports introducing and developing new financial innovations in precious metals (e.g., futures, options, ETFs).

Chapter 4

THE TAIL DEPENDENCE STRUCTURE BETWEEN PRECIOUS METALS AND INTERNATIONAL STOCK MARKETS

The tail dependence structure of precious metals and stock markets could determine if precious metals can act as a safe haven against stock market extremes. This chapter, therefore, studies the tail dependence structure of precious metals and stock markets of G7 and BRICS countries. The analysis of tail dependence structure was performed using both bivariate copulas and multivariate copulas of pair-vine and hierarchical Archimedean copulas types, respectively. The empirical results show that hierarchical Archimedean copulas outperform and are more meaningful than pair-vine copulas, suggesting that

precious metal markets are more closely linked to the global than the individual stock market. In addition, this chapter finds solid evidence of significant tail dependence between precious metals and international stocks. This dependence is time-varying and asymmetric both in bivariate and multivariate analyses. In particular, the bivariate copulas (i.e., vine copulas) show that each precious metal could be an effective safe haven for individual stocks in almost all G7 stock markets during both upward and downward market conditions except for the European stock markets. The multivariate copulas (i.e., hierarchical Archimedean copulas) reveal that each precious metal can serve as a safe haven for all twelve stock markets during market downturns because of zero multi-lower tail dependence between each metal and twelve stocks. Interestingly, the multi-upper tail dependence coefficient of each precious metal return with twelve stocks returns was much higher than its lower tail dependence. This increase in the dependence level during market upturns indicates that risk lovers can hold precious metals and stocks in a bull market situation in order to improve expected returns. Lastly, the results suggest that the tail dependence structure between precious metals and stock markets was highly affected by the global financial crisis of 2008. In particular, the role of precious metals as a safe haven has declined after the 2008 financial crisis.

4.1 Introduction

In a turbulent environment, precious metals widely accepted as safe-haven assets in financial markets ([Baur & McDermott 2010](#), [Baur & Lucey 2010b](#), [Lucey & Li 2015b](#), [Li & Lucey 2017](#)), have attracted much greater attention. Surprisingly, current movements of precious metal markets seem to oppose academic findings when these safe-haven metals also experienced sharp and unpredictable volatility along with coronavirus-afflicted global stocks.

Among the three widely accepted roles of precious metals, including hedge¹, diversifier² and safe haven, only the third one has a specific property of reducing losses in the extreme adverse market conditions. According to the definition of [Baur & Lucey \(2010b\)](#), precious metals would be considered a safe haven against stock prices if these metals are uncorrelated (weak safe-haven) or negatively correlated (strong safe-haven) with stocks in times of extreme market movements. Therefore, the tail (or extreme) dependence structure between stock and precious metal markets tells us whether precious metals are safe haven assets. However, current research has faced significant challenges in measuring the tail dependence structure among financial assets. Many prior works looked into determining extreme correlation coefficients using an approach called Extreme Value Theory ([Longin & Solnik 2001](#), [Ang & Chen 2002](#), [Ang & Bekaert 2002](#), [Patton 2004](#)). On the other hand, several studies use the threshold regression model to estimate marginal effects ([Baur & Lucey 2010a](#), [Wang et al. 2011](#), [Ciner et al. 2013b](#)). However, [Embrechts et al. \(2001\)](#) believes that exceedance correlation is insufficient to account for tail dependency, particularly when the joint distribution of asset returns is not elliptical. Meanwhile, the application of threshold regression cannot completely explain the extreme movements between financial markets at the same time ([Sui et al. 2021](#)).

Applying the copula functions to estimate the tail dependence coefficient is suitable to handle the shortcomings mentioned above. The tail dependence coefficient is a common measure of tail dependence structure among random variables introduced firstly by [Sibuya \(1960\)](#). It can be defined as the probability of the worst event occurring in one market, given that the worst event occurs in another market. The main advantage of the tail dependence coefficient is it can keep its invariance to modifications of marginal distributions that do

¹A hedge is an asset that, on average, is either uncorrelated (weak hedge) or negatively correlated (strong hedge) with another asset or portfolio

²A diversifier is an asset that, on average, has a weakly positive correlation with another asset or portfolio

not exert any effect on the dependence structure (Garcia & Tsafack 2011). The copula approach also provides significant benefits in modeling the dependence structure when several copula functions may deal with non-linear, heavy tails, and asymmetric financial return distributions. Traditional copulas, however, have the disadvantage of being unable to model the dependence structure of multivariate data (i.e., three or more variables) efficiently. Hierarchical Archimedean copulas can interestingly overcome this issue. This is crucial due to the fact that the existing tail dependency literature mainly focuses on the co-movement of extreme returns of two assets or portfolios (i.e., bivariate tail dependence coefficient) (Garcia & Tsafack 2011, Reboredo 2013, Aloui & Aïssa 2016).

In the finance literature, the asymmetric tail dependence (i.e., the lower tail dependence can be larger than the upper tail dependence or vice versa) between international stock markets has been investigated widely (Longin & Solnik 2001, Ang & Chen 2002, Patton 2004, Hong et al. 2007, Kocaarslan et al. 2017, Jiang et al. 2018). Additionally, asymmetric dynamics in the extreme co-movement of global stock and other assets such as bonds, foreign currencies, or commodities have been paid considerable attention (Di Iorio & Faff 2000, Yang et al. 2009, Aloui & Mabrouk 2010, Garcia & Tsafack 2011, Nguyen et al. 2015, Bahmani-Oskooee & Saha 2018). Along with stocks, precious metals have also been found to be asymmetric both in volatility (Baur 2012, Todorova 2017) and in the interdependence themselves (Reboredo & Ugolini 2015, Klein 2017), even in the movements with other financial assets such as bitcoin (Mensi et al. 2019) and US dollar (Miyazaki & Hamori 2016). However, with the exception of a few studies demonstrating the asymmetric dependence between gold and stocks, the direct exploration of the asymmetric tail co-movement between precious metals and stocks, has received very little attention.

For the abovementioned reasons, this chapter applied both the bivariate copulas (pair-vine copulas) and the multivariate copulas (hierarchical Archimedean copulas) to

investigate the extreme dependence structure between international stocks and precious metal markets across three various periods of the global crisis of 2008. These two copula functions allow asymmetric modeling for tail dependence patterns. The former computes the pair-wise upper and lower tail dependence coefficients, while the latter estimates the multi-upper and lower tail dependence ones. Empirically, this chapter was conducted on daily data of G7 and BRICS stock markets and precious metal markets from January 2005 to September 2018. The dataset was divided into three sub-periods related to the global financial crisis of 2008: pre-crisis (from January 2005 to August 2007), during the crisis (from September 2007 to December 2010), and the post-crisis (from January 2011 to September 2018), respectively. The empirical results show evidence of significant tail dependence between precious metals and international stocks. In addition, this dependence is time-varying (i.e. the level and structure of the tail dependence change over three sub-periods of the financial crisis of 2008) and asymmetric both in bivariate and multivariate analyses. In the bivariate analysis, the results from pair-vine copulas exhibit the upper and lower tail independence between each precious metal and most of the stock markets, except for the case of German and Italy markets. This means each precious metal can act as a safe haven against extreme movements of individual stock in G7 markets. Meanwhile, the multivariate tail dependence estimations reveal that each precious metal can serve as safe haven against the global stock markets in market downturns. Meanwhile, the multi-upper tail dependence coefficient of each precious metal return with twelve stocks returns was much higher than its lower tail dependence, suggesting that investors and portfolio managers can hold precious metals and stocks during the upward movement markets to improve their expected returns.

This chapter is organized as follows. Section 4.2 describes the methodology and theoretical design. Data and empirical results are explained in section 4.3. Section 4.4

concludes and discusses the implications of the chapter.

4.2 Methodology and theoretical design

4.2.1 Copulas and multivariate tail dependence coefficients

Copulas are functions that build multivariate structures based on prescribed marginal distributions. The concept was first addressed and solved by [Sklar \(1959\)](#).

Definition 4.1 (Copulas definition). Sklar's theorem states that any joint distribution function can be written as a function C of marginal distribution functions

$$F(x_1, \dots, x_n) = P(X_1 \leq x_1, \dots, X_n \leq x_n) = C(F_1(x_1), \dots, F_n(x_n)), \quad (4.1)$$

where $X = (X_1, \dots, X_n)$ is a vector of an n -dimensional vector and F denotes the joint n -dimensional distribution function. Functions F_1, \dots, F_n are the respective marginal distribution functions of X_1, \dots, X_n and $F_i(x_i) = P(X_i \leq x_i)$.

Note that $F_i(x_i)$ is the uniform marginal distribution in $[0, 1]$. Let denote $u_i = F_i(X_i)$, the equation 4.1 becomes

$$C(u_1, \dots, u_n) = F(F_1^{-1}(u_1), \dots, F_n^{-1}(u_n)).$$

According to [Luca & Rivieccio \(2012\)](#), it is possible to derive the relationship between the survival joint function \hat{F} and the corresponding survival copula function \hat{C} as follows

$$\hat{F}(x_1, \dots, x_n) = \hat{C}(1 - u_1, \dots, 1 - u_n). \quad (4.2)$$

In terms of densities, the equation 4.1 can be rewritten equivalently as below

$$f(x_1, \dots, x_n) = c(F_1(x_1), \dots, F_n(x_n)) \cdot \prod_{i=1}^n f_i(x_i), \quad (4.3)$$

where f implies the joint density function of n -dimensional vector X , f_i denotes the density function of the univariate variables X_1, \dots, X_n and c represents the copula density function which is defined by

$$c(F_1(x_1), \dots, F_n(x_n)) = \frac{\partial^n}{\partial F_1(x_1), \dots, \partial F_n(x_n)} C(F_1(x_1), \dots, F_n(x_n)). \quad (4.4)$$

Di Bernardino & Rullière (2016) denotes set of indexes $I = \{1, \dots, n\}$ for $i \in I$, two probabilities are defined as follows

Definition 4.2 (Multivariate tail dependence coefficient definition).

$$\begin{cases} \lambda_L^i = \lim_{u \rightarrow 0^+} P[U_i \leq u \mid U_j \leq u, j \in I \setminus i], \\ \lambda_U^i = \lim_{u \rightarrow 1^-} P[U_i \geq u \mid U_j \geq u, j \in I \setminus i]. \end{cases} \quad (4.5)$$

The copula is said to have lower or upper tail dependency if λ_L^i or λ_U^i is not equal to 0 and no lower or upper tail dependence if λ_L^i or λ_U^i equal to 0.

This study aims to revisit the safe haven role of each precious metal against stocks' extreme stock price movements. Therefore, the first variable is one precious metal and the other $n - 1$ variables are the stocks. By which, λ_L^1 and λ_U^1 measure the probability that the metal reaches extreme value given that the stock markets reach extreme value. λ_L^1 and λ_U^1 can be rewritten by

$$\begin{cases} \lambda_L^1 = \lim_{u \rightarrow 1^-} \frac{\hat{C}_n(1-u, \dots, 1-u)}{\hat{C}_{n-1}(1-u, \dots, 1-u)}, \\ \lambda_U^1 = \lim_{u \rightarrow 0^+} \frac{C_n(u, \dots, u)}{C_{n-1}(u, \dots, u)}, \end{cases} \quad (4.6)$$

where C_n and \hat{C}_n are same as C and \hat{C} as above. C_{n-1} and \hat{C}_{n-1} are respectively copula and survival copula functions of $n - 1$ last variables.

