Impact and Hedging Attribute of Gold in the International Financial Market

with latest empirical approach and data

DISSERTATION

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vorgelegt von

M.Sc. Xinyi Qian

Erstgutachter: Prof. Dr. Thushyanthan Baskaran
Zweitgutachter: Prof. Dr. Jan Franke-Viebach

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Dekan der Fakultät: Prof. Dr. Marc Hassenzahl

Dedicate to my dearest parents.
You give me everything a child can ever ask for:
a big world and a sweet home.

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List of Abbreviations

ADL	**A**utoregressive **D**istributed **L**ag
AUD	ISO 4217 currency code for the **Au**stralian **D**ollar
CAD	ISO 4217 currency code for the **Ca**nadian **D**ollar
COMEX	**Com**modity **Ex**change, Inc
COVID-19	**Co**ronavirus **D**isease 2019
CNY	ISO 4217 currency code for the **C**hi**n**ese **Y**uan
EUR	ISO 4217 currency code for the **Eur**o
GARCH	**G**eneralized **A**uto **R**egressive **C**onditional **H**eteroskedasticity
GBP	ISO 4217 currency code for the **G**reat **B**ritain **P**ound
INR	ISO 4217 currency code for the **In**dian **R**upee
JPY	ISO 4217 currency code for the **J**a**p**anes **Y**en
MSCI	**M**organ **S**tanley **C**apital **I**nternational
LBMA	**L**ondon **B**ullion **M**arket **A**ssociation
SGE	**S**hanghai **G**old **E**xchange
VAR	**V**ector **A**uto-**R**egressive Model

"Gold and silver are not by nature money, but money consists by its nature of gold and silver."

Karl Marx, A Contribution of Political Economy, 1859

Chapter 1

Introduction

1.1 A brief history of gold

GOLD is an asset of no one's liability, it is the ultimate money being defined by nature itself. Before the 3rd millennium BC, gold was recognised by humans for the first time in ancient Egypt. With its glamorous appearance, it has been used as a precious metal. Due to its natural properties such as scarcity, easy storage, strong ductility, and corrosion resistance, it has been widely accepted by the whole world and has gradually become an international trading object.

The gold standard first emerged in the United Kingdom in 1816, by the end of the 19th century, many countries implemented it. With the formation of the gold standard, gold assumed the general equivalent of the commodities and provided a price unit for them, and became an exchange media. The liquidity of gold increased and the development of the gold market had a mature social condition and economic demand.

After the First World War, the economies of many European and American capitalist countries were affected by hyperinflation and rapid price increases. In addition, the distribution of gold was extremely uneven, making it difficult to restore the gold standard. At the World Currency Conference held in Genoa, Italy in 1922, the proposal was a partial return to the gold-based economy to ease international trade and facilitating economic stability, for "gold is the only common standard which all European countries could at present agree to adopt".[31] Central banks wanted a gold standard with which the gold stocks can be "conserved" in the vaults and meanwhile paper notes should be its representative for the day-to-day transaction.[22] As a result of the Genoa conference, the gold exchange standard had been implemented. Central banks were permitted to keep part of the reserves in their own currencies, which were directly exchangeable for gold coins.

Under the gold exchange standard system, the currency units of banknotes issued by central banks of various countries still stipulate the amount of gold, but gold was only used as a reserve for currency issuance and concentrated in the central bank, instead of casting gold coins and implementing gold coin circulation. The currency in circulation was completely issued by banks. The central bank of various countries controlled the export and import of gold, and private buying and selling of gold were prohibited in order to hold a certain amount of gold reserves to maintain the linkage between gold and currency. On July 1, 1944, economic envoys of 730 delegates and 44 allied nations convened the United Nations Monetary and Financial Conference in Bretton Woods, New Hampshire, United States to establish the link between the U.S. dollar and gold, which is the so-called "Bretton Woods System".

In the 1960s, the United States government fiscal deficit continued to increase due to Vietnam War, the international income situation deteriorated viciously, and the U.S. dollar experienced uncontrollable inflation, the credibility of the U.S. dollar was greatly impacted. During the same time, the economies of European countries began to recover after the Second World War. Gold became the best choice for value preservation. Therefore, in order to avoid the dollar crisis and the demand for wealth preservation, countries had thrown out U.S. dollars to exchange gold based on the exchange rate that the U.S. government once promised. The fixed exchange rate between gold and U.S. Dollar could not be maintained any longer. By 1971, the United States' gold reserves had fallen by more than 60%. The U.S. government was forced to abandon the policy of converting the US dollar into gold at a fixed official price. The currencies of various Western countries had also decoupled from the US dollar. Gold prices entered a period of free-floating and fixed prices in the market.

In 1976, the IMF (International Monetary Fund) passed the "Jamaica Agreement" to abolish the monetization of gold and establish special drawing rights to replace gold. Although the use of gold as currency is abolished, the metal properties of gold have not been abandoned by the world, and it is still favoured by the state and individual investment. Even without the attribute of a currency, the gold price, due to its scarcity and value preservation ability, has been always trended upwards.

Especially in a turbulent global economy nowadays, investing in gold is becoming increasingly welcomed and an important component in maintaining a well-performing and profitable investment portfolio.

1.2 Research objectives

The objectives of this thesis can be stated as follows. In chapter 2 we introduce major gold exchanges, where gold can be officially traded nowadays, and how the spillover effect among them looks like, from which the readers can have a general idea about the gold trading situation, especially since gold is no longer an official currency. The spillover effect will be examined in a dynamic approach so that one can observe how sensitive (or insensitive) the gold market is, toward the geopolitical change from all over the world. The major contribution of this chapter is an investigation into the latest 3 biggest gold exchanges in the world which takes Shanghai Gold Exchange (SGE) into consideration. Using a sounding approach for detecting the strength and direction of return and volatility spillover, the impact of major geopolitical issues happened between 2012 till 2018 can be detected. Since gold is still the linkage between different currencies and works as a hedge and buffer for geopolitical shocks, we will then investigate, how the investment in gold can be used to hedge the risk from the other changes such as exchange rates and stock markets. Furthermore, we also want to examine the strength of the hedging attribute during different situations such as normal economical time or under extreme turbulences.

1.3 Outline of the thesis

This thesis consists of five chapters. This introduction here is the first chapter. In the second chapter, empirical research of the return and volatility spillover of the gold price among the three world major gold exchanges will be presented. In chapter 3, the risk from the exchange rates change from 16 major currency pairs will be examined. Based on the historical empirical result, we can have a general idea that for which currency under which situation, one can use gold either as a hedge or as a safe haven. Chapter 4 then examined the risk as well as extreme negative return from the stock market, and how the investors can hedge these using educated investment strategies with gold. The major contribution from this chapter is the investigation into the latest COVID-19 crisis, which severely affected the global financial market. The research targets have been focused on the United States, Germany, and China. We will see how the stock markets in these three countries have been affected and whether gold can be used to hedge this kind of extreme negative downturn. And the last chapter concludes.This thesis consists of five chapters. This introduction here is the first chapter. In the second chapter, empirical research of the return and volatility spillover of the gold price among the three world major gold exchanges will be