For example, in the case $n = 2$, the bivariate tail dependence coefficients are defined

easily as follows

$$\begin{aligned}
P(U_1 > u \mid U_2 > u) &= \frac{P(U_1 > u, U_2 > u)}{P(U_2 > u)} \\
&= \frac{1 - P(U_1 \leq u) - P(U_2 \leq u) + P(U_1 \leq u, U_2 \leq u)}{1 - P(U_2 \leq u)} \\
&= \frac{1 - 2u + C(u, u)}{1 - u}.
\end{aligned}$$

So, one has

$$\lambda_U^1 = \lim_{u \rightarrow 1^-} \frac{1 - 2u + C(u, u)}{1 - u}.$$

In the same manner, the lower tail coefficient is defined by

$$\lambda_L^1 = \lim_{u \rightarrow 0^+} \frac{C(u, u)}{u}.$$

However, it finds difficult to have an analytical formula in the case of multivariate (greater than two dimensions). Hence that depends on the copula structure C . This challenge can be overcome by using the numerical limit. In particular, the limit of an arbitrary function $f(x)$ as x approaches c is approximated by $f(c + \delta)$ with δ as a sufficiently small value (i.e. the above λ_L^1 is approximately equal to $\frac{C(0.001, 0.001)}{0.001}$). But above all, I need to estimate the copula function.

This research uses two following copula structures: vine and hierarchical Archimedean copulas, to estimate the bivariate and multivariate tail dependence coefficients, respectively, between precious metals and stock markets.

4.2.2 Vine copulas

Vine copulas are based on the idea of decomposing a copula (a joint density function) into three kinds of components: marginal density functions, bivariate density functions,

and conditional joint distribution functions. In the following example with the case of three dimensions, the three separate lines are illustrated by the below equation

$$\begin{aligned}
 f_{123}(x_1, x_2, x_3) &= f_1(x_1) * f_2(x_2) * f_3(x_3) \\
 & c_{12}(F_1(x_1), F_2(x_2)) * c_{23}(F_2(x_2), F_3(x_3)) \\
 & c_{13|2}(F_{1|2}(x_1 | x_2), F_{3|2}(x_3 | x_2)).
 \end{aligned}$$

In general,

$$\begin{aligned}
 f(x_1, x_2, \dots, x_d) &= \prod_{k=1}^d f_k(x_k) \prod_{h=2}^d c_{1,h}(F_1(x_1), F_h(x_h)) \\
 & \prod_{j=2}^{d-1} \prod_{i=1}^{d-j} c_{j,j+i|1,\dots,j-1}(F(x_j | x_1, \dots, x_{j-1}), F(x_{j+i} | x_1, \dots, x_{j-1})).
 \end{aligned}$$

Vine copula has many decomposition strategies, of which there are three main types, including canonical vines (C-vines), drawable vines (D-vines), and regular vines (R-vines). The C-vines and D-vines, both are subsets of the R-vines. C-vines have star-like shapes whereas line tree shapes are found in D-vines. The C-vine structure is made up of trees, with each tree having a root node variable chosen based on the highest correlation values with the other variables. Meanwhile, each D-vine tree's nodes cannot have more than two edges connected to them. In addition, in terms of high correlation values, the D-vines have been found to better fit multivariate data sets where a group of factors has a significant impact on the other variables ([Arreola Hernandez et al. 2017](#)). Unlike the C-vine and D-vine, the form of the R-vine can vary greatly depending on the statistical properties of the multivariate distribution being represented.

The best-fitted pair-vine copula among the three types of vine copulas can be chosen by using criteria like the Akaike information criterion (AIC), Bayesian Information Criteria

(BIC), and maximum log-likelihood estimates.

4.2.3 Hierarchical Archimedean copulas

The Archimedean copulas family is built on the definition of a generator function (Cherubini et al. 2004). The generator function $\Phi : I = [0, 1]$ is a continuous, decreasing, and convex function, such that $\Phi(1) = 0$. In addition, $\Phi^{[-1]}(t)$ is defined the "pseudo-inverse" of $\Phi(t)$, denoted by $\Phi^{[-1]}(t) = \Phi^{-1}(t) \forall t \in [0, \Phi(0)]$ and $\Phi^{[-1]}(t) = 0$ for $t \geq \Phi(0)$.

According to Nelsen (2007), if $\Phi(0) = \infty$, then $\Phi(t)$ and C are strict. Meanwhile, if $\Phi(0) < \infty$, $\Phi(t)$ and C are non-strict.

Definition 4.3 (Hierarchical Archimedean copula). Let $\Phi^{-1}(t)$ be the inverse of $\Phi(t)$ a strict generator of an Archimedean copula, the Archimedean copula can then be written as

$$C(u_1, \dots, u_n) = \Phi^{-1}(\Phi(u_1) + \dots + \Phi(u_n)).$$

The main purpose of this chapter is to estimate multivariate tail dependence coefficients which can cover the asymmetric relationships between precious metals and stocks. Meanwhile, the main characteristics of Archimedean copulas are that they are symmetric and associative. Moreover, these copula functions only cover bivariate dependence measures. Therefore, to accomplish the purpose of this study, a generalization of multivariate Archimedean copulas named hierarchical Archimedean copulas with r nodes is employed.

The tail dependence coefficient of Archimedean copulas is totally defined by the single generator's index of regular variation, the tail dependency of hierarchical Archimedean copulas is dependent on the interconnection of the generators at different levels. Therefore, the case of hierarchical Archimedean copulas is more complicated.

The expression of the survival copula \hat{C} is generalized for an Archimedean copula C

with generator function Φ , that is

$$\hat{C}(1 - u_1, \dots, 1 - u_n) = \sum_{i=0}^n \left\{ \binom{n}{n-i} (-1)^i \left[\Phi^{-1} \left(\sum_{j=0}^i \Phi(u_j) \right) \right] \right\}, \quad (4.7)$$

where $\Phi^{-1}(\Phi(u_0)) = 1$ and $\Phi^{-1}(\Phi(u_1)) = u_1$.

Theorem 4.1 (Multivariate upper and lower tail dependence coefficients).

$$\lambda_U^1 = \lim_{t \rightarrow 0^+} \frac{\sum_{i=1}^n \left\{ \binom{n}{n-i} i (-1)^i [\Phi^{-1'}(it)] \right\}}{\sum_{i=1}^{n-1} \left\{ \binom{n-1}{n-1-i} i (-1)^i [\Phi^{-1'}(it)] \right\}} \quad (4.8)$$

$$\lambda_L^1 = \frac{n}{n-1} \lim_{t \rightarrow \infty} \frac{\Phi^{-1'}(nt)}{\Phi^{-1'}((n-1)t)}. \quad (4.9)$$

Proof. Replacing (4.7) in (4.6),

$$\lambda_U^1 = \lim_{u \rightarrow 1^-} \frac{\sum_{i=0}^n \left\{ \binom{n}{n-i} (-1)^i [\Phi^{-1}(i\Phi(u))] \right\}}{\sum_{i=0}^{n-1} \left\{ \binom{n-1}{n-1-i} (-1)^i [\Phi^{-1}(i\Phi(u))] \right\}}. \quad (4.10)$$

Applying de L'Hôpital theorem,

$$\lambda_U^1 = \lim_{t \rightarrow 0^+} \frac{\sum_{i=1}^n \left\{ \binom{n}{n-i} i (-1)^i [\Phi^{-1'}(it)] \right\}}{\sum_{i=1}^{n-1} \left\{ \binom{n-1}{n-1-i} i (-1)^i [\Phi^{-1'}(it)] \right\}}.$$

In a similar way, the multivariate lower tail dependence coefficient has the following close form

$$\lambda_L^1 = \frac{n}{n-1} \lim_{t \rightarrow \infty} \frac{\Phi^{-1'}(nt)}{\Phi^{-1'}((n-1)t)}.$$

□

As a suggestion from [Luca & Rivieccio \(2012\)](#), two multivariate bi-parametric (MB) copula functions, MB1 and MB7, which extended from BB1 and BB7 copulas, are considered for Φ .

Definition 4.4 (MB1 Copula and MB7 Copula). These copulas are defined by the following formulas

$$C_{MB1}(u_1, \dots, u_n) = \left\{ 1 + \left[\sum_{i=1}^n (u_i^{-\theta} - 1)^\kappa \right]^{1/\kappa} \right\}^{-1/\theta}, \quad (4.11)$$

$$C_{MB7}(u_1, \dots, u_n) = 1 - \left(1 - \left[\sum_{i=1}^n (1 - (1 - u_i)^\theta)^{-\kappa} - (n - 1) \right]^{-1/\kappa} \right)^{1/\theta}, \quad (4.12)$$

where κ and θ are parameters of copula families.

Finally, the best-fitted model is selected by AIC, BIC, and log-likelihood as above.

4.3 Empirical applications

4.3.1 Data and properties

The daily closing spot prices of twelve stock-market indices of G7³ and BRICS⁴ nations and four precious metals (i.e., gold, silver, platinum, and palladium) over the period from January 03, 2005, to September 20, 2018, has been used.

Table 21 summarizes the descriptive statistics for all asset returns in a full sample period. It can be seen that the mean is small and positive for most return series, except for the case of the Italy stock market (i.e. its mean is negative). Among the four precious metals, palladium returns exhibit the highest mean, but gold volatility is the smallest.

³S&P 500 of the United States, FTSE 100 of the United Kingdom, NIKKEI 225 of Japan, S&P/TSX Composite Index of Canada, CAC 40 of France, DAX of Germany and FTSE MIB of Italy

⁴BOVESPA of Brazil, MOEX of Russia, NIFTY50 of India, SSE Composite Index of China and FTSE/JSE Africa All Shares Index of South Africa

Moreover, stock returns of BRICS markets seem to be higher than those of G7 markets in terms of the mean value. Table 21 also reports the results of skewness and kurtosis. The skewness is all negative, while the kurtosis values are positive and higher than three for all return series, indicating non-Gaussian distributions, which is confirmed by a Jarque-Bera statistical test. Thus, copula functions are the most suitable to describe these properties of the data having fat tails and changes in distributional characteristics.

In addition to the descriptive statistics, the p -values of Ljung-Box (LB) statistics of order 15 for return series show the existence of auto-correlation in most of them. For the squared returns series, however, p -values of LB are highly significant, which reveals high dependence on the long horizon.

Finally, Table 21 provides the results of the traditional unit roots tests including ADF, PP, and KPSS, respectively. Strong evidence against the null hypothesis of a unit root, reflects that all the return series are stationary with a high level of significance.

Table 22 reports Pearson's pairwise correlation among sixteen assets, including four precious metals and twelve stocks of G7 and BRICS markets. Considerably, several notable points can be observed from the correlation results. Firstly, a high and positive correlation between precious metals can be seen. Secondly, a positive correlation can also be found in all stocks of both G7 and BRICS markets, in which the U.S. stock market tends to be highest correlated with the remaining stock markets. In contrast, European stock markets create a significantly close link. Thirdly, precious metals tend to co-move more between themselves than their cross-correlation with stocks. Finally, cross-correlations between precious metals and stocks are low (e.g., almost the correlations between precious metals and stocks are below 0.3) and positive, except for the negative correlation between gold and Italy stock or gold and the U.S. stock. Among four precious metals, gold is nevertheless found to have the least correlation with stocks.

Table 21: Descriptive statistics and stationary tests of precious metals and stocks

	Mean	Sd.Dev	Skewness	Kurtosis	J.B.	Q(15)	Q ² (15)	ARCH(15)	ADF	PP	KPSS
<i>Precious Metals</i>											
gold	0.0277	1.1236	-0.2539	4.9659	0.0000	0.0162	0.0000	0.0000	-15.7651	-62.2210	0.3712
silver	0.0228	1.9756	-0.7718	6.4655	0.0000	0.7396	0.0000	0.0000	-15.8727	-61.2131	0.2842
platinum	0.0006	1.3697	-0.6754	4.7086	0.0000	0.2151	0.0000	0.0000	-14.2532	-58.9600	0.2641
palladium	0.0441	1.9443	-0.5534	3.6329	0.0000	0.3545	0.0000	0.0000	-15.5046	-59.1476	0.0473
<i>G7 Stocks</i>											
US	0.0252	1.1350	-0.3832	12.9548	0.0000	0.0000	0.0000	0.0000	-16.5198	-69.1288	0.1831
UK	0.0130	1.0931	-0.1632	9.2012	0.0000	0.0000	0.0000	0.0000	-16.5735	-64.6610	0.0367
Japan	0.0207	1.4412	-0.5347	8.9944	0.0000	0.4965	0.0000	0.0000	-15.4273	-63.9749	0.1483
Canada	0.1770	1.0402	-0.7316	12.6281	0.0000	0.0000	0.0000	0.0000	-16.5755	-63.7594	0.0678
France	0.0111	1.3231	-0.0506	7.3150	0.0000	0.0000	0.0000	0.0000	-16.3350	-64.9301	0.0777
Germany	0.0295	1.2945	-0.0518	6.7028	0.0000	0.0874	0.0000	0.0000	-15.8998	-62.0145	0.0426
Italy	0.0059	1.5023	-0.2530	6.2167	0.0000	0.0010	0.0000	0.0000	-14.7782	-64.0003	0.0973
<i>BRICS Stocks</i>											
Brazil	0.0327	1.6802	-0.0726	5.5742	0.0000	0.0382	0.0000	0.0000	-15.1019	-63.3375	0.1224
Russia	0.0401	1.9525	-0.2481	21.9839	0.0000	0.0000	0.0000	0.0000	-15.4614	-61.8519	0.1008
India	0.0461	1.4013	-0.2708	12.0668	0.0000	0.0000	0.0000	0.0000	-14.3457	-59.1694	0.0569
China	0.0156	1.5821	-0.5408	4.8830	0.0000	0.0000	0.0000	0.0000	-13.7815	-61.2449	0.1299
South-Africa	0.0441	1.1643	-0.1847	4.1484	0.0000	0.0011	0.0000	0.0000	-16.1608	-61.1809	0.2099

Notes: The table shows the descriptive statistics for the daily returns series of four precious metals markets and twelve stocks markets from G7 and BRICS nations from Jan 03, 2005, to Sep 20, 2018. J.B. refers P-value of the Jarque-Bera test for normality. Q(15) and Q²(15) denote the Ljung-Box Q-test statistics for auto-correlation in the return and squared return series, respectively, up to 15 lag. Furthermore, ARCH(15) is the (Engle 1982) LM test for ARCH effects up to 15 lags. Finally, the ADF, PP, and KPSS represent the Augmented (Dickey & Fuller 1981), (Phillips & Perron 1988), and (Kwiatkowski et al. 1992) unit root tests. With the critical values at significance levels 10%, 5%, and 1% being -1.62 , -1.95 , and -2.58 , respectively, all three tests show that all series are stationary.

However, Pearson's linear correlation has several drawbacks. In particular, it is unable to cover the non-linear dependence and does not account for dependency asymmetries. As a result, a rank correlation emerges as a solution to this issue. To find potential independent conditional pairs, an initial bivariate independence test based on Kendall's tau is conducted. Tables 23, 24 and 25 show Kendall's tau values between stock-precious metal pairs over three sample sub-periods in order to highlight better comparison. Over the pre-crisis time, the strongest positive dependence is between two pairs: gold-German stock and silver-Italy stock, as shown by Kendall's tau value in Table 23. In fact, it can be seen that the majority of precious metals-stock pairs show positive dependence in the years leading up to the financial crisis. This means that an increase in the price of precious metals is associated with an appreciation of stock prices. However, except for gold, the dependence between all precious metals and US stock is significantly negative for this period. These results suggest that precious metals could be a good diversified choice for the stock portfolio of the G7 markets. The dependence on precious metals and stocks became apparent during the financial crisis of 2008. In particular, the results of Table 24 show that the Italian stock market has the strongest positive dependency on precious metals regarding the empirical value of pairwise Kendall's tau. Notably, there is a significant variation in the dependence between gold and G7 stocks. If before the 2008 financial crisis, the estimated Kendall's tau values of gold-G7 stock pairs were positive, most of them were negative during the crisis. This indicates that gold can be served as a hedger for G7 stocks in periods of extreme turbulence. The post-crisis picture clearly shows the difference between gold and white precious metals (i.e., silver, platinum, and palladium) in their dependent relationship with G7 stocks (see Table 25). Particularly, the positive dependence is between gold and each G7 stock, while it is negative between each white precious metal and each stock of this group. This is in line with several recent

findings that point out the distinct differences in financial role between white precious metals and gold (Batten et al. 2015, Lau et al. 2017).

Table 22: Pearson correlation matrix between precious metals and stocks

	Au	Ag	Pt	Pd	US	UK	JP	CA	FR	DE	IT	BR	RU	IN	CN
Ag	0.8107														
Pt	0.6375	0.6545													
Pd	0.4839	0.5566	0.6551												
US	-0.0051	0.1215	0.1671	0.2294											
UK	0.0560	0.2245	0.2638	0.3254	0.5680										
JP	0.0197	0.1120	0.1678	0.1841	0.1257	0.3241									
CA	0.1884	0.2920	0.3256	0.3404	0.7337	0.5687	0.2237								
FR	0.0055	0.1823	0.2157	0.2978	0.5881	0.8949	0.3198	0.5501							
DE	0.0090	0.1725	0.2057	0.2788	0.6005	0.8468	0.3036	0.5302	0.9267						
IT	-0.0019	0.1643	0.2014	0.2826	0.5329	0.7890	0.2734	0.4977	0.8893	0.8356					
BR	0.1124	0.2107	0.2338	0.2542	0.6231	0.5028	0.1644	0.6002	0.4943	0.4791	0.4448				
RU	0.0997	0.2359	0.2887	0.2832	0.3025	0.5423	0.2898	0.3835	0.5190	0.4998	0.4636	0.3483			
IN	0.0896	0.1615	0.1924	0.2029	0.2568	0.3949	0.3385	0.2744	0.3860	0.3893	0.3486	0.2811	0.3395		
CN	0.0227	0.0757	0.1315	0.1157	0.0775	0.1525	0.2507	0.1203	0.1450	0.1372	0.1213	0.1526	0.1517	0.2176	
SA	0.1701	0.2954	0.3282	0.3384	0.3733	0.6558	0.3647	0.4498	0.6268	0.6015	0.5493	0.4122	0.5419	0.4191	0.1856

Notes: see abbreviations at Table 34.

Table 23: Empirical Kendall's tau over the pre-crisis period

	gold	silver	platinum	palladium	US	UK	Japan	Canada	France	Germany	Italy
gold											
silver	0.0008										
platinum	-0.0058	0.0349									
palladium	-0.0189	0.0253	0.0426								
US	0.0791	-0.0036	-0.0093	-0.0249							
UK	0.0002	0.0820	0.0330	0.0139	-0.0479						
Japan	0.1237	0.0402	-0.0007	0.2421	0.0639	-0.0159					
Canada	0.0324	0.1640	-0.0433	-0.0083	0.0256	-0.0290	0.2125				
France	0.0314	0.0631	-0.0347	0.0154	0.3623	-0.0116	0.0724	0.0702			
Germany	0.6137	0.0986	0.0880	0.3971	0.1659	0.3690	-0.0041	0.0205	0.0347		
Italy	0.0773	0.6542	0.2019	0.0477	0.2617	0.0622	0.7612	0.2769	0.0469	0.6826	

4.3.2 Results and discussions

This section focuses on estimating the lower and upper tail dependence coefficient to test the safe-haven property of precious metals in both cases of bear and bull market periods in periods before, during, and after the 2008 global financial crisis. Accordingly, the empirical results have been divided into two parts. The first part exploits the bivariate tail dependence structure of four precious metals and G7's stocks using the suitable vine copulas while the second one focuses on modeling the multivariate tail dependence structure of four precious metals and twelve stocks of G7 and BRICS countries by

Table 24: Empirical Kendall's tau over the crisis period

	gold	silver	platinum	palladium	US	UK	Japan	Canada	France	Germany	Italy
gold											
silver	-0.0268										
platinum	-0.0427	-0.0146									
palladium	-0.0756	0.0381	-0.0074								
US	-0.0275	-0.0336	0.0003	0.0058							
UK	-0.1223	0.0062	-0.0018	-0.0199	0.0223						
Japan	-0.1076	-0.0334	0.0233	0.0249	0.0010	-0.0214					
Canada	-0.0874	-0.0525	-0.0392	0.0608	0.0325	0.0033	0.0278				
France	-0.0750	0.0677	-0.0625	0.0845	0.0876	-0.0354	0.0714	-0.0106			
Germany	0.1939	0.0951	0.0883	0.0413	0.1163	0.0425	0.1039	0.0919	0.0518		
Italy	0.6273	0.5126	0.4638	0.2463	0.5153	0.1571	0.4186	0.6516	0.7515	0.6710	

Table 25: Empirical Kendall's tau over the post-crisis period

	gold	silver	platinum	palladium	US	UK	Japan	Canada	France	Germany	Italy
gold											
silver	0.6239										
platinum	0.5045	0.4984									
palladium	0.2837	0.3334	0.4435								
US	-0.0060	0.0819	0.1168	0.1847							
UK	-0.0111	0.0855	0.1258	0.1955	0.3917						
Japan	-0.0333	0.0193	0.0405	0.0681	0.0841	0.1640					
Canada	0.0999	0.1768	0.1941	0.2259	0.5006	0.3673	0.1196				
France	-0.0551	0.0450	0.0899	0.1751	0.4130	0.6225	0.1510	0.3618			
Germany	-0.0505	0.0585	0.0883	0.1686	0.4012	0.5847	0.1575	0.3432	0.7363		
Italy	-0.0438	0.0471	0.0895	0.1602	0.3545	0.4988	0.1137	0.3233	0.6493	0.5833	

employing hierarchical Archimedean copulas.

Pair-vine copulas results

First, a copula family is selected among the Bivariate copulas families listed in table 35 (e.g., Independence, Gaussian, Student-t, Clayton, Gumbel, Frank, Joe, BB1, BB6, BB7, BB8, Survival Clayton, Survival Gumbel, Survival Joe, Survival BB1, Survival BB6, Survival BB7, and Survival BB8 copula) which may cover many different types of dependent structures.

Table 26 presents the results of the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and LogLikelihood (LL) of C-Vine, D-Vine, and R-Vine over the three sub-periods. The results from Table 26 show that the C-vine copula is best suited to the pre-crisis period. Meanwhile, the R-vine copula outperforms other pair vines during the crisis and post-crisis periods. C-vine, therefore, is chosen to estimate the tail dependence coefficients before the global crisis of 2008, and R-vine is for the two

remaining periods.

In addition, the absolute values of pairwise Kendall's taus from Tables 23, 24, and 25 are used as weights in order to choose the appropriate vine structure. According to Czado et al. (2012), the first node in the vine model should be variable with the highest correlation measured by the absolute empirical values of pairwise Kendall's tau. The first tree of vine copulas for three periods is shown in figure 10 in the Appendix.

Table 26: Vine copulas model selection

	pre-crisis			crisis			post-crisis		
	C-vine	D-vine	R-vine	C-vine	D-vine	R-vine	C-vine	D-vine	R-vine
AIC	-7827.60	-7780.44	-7811.05	-3665.93	-3734.88	-3837.49	-23860.91	-24012.22	-24192.78
BIC	-7628.83	-7557.43	-7612.28	-3501.29	-3554.92	-3669.02	-23458.39	-23615.54	-23761.09
LL	3954.80	3936.22	3946.52	1875.96	1914.44	1962.74	11999.46	12074.11	12170.39

Note: The table summarizes the results of the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Log-Likelihood (LL) of C-Vine, D-Vine, and R-Vine over the three sub-periods: the pre-crisis period (Mar 02, 1998, to Aug 31, 2007), the crisis period (Sept 03, 2007, to Dec 31, 2010) and the post-crisis period (Jan 03, 2011, to Sep 20, 2018). The criterion in bold corresponds to the best-performing model.

The reported results from table 27 to 32 show that the degree and the structure of tail dependence witnessed notable changes over three periods of the financial crisis of 2008. Therefore, the result analyses were divided into three parts corresponding to each sub-period.

The pre-crisis period

In this period, the C-vine structure provides the lower and upper tail dependence coefficients for each metal-stock pair before the financial crisis of 2008 (see tables 27 and 28). First of all, the results from these two tables exhibit asymmetric tail dependence between precious metals and stocks in most G7 markets, except the pair of Japanese stock and gold, which has the same upper and lower tail coefficient. Notably, there exists both lower and upper tail independence between the vast majority of precious metal-stock pairs with the threshold probability for zero dependence equal to 0.1%.

This finding indicates that in major G7 countries, precious metals may act as a safe haven against both the downward and upward movements in the stock markets of these nations. Exceptionally, table 27 shows positive tail coefficients in the following pairs: gold-Japanese stock, gold-German stock, and gold-Italian stock, suggesting that gold cannot be seen as a safe haven asset in the stock markets of Japan, Germany, and Italy during market downturns. Similarly, silver is not an effective safe haven against Italian stock markets during bearish conditions. Also, platinum and palladium cannot serve as a safe haven against the extreme downtrend of Italian and German stock markets. During the bullish market conditions, table 28 shows that most metal-stock pairs have zero upper tail dependency, with the exception of those with positive upper tail dependence (e.g. gold-Japan, gold-Germany, silver-Italy, and palladium-Germany). This result reveals that precious metals can act as a safe haven in case of upward movements in the G7 stock markets.

Table 27: The bivariate lower tail dependence coefficient estimation from C-vine over the pre-crisis period

	gold	silver	platinum	palladium
US	0.0000	0.0000	0.0000	0.0000
UK	0.0000	0.0000	0.0000	0.0000
Japan	0.0045	0.0000	0.0000	0.0000
Canada	0.0000	0.0000	0.0000	0.0000
France	0.0000	0.0000	0.0000	0.0000
Germany	0.6349	0.0000	0.1124	0.1622
Italy	0.1198	0.7085	0.2602	0.1317

Note: The estimations of the bivariate lower tail dependence coefficients between the precious metal - G7 stock pairs from C-vine in the pre-crisis period (the threshold probability for zero dependence is equal to 0.1%).

The crisis period

Tables 29 and 30 exhibit the results from the R-vine structure for the pair lower and upper tail dependence coefficients between metals and stocks during the financial crisis of

Table 28: The bivariate upper tail dependence coefficient estimation from C-vine over the pre-crisis period

	gold	silver	platinum	palladium
US	0.0000	0.0000	0.0000	0.0000
UK	0.0000	0.0000	0.0000	0.0000
Japan	0.0045	0.0000	0.0000	0.0000
Canada	0.0000	0.0000	0.0000	0.0000
France	0.0000	0.0000	0.0000	0.0000
Germany	0.2377	0.0000	0.0000	0.1622
Italy	0.0000	0.5706	0.0000	0.0000

Note: The estimations of the bivariate upper tail dependence coefficients between the precious metal - G7 stock pairs from C-vine in the pre-crisis period (the threshold probability for zero dependence equals 0.1%).

2008. Unlike the pre-crisis period, the results of the crisis period exhibit both symmetric positive tail dependence between several pairs (e.g., gold and German stock, gold and Italian stock, silver and Canadian stock, platinum and German stock) and asymmetric positive tail between other pairs including silver and Canadian stock, palladium and Japanese stock, palladium, and Italian stock). With the threshold probability for zero dependence equal to 0.1%, there is no upper and lower tail dependence in the remaining precious metal-stock pairs. This result indicates that precious metals can serve as a safe haven against almost all of the G7 stock markets in both tails.

The post-crisis period

The R-vine provides the lower and upper tail dependence coefficients for each metal-stock pair in the post-crisis in tables 31 and 32). After the global crisis, both the pair lower and upper dependence structures among precious metals and international stocks have changed. The empirical results also show both asymmetric and symmetric tail dependence. In comparison to the preceding two periods, however, the number of metal-stock pairs with zero upper and lower tail dependence decreased. This indicates that the role of precious metals as a safe haven has declined since the crisis. Notably, a positive tail

Table 29: The bivariate lower tail dependence coefficient estimation from R-vine over the crisis period

	gold	silver	platinum	palladium
US	0.0000	0.0000	0.0000	0.0000
UK	0.0000	0.0000	0.0000	0.0000
Japan	0.0000	0.0000	0.0000	0.1016
Canada	0.0000	0.0154	0.0000	0.0981
France	0.0000	0.0000	0.0000	0.0000
Germany	0.0835	0.0000	0.1092	0.0000
Italy	0.5763	0.5940	0.0000	0.2387

Note: The estimations of the lower tail dependence coefficients between the precious metal - G7 stock pairs from R-vine in the crisis period (the threshold probability for zero dependence equals 0.1%).

Table 30: The bivariate upper tail dependence coefficient estimation from R-vine over the crisis period

	gold	silver	platinum	palladium
UK	0.0000	0.0000	0.0000	0.0000
Japan	0.0000	0.0000	0.0000	0.0086
Canada	0.0000	0.0154	0.0000	0.0000
France	0.0000	0.0000	0.0000	0.0000
Germany	0.0835	0.0000	0.1092	0.0000
Italy	0.5763	0.0000	0.0000	0.2387

Note: The estimations of the bivariate upper tail dependence coefficients between the precious metal - G7 stock pairs from R-vine in the crisis period (the threshold probability for zero dependence is equal to 0.1%).

dependence between each precious metal and each Europe stock (i.e., France, Germany, and Italy) prevents these metals to act as a safe haven for Europe stock investors.

Table 31: The bivariate lower tail coefficient estimation from R-vine over the post-crisis period

	gold	silver	platinum	palladium
US	0.0000	0.0000	0.0000	0.0000
UK	0.0000	0.0000	0.0000	0.0000
Japan	0.0000	0.0001	0.0000	0.0000
Canada	0.0019	0.0000	0.0000	0.0002
France	0.0000	0.0081	0.0000	0.1123
Germany	0.0295	0.0047	0.0236	0.0110
Italy	0.3861	0.5290	0.4814	0.1543

Note: The estimations of the bivariate lower tail dependence coefficients between the precious metal - G7 stock pairs from R-vine in the post-crisis period (the threshold probability for zero dependence equals to 0.1%).

Table 32: The bivariate upper tail coefficient estimation from R-vine over the post-crisis period

	gold	silver	platinum	palladium
US	0.0000	0.0000	0.0000	0.0000
UK	0.0000	0.0000	0.0000	0.0000
Japan	0.0000	0.0001	0.0000	0.0000
Canada	0.0019	0.0000	0.0000	0.0294
France	0.0000	0.0081	0.0000	0.0000
Germany	0.0295	0.0047	0.0236	0.0110
Italy	0.3861	0.1539	0.1299	0.1673

Note: The estimations of the bivariate upper tail dependence coefficients between the precious metal - G7 stock pairs from R-vine in the post-crisis period (the threshold probability for zero dependence is equal to 0.1%)

Hierarchical Archimedean copula results

Hierarchical Archimedean copulas were applied to estimate the multivariate upper- and lower-tail dependence coefficients. This work is to observe the tail behavior of each precious metal in the case of extreme upward or downward movements in all twelve stock markets simultaneously (i.e, G7 and BRICS markets).

Figure 9 shows the hierarchical structures of copulas for my multivariate data of precious metals and G7 and BRICS stock markets across the three periods of the 2008 global crisis.

Table 33 reports both the multi-lower and multi-upper tail dependence coefficients. There exists the presence of asymmetric dependence in multivariate analysis because the multi-upper tail dependence coefficient of each precious metal return with twelve stocks returns is much bigger than its lower tail dependence. In addition, if a threshold probability for a zero tail dependence equal to 0.1% as above, zero lower tail dependence can be observed between most precious metals and international stocks in any considered sub-period, with the exception of the lower tail between platinum and twelve stocks during crisis time as well as palladium and stocks in the crisis and post-crisis periods. These results mean that each precious metal, especially gold and silver, can act as an effective safe haven against extreme downward movements in global stock markets. On the other hand, the results from Table 33 give evidence of positive upper tail dependence in all cases. Moreover, the values of these upper tail coefficients are so large, especially in the case of platinum and palladium. This finding reveals that in market upturns, precious metals are not safe haven for international stocks.

4.4 Conclusion

This chapter explores the tail dependence structure between four precious metal markets and twelve stock markets of G7 and BRICS countries over three periods of the 2008 global financial crisis. By applying pair-vine copulas and hierarchical archimedean copulas, the study shows the presence of asymmetric tail co-movements between precious metal markets and G7 and BRICS stock markets in both bivariate and multivariate estimations. These results suggest that investors in stocks and precious metals cannot make investment decisions similarly between the extreme downturns and upturns of

Figure 9: Samples of selected hierarchical structures for four precious metals and international stock markets (G7 and BRICS)



Table 33: Multivariate Tail Dependence Coefficients

	gold	silver	platinum	palladium
<i>Lower Tail Dependence Coefficient</i>				
pre-crisis	4.18e-4	6.25e-4	3.18e-4	2.03e-4
crisis	1.67e-5	1.44e-4	1.92e-3	1.28e-3
post-crisis	3.65e-5	1.58e-4	6.15e-4	2.02e-3
<i>Upper Tail Dependence Coefficient</i>				
pre-crisis	0.9246	0.9352	0.9154	0.9055
crisis	0.1123	0.5885	0.9176	0.9051
post-crisis	0.2914	0.6230	0.9326	0.9526

Note: The table summarizes the estimation results of the multi-lower tail dependence coefficient and multi-upper tail dependence coefficient from hierarchical Archimedean copulas between each precious metal with all 12 stock indices of G7 and BRICS countries over the three sub-periods of the 2008 financial crisis.

the market. Interestingly, the bivariate copulas show that each precious metal could be an effective safe haven for individual stock in almost the G7 stock markets during both the bearish and bullish market conditions, excluding the European stock markets, especially Germany and Italy. Thus, investors in the stock markets of the US, UK, Canada, and Japan can consider investing in precious metals in order to deal with the extreme movements of stock markets. On the other hand, the multivariate copulas (i.e., hierarchical Archimedean copulas) reveal that each precious metal can serve as a safe haven for all twelve stock markets during market downturns because of zero multi-lower tail dependence between each metal and twelve stocks. Meanwhile, the multi-upper tail dependence coefficients are significantly positive, indicating that investors cannot use precious metals as safe haven in case of extreme upward movements in G7 and BRICS stock returns. These findings strongly recommend that investors should hold precious metals during extreme downturns of global stock markets to protect their investment portfolios, but not the upward movement of stock markets. It is noteworthy that the multi-upper tail dependence coefficient of each precious metal return with respect to the returns of the twelve stocks was significantly larger than their lower tail dependence

coefficient. This rise in dependency during bull markets suggests that investors can profit by holding stocks and precious metals at the same time. Finally, the global financial crisis of 2008 significantly affected the tail dependence structure between precious metals and international stock markets. Particularly, the role of precious metals as a safe haven has declined after the 2008 financial crisis.

Appendix

Table 34: Abbreviations

Au	gold	FR	CAC 40
Ag	silver	DE	DAX
Pt	platinum	IT	FTSE MIB
Pd	palladium	BR	BOVESPA
US	S&P 500	RU	MOEX
UK	FTSE 100	IN	NIFTY50
JP	NIKKEI 225	CN	SSE
CA	S&P/TSX	SA	FTSE/JSE Africa

Table 35: Considered Bivariate copulas families for Vine copulas

Independence copula	BB7 copula	Frank copula	survival BB1
Gaussian copula	BB8 copula	Joe copula	survival BB6
Student copula	survival Clayton	BB1 copula	survival BB7
Clayton copula	survival Gumbel	BB6 copula	survival BB8
Gumbel copula	survival Joe		

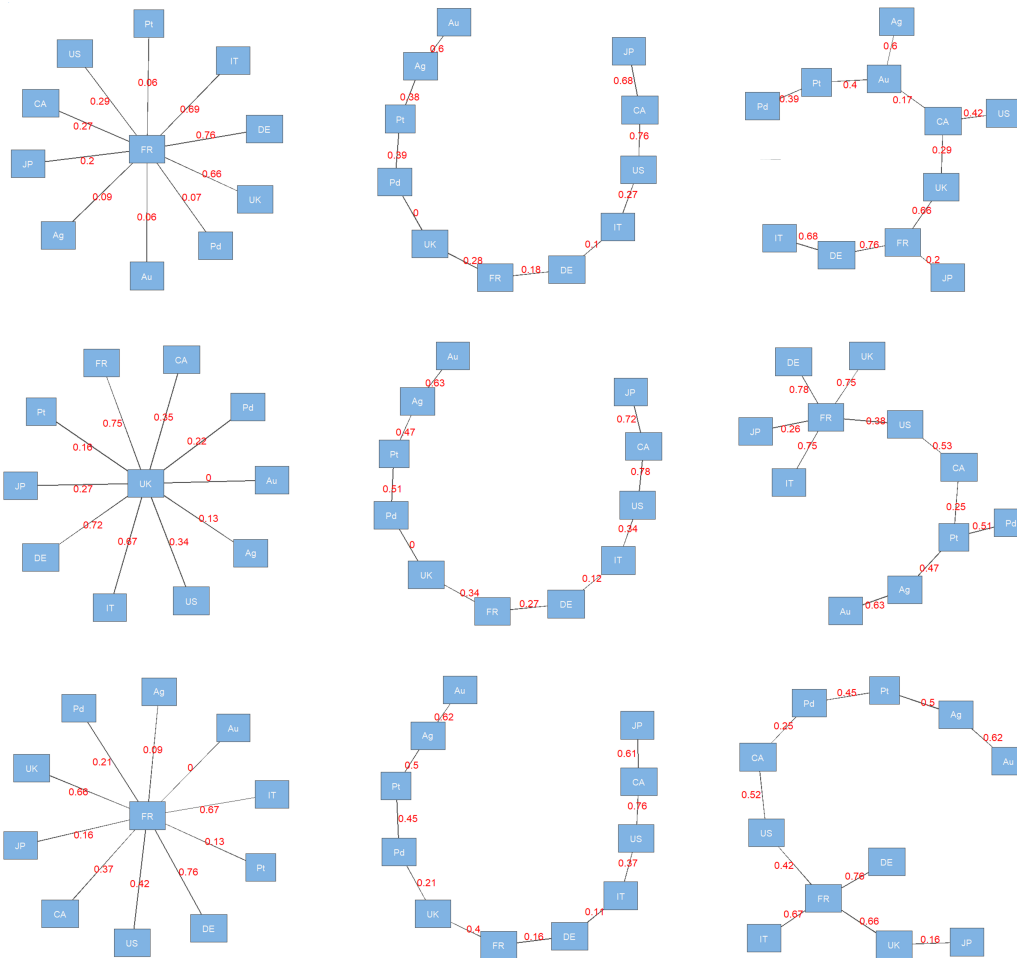


Figure 10: C-vine (Tree 1) decomposition for pre-crisis, R-vine (Tree 1) for crisis and post-crisis

Chapter 5

GENERAL CONCLUSION

5.1 Summary of main findings

This thesis makes a considerable contribution to the existing literature on behavior finance, crises, and the future markets of precious metals by investigating the impact of macroeconomic and financial drivers on the long-term volatility and correlation of precious metals markets over the last 20 years. Also, it has confirmed the diversification potential of precious metals investment and the role of these metals as the safe haven against the extreme movements in the global stock markets. By applying the advanced methods, particularly GARCH-MIDAS-X and DCC-MIDAS-X in chapter 2, stochastic spanning test in chapter 3, vine copulas and hierarchical Archimedean copula in chapter 4), the empirical results provide main findings as below.

Firstly, by investigating the macro-finance drivers of the dynamics of precious metal markets, this thesis proves that the stock market returns of G7 and BRICS countries play the most important role in driving both the long-term volatility and correlations among precious metals. In particular, stock returns have a negative impact on long-term volatility while having a positive effect on the long-run correlation of these metals. In addition to stock market returns, other variables, including M1, M2, inflation rate, and

the short-term interest rate of considered countries, are also helpful predictors of both volatility and correlations. Notably, the economic drivers cause a stronger effect on the volatility than on the correlation. Furthermore, considerable differences in the impact of drivers between G7 and BRICS can also be seen, especially in terms of consumer confidence. In detail, consumer confidence in G7 countries could lead the volatility of precious metals to follow a negative direction but drives the pairwise correlation in a positive way. On the contrary, consumer confidence in BRICS countries has almost no effect on either volatility or correlation. As a result, it can be seen that the more consumer confidence is improved in G7 countries, the better the portfolio hedging benefits that precious metals would offer. Similarly, this trend can be investigated in the influence of industrial production on both volatility and correlation, bond return on volatility, or short-term interest rate on correlation. Especially the return volatility of gold markets and the correlation between gold and silver have the closest relationship to the changes in the economic drivers of both the G7 and BRICS countries.

Secondly, a stochastic spanning test was carried out to consider whether investors may be better off by augmenting their traditional portfolio of stocks, bonds, cash, and currencies of G7 countries with spots or futures of precious metals. This work also emphasizes the behavior of the spot and future returns of all four metals in order to answer the question, "Do precious metals serve as diversifiers for traditional assets?". Accordingly, the empirical results conclude that precious metals can offer diversification benefits for an international investment portfolio of equities, bonds, cash, and currencies. Additionally, the comparison of diversification benefit potential between spot and future returns of precious metals has also been provided in my out-of-sample analysis. Interestingly, the study reveals precious metal futures significantly outperform their spots in the aftermath of the 2008 global crisis. This finding also explains the reason for the increasing prevalence of precious metal

futures over the last few decades. Consequently, this thesis strongly advocates for the introduction of new financial innovations in precious metals (e.g., futures, options, ETFs, etc.).

Thirdly, the tail dependence coefficients were estimated in order to test the role of each precious metal as a safe haven in both cases of bull and bear market scenarios. By applying pair-vine copulas and hierarchical Archimedean copulas, this chapter reveals the presence of time-varying asymmetric tail co-movements between precious metal markets and G7 and BRICS stock markets in both bivariate and multivariate estimations. It is noteworthy that hierarchical Archimedean copulas outperform pair-vine copulas, indicating that precious metal markets are more closely related to the global stock market than to any particular stock market. The empirical results from the bivariate copulas (i.e., vine copulas) show that each precious metal could be an effective safe haven for stocks in almost all of the G7 stock markets during the bearish and bullish market conditions, excluding the European stock markets. The multivariate copulas (i.e., hierarchical Archimedean copulas) estimate minor lower tail dependence coefficients. This result confirms the safe-haven properties of precious metals for all twelve stock markets (i.e., G7 and BRICS) in extreme bearish conditions. Meanwhile, the multi-upper tail dependence coefficients are significantly positive, indicating investors cannot use precious metals as safe haven in case of extreme upward movements in G7 and BRICS stock markets.

Notably, this thesis shows that the 2008 global financial crisis played a key role in changing the impact of economic drivers on precious metal markets as well as changing the role of precious metals as a safe haven and diversifier of traditional assets. Regarding the diversifier role, precious metal futures gain more diversification benefits for traditional portfolios in the aftermath of this crisis. Meanwhile, the role of precious metals as a safe haven declined after the 2008 financial crisis. Among the four precious metals,

palladium is the most strongly influenced by the global crisis of 2008, while silver is the least responsive to this crisis.

Among the twelve countries of the G7 and BRICS, economic activities, as well as traditional financial markets in the U.S., still play the most influential role in driving the precious metal markets. This study also found evidence that denotes the growing influence of China on the precious metals market after the financial crisis of 2008.

5.2 Practical implications

With the findings summarized in section 5.1, the thesis may help both investors and portfolio managers to make optimal investment choices based on forecasting the changes in traditional markets as well as economic activities. In addition, predicting the future development of low-frequency real economic variables also helps policymakers to formulate appropriate and early policy responses to prevent possible recessions. Specifically, practical applications from the results of each chapter are presented below.

First, The conclusions of chapter 2 regarding the economic drivers of the precious metals markets may assist both investors and portfolio managers in making the best decisions possible in light of forecasting changes in both the financial markets and economic activity. In addition, predicting the future development of low-frequency real economic variables also helps policymakers to formulate appropriate and early policy responses to prevent possible recessions.

Second, the findings of chapter 3 strongly suggest that investors should hold precious metals to gain diversification benefits for their investment portfolios. More importantly, in the aftermath of financial crises, investors can invest in future contracts of precious metals in order to maximize their benefits of diversification.

Third, chapter 4 suggests that investors in stocks and precious metals cannot make investment decisions similarly between the extreme downturns and upturns of the market.

Additionally, investors in the individual stock market of the US, UK, Canada, and Japan can consider investing in precious metals in order to deal with the extreme movements (both downturns and upturns) of stock markets. Notably, the findings of this chapter strongly recommend that investors should hold precious metals during extreme downturns of global stock markets to protect their investment portfolios, but not in upward movements.

In summary, all findings of this thesis are very timely and helpful for financial market participants as the global financial markets consistently experience unprecedented volatility and high demand for investment in precious metals due to the COVID-19 pandemic.

Bibliography

- Agyei-Ampomah, S., Gounopoulos, D. & Mazouz, K. (2014), 'Does gold offer a better protection against losses in sovereign debt bonds than other metals?', *Journal of Banking & Finance* **40**, 507–521.
- Akram, Q. F. (2009), 'Commodity prices, interest rates and the dollar', *Energy economics* **31**(6), 838–851.
- Aloui, C. & Mabrouk, S. (2010), 'Value-at-risk estimations of energy commodities via long-memory, asymmetry and fat-tailed garch models', *Energy Policy* **38**(5), 2326–2339.
- Aloui, R. & Aïssa, M. S. B. (2016), 'Relationship between oil, stock prices and exchange rates: A vine copula based garch method', *The North American Journal of Economics and Finance* **37**, 458–471.
- Andersen, T. G., Bollerslev, T., Diebold, F. X. & Labys, P. (2003), 'Modeling and forecasting realized volatility', *Econometrica* **71**(2), 579–625.
- Ang, A. & Bekaert, G. (2002), 'International asset allocation with regime shifts', *The review of financial studies* **15**(4), 1137–1187.
- Ang, A. & Chen, J. (2002), 'Asymmetric correlations of equity portfolios', *Journal of financial Economics* **63**(3), 443–494.

- Anson, M. J. (2008), ‘The pricing and economics of commodity futures’, *Handbook of Finance* **3**.
- Anyfantaki, S. & Topaloglou, N. (2018), ‘Diversification, integration and cryptocurrency market’, *Integration and Cryptocurrency Market (March 29, 2018)* .
- Apergis, N. (2014), ‘Can gold prices forecast the Australian dollar movements?’, *International Review of Economics & Finance* **29**, 75–82.
- Apergis, N., Christou, C. & Payne, J. E. (2014), ‘Precious metal markets, stock markets and the macroeconomic environment: a favor model approach’, *Applied Financial Economics* **24**(10), 691–703.
- Arouri, M. E. H., Lahiani, A. & Nguyen, D. K. (2015), ‘World gold prices and stock returns in China: Insights for hedging and diversification strategies’, *Economic Modelling* **44**, 273–282.
- Arreola Hernandez, J., Hammoudeh, S., Nguyen, D. K., Al Janabi, M. A. & Reboredo, J. C. (2017), ‘Global financial crisis and dependence risk analysis of sector portfolios: a vine copula approach’, *Applied Economics* **49**(25), 2409–2427.
- Arvanitis, S., Hallam, M., Post, T. & Topaloglou, N. (2019), ‘Stochastic spanning’, *Journal of Business & Economic Statistics* **37**(4), 573–585.
- Asgharian, H., Christiansen, C. & Hou, A. J. (2015), ‘Macro-finance determinants of the long-run stock–bond correlation: The dcc-midas specification’, *Journal of Financial Econometrics* **14**(3), 617–642.
- Aslanidis, N. & Christiansen, C. (2014), ‘Quantiles of the realized stock–bond correlation and links to the macroeconomy’, *Journal of Empirical Finance* **28**, 321–331.

- Bahmani-Oskooee, M. & Saha, S. (2018), 'On the relation between exchange rates and stock prices: a non-linear ardl approach and asymmetry analysis', *Journal of Economics and Finance* **42**(1), 112–137.
- Bailey, W. (1988), 'Money supply announcements and the ex ante volatility of asset prices', *Journal of Money, Credit and Banking* **20**(4), 611–620.
- Balcilar, M., Gupta, R. & Pierdzioch, C. (2016), 'Does uncertainty move the gold price? new evidence from a nonparametric causality-in-quantiles test', *Resources Policy* **49**, 74–80.
- Balcilar, M., Hammoudeh, S. & Asaba, N.-A. F. (2015), 'A regime-dependent assessment of the information transmission dynamics between oil prices, precious metal prices and exchange rates', *International Review of Economics & Finance* **40**, 72–89.
- Batten, J. A., Ciner, C. & Lucey, B. M. (2015), 'Which precious metals spill over on which, when and why? some evidence', *Applied Economics Letters* **22**(6), 466–473.
- Baur, D. G. (2012), 'Asymmetric volatility in the gold market', *The Journal of Alternative Investments* **14**(4), 26–38.
- Baur, D. G. & Lucey, B. M. (2010a), 'Is gold a hedge or a safe haven? an analysis of stocks, bonds and gold', *Financial Review* **45**(2), 217–229.
- Baur, D. G. & Lucey, B. M. (2010b), 'Is gold a hedge or a safe haven? an analysis of stocks, bonds and gold', *Financial Review* **45**(2), 217–229.
- Baur, D. G. & McDermott, T. K. (2010), 'Is gold a safe haven? international evidence', *Journal of Banking & Finance* **34**(8), 1886–1898.

- Bawa, V. S. (1975), 'Optimal rules for ordering uncertain prospects', *Journal of Financial Economics* **2**(1), 95–121.
- Bawa, V. S., Lindenberg, E. B. & Rafsky, L. C. (1979), 'An efficient algorithm to determine stochastic dominance admissible sets', *Management Science* **25**(7), 609–622.
- Bedoui, R., Braeik, S., Goutte, S. & Guesmi, K. (2018a), 'On the study of conditional dependence structure between oil, gold and usd exchange rates', *International Review of Financial Analysis* **59**, 134–146.
- Bedoui, R., Braeik, S., Goutte, S. & Guesmi, K. (2018b), 'On the study of conditional dependence structure between oil, gold and usd exchange rates', *International Review of Financial Analysis* **59**, 134–146.
- Bekaert, G. & Urias, M. S. (1996), 'Diversification, integration and emerging market closed-end funds', *the Journal of Finance* **51**(3), 835–869.
- Belousova, J. & Dorfleitner, G. (2012a), 'On the diversification benefits of commodities from the perspective of euro investors', *Journal of Banking & Finance* **36**(9), 2455–2472.
- Belousova, J. & Dorfleitner, G. (2012b), 'On the diversification benefits of commodities from the perspective of euro investors', *Journal of Banking & Finance* **36**(9), 2455–2472.
- Belousova, J. & Dorfleitner, G. (2012c), 'On the diversification benefits of commodities from the perspective of euro investors', *Journal of Banking & Finance* **36**(9), 2455–2472.
- Bernanke, B. S., Gertler, M. & Gilchrist, S. (1994), 'The financial accelerator and the flight to quality'.
- Bessler, W. & Wolff, D. (2015), 'Do commodities add value in multi-asset portfolios?'

- an out-of-sample analysis for different investment strategies’, *Journal of Banking & Finance* **60**, 1–20.
- Białkowski, J., Bohl, M. T., Stephan, P. M. & Wisniewski, T. P. (2015*a*), ‘The gold price in times of crisis’, *International Review of Financial Analysis* **41**, 329–339.
- Białkowski, J., Bohl, M. T., Stephan, P. M. & Wisniewski, T. P. (2015*b*), ‘The gold price in times of crisis’, *International Review of Financial Analysis* **41**, 329–339.
- Boako, G., Tiwari, A. K., Ibrahim, M. & Ji, Q. (2019), ‘Analysing dynamic dependence between gold and stock returns: Evidence using stochastic and full-range tail dependence copula models’, *Finance Research Letters* **31**.
- Bodie, Z., Merton, R. C. & Samuelson, W. F. (1992), ‘Labor supply flexibility and portfolio choice in a life cycle model’, *Journal of economic dynamics and control* **16**(3-4), 427–449.
- Brewer, H. (1981), ‘Investor benefits from corporate international diversification’, *Journal of Financial and Quantitative Analysis* pp. 113–126.
- Bulut, L. & Rizvanoghlu, I. (2019), ‘Is gold a safe haven? international evidence revisited’, *International Evidence Revisited (January 3, 2019)* .
- Cai, J., Cheung, Y.-L. & Wong, M. C. (2001), ‘What moves the gold market?’, *Journal of Futures Markets: Futures, Options, and Other Derivative Products* **21**(3), 257–278.
- Campbell, J. Y., Viceira, L. M., Viceira, L. M. et al. (2002), *Strategic asset allocation: portfolio choice for long-term investors*, Clarendon Lectures in Economic.
- Cao, B., Jayasuriya, S., Shambora, W. et al. (2010), ‘Holding a commodity futures

- index fund in a globally diversified portfolio: A placebo effect', *Economics Bulletin* **30**(3), 1842–1851.
- Chalamandaris, G., Pagratis, S. & Topaloglou, N. (2018), 'Re-assessing stock market anomalies using a stochastic spanning framework'.
- Cherubini, U., Luciano, E. & Vecchiato, W. (2004), *Copula methods in finance*, John Wiley & Sons.
- Chong, J. & Miffre, J. (2010), 'Conditional return correlations between commodity futures and traditional assets', *Journal of Alternative Investments* **12**(3), 61–75.
- Christiansen, C., Schmeling, M. & Schrimpf, A. (2012), 'A comprehensive look at financial volatility prediction by economic variables', *Journal of Applied Econometrics* **27**(6), 956–977.
- Christoffersen, P., Errunza, V., Jacobs, K. & Jin, X. (2014), 'Correlation dynamics and international diversification benefits', *International Journal of Forecasting* **30**(3), 807–824.
- Chua, J. H., Sick, G. & Woodward, R. S. (1990a), 'Diversifying with gold stocks', *Financial Analysts Journal* **46**(4), 76–79.
- Chua, J. H., Sick, G. & Woodward, R. S. (1990b), 'Diversifying with gold stocks', *Financial Analysts Journal* **46**(4), 76–79.
- Ciner, C., Gurdgiev, C. & Lucey, B. M. (2013a), 'Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates', *International Review of Financial Analysis* **29**, 202–211.

- Ciner, C., Gurdgiev, C. & Lucey, B. M. (2013b), ‘Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates’, *International Review of Financial Analysis* **29**, 202–211.
- Colacito, R., Engle, R. F. & Ghysels, E. (2011), ‘A component model for dynamic correlations’, *Journal of Econometrics* **164**(1), 45–59.
- Conover, C. M., Jensen, G. R., Johnson, R. R. & Mercer, J. M. (2009), ‘Can precious metals make your portfolio shine?’, *The Journal of Investing* **18**(1), 75–86.
- Conrad, C., Loch, K. & Rittler, D. (2014), ‘On the macroeconomic determinants of long-term volatilities and correlations in us stock and crude oil markets’, *Journal of Empirical Finance* **29**, 26–40.
- Creti, A., Joëts, M. & Mignon, V. (2013), ‘On the links between stock and commodity markets’ volatility’, *Energy Economics* **37**, 16–28.
- Czado, C., Kastenmeier, R., Brechmann, E. C. & Min, A. (2012), ‘A mixed copula model for insurance claims and claim sizes’, *Scandinavian Actuarial Journal* **2012**(4), 278–305.
- Daskalaki, C. & Skiadopoulos, G. (2011a), ‘Should investors include commodities in their portfolios after all? new evidence’, *Journal of Banking & Finance* **35**(10), 2606–2626.
- Daskalaki, C. & Skiadopoulos, G. (2011b), ‘Should investors include commodities in their portfolios after all? new evidence’, *Journal of Banking & Finance* **35**(10), 2606–2626.
- Daskalaki, C., Skiadopoulos, G. & Topaloglou, N. (2017a), ‘Diversification benefits of commodities: A stochastic dominance efficiency approach’, *Journal of Empirical Finance* **44**, 250–269.

- Daskalaki, C., Skiadopoulos, G. & Topaloglou, N. (2017b), ‘Diversification benefits of commodities: A stochastic dominance efficiency approach’, *Journal of Empirical Finance* **44**, 250–269.
- De Santis, G. & Gerard, B. (1997), ‘International asset pricing and portfolio diversification with time-varying risk’, *The Journal of Finance* **52**(5), 1881–1912.
- De Santis, G. et al. (1997), ‘Stock returns and volatility in emerging financial markets’, *Journal of International Money and finance* **16**(4), 561–579.
- Delatte, A.-L. & Lopez, C. (2013), ‘Commodity and equity markets: Some stylized facts from a copula approach’, *Journal of Banking & Finance* **37**(12), 5346–5356.
- DeMiguel, V., Garlappi, L. & Uppal, R. (2007), ‘Optimal versus naive diversification: How inefficient is the 1/n portfolio strategy?’, *The review of Financial studies* **22**(5), 1915–1953.
- Di Bernardino, E. & Rullière, D. (2016), ‘On tail dependence coefficients of transformed multivariate archimedean copulas’, *Fuzzy sets and systems* **284**, 89–112.
- Di Iorio, A. & Faff, R. (2000), ‘An analysis of asymmetry in foreign currency exposure of the Australian equities market’, *Journal of Multinational Financial Management* **10**(2), 133–159.
- Díaz, J. D., Hansen, E. & Cabrera, G. (2021), ‘Economic drivers of commodity volatility: The case of copper’, *Resources Policy* **73**, 102224.
- Dickey, D. A. & Fuller, W. A. (1981), ‘Likelihood ratio statistics for autoregressive time series with a unit root’, *Econometrica: journal of the Econometric Society* pp. 1057–1072.

- Embrechts, P., Lindskog, F. & McNeil, A. (2001), ‘Modelling dependence with copulas’, *Rapport technique, Département de mathématiques, Institut Fédéral de Technologie de Zurich, Zurich* **14**.
- Engle, R. (2002), ‘Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models’, *Journal of Business & Economic Statistics* **20**(3), 339–350.
- Engle, R. F. (1982), ‘Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation’, *Econometrica: Journal of the Econometric Society* pp. 987–1007.
- Engle, R. F., Ghysels, E. & Sohn, B. (2013), ‘Stock market volatility and macroeconomic fundamentals’, *Review of Economics and Statistics* **95**(3), 776–797.
- Engle, R. F. & Rangel, J. G. (2008), ‘The spline-garch model for low-frequency volatility and its global macroeconomic causes’, *The Review of Financial Studies* **21**(3), 1187–1222.
- Fang, L., Chen, B., Yu, H. & Qian, Y. (2018), ‘The importance of global economic policy uncertainty in predicting gold futures market volatility: A garch-midas approach’, *Journal of Futures Markets* **38**(3), 413–422.
- Fang, L., Chen, B., Yu, H. & Xiong, C. (2018), ‘The effect of economic policy uncertainty on the long-run correlation between crude oil and the us stock markets’, *Finance Research Letters* **24**, 56–63.
- Fang, L., Yu, H. & Xiao, W. (2018), ‘Forecasting gold futures market volatility using macroeconomic variables in the united states’, *Economic Modelling* **72**, 249–259.

- Fernandez-Diaz, J. M. & Morley, B. (2019), ‘Interdependence among agricultural commodity markets, macroeconomic factors, crude oil and commodity index’, *Research in International Business and Finance* **47**, 174–194.
- Ferson, W. E., Foerster, S. R. & Keim, D. B. (1993), ‘General tests of latent variable models and mean-variance spanning’, *the Journal of Finance* **48**(1), 131–156.
- Figuerola-Ferretti, I. & McCrorie, J. R. (2016a), ‘The shine of precious metals around the global financial crisis’, *Journal of Empirical Finance* **38**, 717–738.
- Figuerola-Ferretti, I. & McCrorie, J. R. (2016b), ‘The shine of precious metals around the global financial crisis’, *Journal of Empirical Finance* **38**, 717–738.
- Fortune, J. N. (1987), ‘The inflation rate of the price of gold, expected prices and interest rates’, *Journal of Macroeconomics* **9**(1), 71–82.
- Gao, X. & Nardari, F. (2018), ‘Do commodities add economic value in asset allocation? new evidence from time-varying moments’, *Journal of Financial and Quantitative Analysis* **53**(1), 365–393.
- Garcia, R. & Tsafack, G. (2011), ‘Dependence structure and extreme comovements in international equity and bond markets’, *Journal of Banking & Finance* **35**(8), 1954–1970.
- Ghosh, D., Levin, E. J., Macmillan, P. & Wright, R. E. (2004), ‘Gold as an inflation hedge?’, *Studies in Economics and Finance* **22**(1), 1–25.
- Ghysels, E., Sinko, A. & Valkanov, R. (2007), ‘Midas regressions: Further results and new directions’, *Econometric Reviews* **26**(1), 53–90.

- Gorton, G. & Rouwenhorst, K. G. (2006a), 'Facts and fantasies about commodity futures', *Financial Analysts Journal* **62**(2), 47–68.
- Gorton, G. & Rouwenhorst, K. G. (2006b), 'Facts and fantasies about commodity futures', *Financial Analysts Journal* **62**(2), 47–68.
- Hadar, J. & Russell, W. R. (1969), 'Rules for ordering uncertain prospects', *The American economic review* **59**(1), 25–34.
- Hammoudeh, S., Malik, F. & McAleer, M. (2011a), 'Risk management of precious metals', *The Quarterly Review of Economics and Finance* **51**(4), 435–441.
- Hammoudeh, S., Malik, F. & McAleer, M. (2011b), 'Risk management of precious metals', *The Quarterly Review of Economics and Finance* **51**(4), 435–441.
- Hammoudeh, S., Nguyen, D. K. & Sousa, R. M. (2015), 'Us monetary policy and sectoral commodity prices', *Journal of International Money and Finance* **57**, 61–85.
- Hammoudeh, S. & Yuan, Y. (2008), 'Metal volatility in presence of oil and interest rate shocks', *Energy Economics* **30**(2), 606–620.
- Hanoch, G. & Levy, H. (2013), The efficiency analysis of choices involving risk, in 'HANDBOOK OF THE FUNDAMENTALS OF FINANCIAL DECISION MAKING: Part I', World Scientific, pp. 287–298.
- Hillier, D., Draper, P. & Faff, R. (2006a), 'Do precious metals shine? an investment perspective', *Financial Analysts Journal* **62**(2), 98–106.
- Hillier, D., Draper, P. & Faff, R. (2006b), 'Do precious metals shine? an investment perspective', *Financial Analysts Journal* **62**(2), 98–106.

- Hong, Y., Tu, J. & Zhou, G. (2007), 'Asymmetries in stock returns: Statistical tests and economic evaluation', *The Review of Financial Studies* **20**(5), 1547–1581.
- Huberman, G. & Kandel, S. (1987), 'Mean-variance spanning', *The Journal of Finance* **42**(4), 873–888.
- Huynh, T. L. D. (2020), 'The effect of uncertainty on the precious metals market: New insights from transfer entropy and neural network var', *Resources Policy* **66**, 101623.
- Jaffe, J. F. (1989a), 'Gold and gold stocks as investments for institutional portfolios', *Financial Analysts Journal* **45**(2), 53–59.
- Jaffe, J. F. (1989b), 'Gold and gold stocks as investments for institutional portfolios', *Financial Analysts Journal* **45**(2), 53–59.
- Jain, A. & Biswal, P. (2016a), 'Dynamic linkages among oil price, gold price, exchange rate, and stock market in india', *Resources Policy* **49**, 179–185.
- Jain, A. & Biswal, P. (2016b), 'Dynamic linkages among oil price, gold price, exchange rate, and stock market in india', *Resources Policy* **49**, 179–185.
- Jiang, L., Wu, K. & Zhou, G. (2018), 'Asymmetry in stock comovements: An entropy approach', *Journal of Financial and Quantitative Analysis* **53**(4), 1479–1507.
- Johnson, R. & Soenen, L. A. (1997), 'Gold as an investment asset: Perspectives from different countries', *Journal of Investing, Fall* .
- Kan, R. & Zhou, G. (2008), 'Tests of mean-variance spanning'.
- Kan, R. & Zhou, G. (2012), 'Tests of mean-variance spanning', *Annals of Economics and Finance* **13**(1), 139–187.

- Kang, S. H., McIver, R. & Yoon, S.-M. (2017), ‘Dynamic spillover effects among crude oil, precious metal, and agricultural commodity futures markets’, *Energy Economics* **62**, 19–32.
- Klein, T. (2017), ‘Dynamic correlation of precious metals and flight-to-quality in developed markets’, *Finance Research Letters* **23**, 283–290.
- Klein, T., Thu, H. P. & Walther, T. (2018), ‘Bitcoin is not the new gold—a comparison of volatility, correlation, and portfolio performance’, *International Review of Financial Analysis* **59**, 105–116.
- Klein, T. & Todorova, N. (2019), ‘Night trading with futures in china: The case of aluminum and copper’, *QMS Research Paper* **6**.
- Klein, T. & Todorova, N. (2021), ‘Night trading with futures in china: The case of aluminum and copper’, *Resources Policy* **73**, 102205.
- Klein, T. & Walther, T. (2022), Dynamic correlation of precious metals and equity markets: A mixed data sampling approach, in T. Klein, S. Lossagk, M. Strassberger & T. Walther, eds, ‘Modern Finance and Risk Management’, World Scientific, pp. 410–424.
- Kocaarslan, B., Sari, R., Gormus, A. & Soytas, U. (2017), ‘Dynamic correlations between bric and us stock markets: The asymmetric impact of volatility expectations in oil, gold and financial markets’, *Journal of Commodity Markets* **7**, 41–56.
- Kucher, O. & McCoskey, S. (2017), ‘The long-run relationship between precious metal prices and the business cycle’, *The Quarterly Review of Economics and Finance* **65**, 263–275.

- Kwiatkowski, D., Phillips, P. C., Schmidt, P., Shin, Y. et al. (1992), ‘Testing the null hypothesis of stationarity against the alternative of a unit root’, *Journal of econometrics* **54**(1-3), 159–178.
- Lau, M. C. K., Vigne, S. A., Wang, S. & Yarovaya, L. (2017), ‘Return spillovers between white precious metal etfs: The role of oil, gold, and global equity’, *International Review of Financial Analysis* **52**, 316–332.
- Li, K., Sarkar, A. & Wang, Z. (2003), ‘Diversification benefits of emerging markets subject to portfolio constraints’, *Journal of Empirical Finance* **10**(1-2), 57–80.
- Li, S. & Lucey, B. M. (2017), ‘Reassessing the role of precious metals as safe havens—what colour is your haven and why?’, *Journal of Commodity Markets* **7**, 1–14.
- Liberda, M. et al. (2017), ‘Mixed-frequency drivers of precious metal prices’, *Acta universitatis agriculturae et silviculturae mendelianae brunensis* **65**(6), 2007–2015.
- Longin, F. & Solnik, B. (2001), ‘Extreme correlation of international equity markets’, *The journal of finance* **56**(2), 649–676.
- Luca, G. D. & Riviuccio, G. (2012), Multivariate tail dependence coefficients for archimedean copulae, in ‘Advanced statistical methods for the analysis of large datasets’, Springer, pp. 287–296.
- Lucey, B. M. & Li, S. (2015a), ‘What precious metals act as safe havens, and when? some us evidence’, *Applied Economics Letters* **22**(1), 35–45.
- Lucey, B. M. & Li, S. (2015b), ‘What precious metals act as safe havens, and when? some us evidence’, *Applied Economics Letters* **22**(1), 35–45.

- Ludvigson, S. C. & Ng, S. (2009), 'Macro factors in bond risk premia', *The Review of Financial Studies* **22**(12), 5027–5067.
- Markowitz, H. (1952), 'Portfolio selection', *The journal of finance* **7**(1), 77–91.
- McCown, J. R. & Shaw, R. (2017), 'Investment potential and risk hedging characteristics of platinum group metals', *The Quarterly Review of Economics and Finance* **63**, 328–337.
- Mensi, W., Beljid, M., Boubaker, A. & Managi, S. (2013), 'Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold', *Economic Modelling* **32**, 15–22.
- Mensi, W., Nekhili, R., Vo, X. V. & Kang, S. H. (2021), 'Oil and precious metals: Volatility transmission, hedging, and safe haven analysis from the asian crisis to the covid-19 crisis', *Economic Analysis and Policy* **71**, 73–96.
- Mensi, W., Sensoy, A., Aslan, A. & Kang, S. H. (2019), 'High-frequency asymmetric volatility connectedness between bitcoin and major precious metals markets', *The North American Journal of Economics and Finance* **50**, 101031.
- Mishra, P. K., Das, J. & Mishra, S. K. (2010), 'Gold price volatility and stock market returns in india', *American Journal of Scientific Research* **9**(9), 47–55.
- Mittnik, S., Robinzonov, N. & Spindler, M. (2015), 'Stock market volatility: Identifying major drivers and the nature of their impact', *Journal of banking & Finance* **58**, 1–14.
- Miyazaki, T. & Hamori, S. (2016), 'Asymmetric correlations in gold and other financial markets', *Applied Economics* **48**(46), 4419–4425.
- Mo, D., Gupta, R., Li, B. & Singh, T. (2018), 'The macroeconomic determinants of

- commodity futures volatility: Evidence from chinese and indian markets', *Economic Modelling* **70**, 543–560.
- Morales, L. & Andreosso-O'Callaghan, B. (2011a), 'Comparative analysis on the effects of the asian and global financial crises on precious metal markets', *Research in International Business and Finance* **25**(2), 203–227.
- Morales, L. & Andreosso-O'Callaghan, B. (2011b), 'Comparative analysis on the effects of the asian and global financial crises on precious metal markets', *Research in International Business and Finance* **25**(2), 203–227.
- Nelsen, R. B. (2007), *An introduction to copulas*, Springer Science & Business Media.
- Newey, W. K. & West, K. D. (1987), 'Hypothesis testing with efficient method of moments estimation', *International Economic Review* pp. 777–787.
- Nguyen, D. K., Sousa, R. M. & Uddin, G. S. (2015), 'Testing for asymmetric causality between us equity returns and commodity futures returns', *Finance Research Letters* **12**, 38–47.
- Nguyen, D. K. & Walther, T. (2020), 'Modeling and forecasting commodity market volatility with long-term economic and financial variables', *Journal of Forecasting* **39**(2), 126–142.
- Pal, M., Rao, P. M. & Manimaran, P. (2014), 'Multifractal detrended cross-correlation analysis on gold, crude oil and foreign exchange rate time series', *Physica A: statistical mechanics and its applications* **416**, 452–460.
- Pan, Z., Wang, Y., Wu, C. & Yin, L. (2017), 'Oil price volatility and macroeconomic fundamentals: A regime switching garch-midas model', *Journal of Empirical Finance* **43**, 130–142.

- Patton, A. J. (2004), 'On the out-of-sample importance of skewness and asymmetric dependence for asset allocation', *Journal of Financial Econometrics* **2**(1), 130–168.
- Phillips, P. C. & Perron, P. (1988), 'Testing for a unit root in time series regression', *Biometrika* **75**(2), 335–346.
- Pindyck, R. S. (2001), 'The dynamics of commodity spot and futures markets: a primer', *The energy journal* **22**(3).
- Post, T. (2003), 'Empirical tests for stochastic dominance efficiency', *The Journal of Finance* **58**(5), 1905–1931.
- Prakash, V., & Mitra, R. (2003), 'Characteristic basis function method: A new technique for efficient solution of method of moments matrix equations', *Microwave and Optical Technology Letters* **36**(2), 95–100.
- Prokopczuk, M., Stancu, A. & Symeonidis, L. (2019), 'The economic drivers of commodity market volatility', *Journal of International Money and Finance* **98**, 102063.
- Quirk, J. P. & Saposnik, R. (1962), 'Admissibility and measurable utility functions', *The Review of Economic Studies* **29**(2), 140–146.
- Radetzki, M. (1989), 'Precious metals: The fundamental determinants of their price behaviour', *Resources Policy* **15**(3), 194–208.
- Ratner, M. & Klein, S. (2008), 'The portfolio implications of gold investment', *The Journal of Investing* **17**(1), 77–87.
- Reboredo, J. C. (2013), 'Is gold a safe haven or a hedge for the us dollar? implications for risk management', *Journal of Banking & Finance* **37**(8), 2665–2676.

- Reboredo, J. C. (2018), 'Green bond and financial markets: Co-movement, diversification and price spillover effects', *Energy Economics* **74**, 38–50.
- Reboredo, J. C. & Ugolini, A. (2015), 'Downside/upside price spillovers between precious metals: A vine copula approach', *The North American Journal of Economics and Finance* **34**, 84–102.
- Rothschild, M. & Stiglitz, J. E. (1970), 'Increasing risk: I. a definition', *Journal of Economic theory* **2**(3), 225–243.
- Russell, W. R. & Seo, T. K. (1989), Representative sets for stochastic dominance rules, in 'Studies in the Economics of Uncertainty', Springer, pp. 59–76.
- Sari, R., Hammoudeh, S. & Soytas, U. (2010), 'Dynamics of oil price, precious metal prices, and exchange rate', *Energy Economics* **32**(2), 351–362.
- Scaillet, O. & Topaloglou, N. (2010), 'Testing for stochastic dominance efficiency', *Journal of Business & Economic Statistics* **28**(1), 169–180.
- Sensoy, A. (2013), 'Dynamic relationship between precious metals', *Resources Policy* **38**(4), 504–511.
- Sibuya, M. (1960), 'Bivariate extreme statistics, i', *Annals of the Institute of Statistical Mathematics* **11**(3), 195–210.
- Simaan, Y. (1993), 'Portfolio selection and asset pricing—three-parameter framework', *Management Science* **39**(5), 568–577.
- Šimáková, J. (2011), 'Analysis of the relationship between oil and gold prices', *Journal of finance* **51**(1), 651–662.

- Sklar, M. (1959), 'Fonctions de repartition an dimensions et leurs marges', *Publ. inst. statist. univ. Paris* **8**, 229–231.
- Smales, L. A. (2017), 'Commodity market volatility in the presence of us and chinese macroeconomic news', *Journal of Commodity Markets* **7**, 15–27.
- Sortino, F. A. & Van Der Meer, R. (1991), 'Downside risk', *Journal of Portfolio Management* **17**(4), 27.
- Sui, M., Rengifo, E. W. & Court, E. (2021), 'Gold, inflation and exchange rate in dollarized economies—a comparative study of turkey, peru and the united states', *International Review of Economics & Finance* **71**, 82–99.
- Todorova, N. (2017), 'The asymmetric volatility in the gold market revisited', *Economics Letters* **150**, 138–141.
- Tully, E. & Lucey, B. M. (2007a), 'A power garch examination of the gold market', *Research in International Business and Finance* **21**(2), 316–325.
- Tully, E. & Lucey, B. M. (2007b), 'A power garch examination of the gold market', *Research in International Business and Finance* **21**(2), 316–325.
- Uddin, G. S., Hernandez, J. A., Shahzad, S. J. H. & Kang, S. H. (2020), 'Characteristics of spillovers between the us stock market and precious metals and oil', *Resources Policy* **66**, 101601.
- Van Hoang, T. H., Lahiani, A. & Heller, D. (2016), 'Is gold a hedge against inflation? new evidence from a nonlinear ardl approach', *Economic Modelling* **54**, 54–66.
- Von Neumann, J., Morgenstern, O. & Kuhn, H. W. (2007), *Theory of games and economic behavior (commemorative edition)*, Princeton university press.

- Walther, T., Klein, T. & Bouri, E. (2019), 'Exogenous drivers of bitcoin and cryptocurrency volatility—a mixed data sampling approach to forecasting', *Journal of International Financial Markets, Institutions and Money* **63**, 101133.
- Wang, K.-M., Lee, Y.-M. & Thi, T.-B. N. (2011), 'Time and place where gold acts as an inflation hedge: An application of long-run and short-run threshold model', *Economic Modelling* **28**(3), 806–819.
- Whang, Y.-J. (2019), *Econometric Analysis of Stochastic Dominance: Concepts, Methods, Tools, and Applications*, Cambridge University Press.
- Yaari, M. E. (1987), 'The dual theory of choice under risk', *Econometrica: Journal of the Econometric Society* pp. 95–115.
- Yang, J., Zhou, Y. & Wang, Z. (2009), 'The stock–bond correlation and macroeconomic conditions: One and a half centuries of evidence', *Journal of Banking & Finance* **33**(4), 670–680.
- Zhou, Y., Han, L. & Yin, L. (2018), 'Is the relationship between gold and the us dollar always negative? the role of macroeconomic uncertainty', *Applied Economics* **50**(4), 354–370.
- Ziembra, W. T. (2005), 'The symmetric downside-risk sharpe ratio', *The Journal of Portfolio Management* **32**(1), 108–122.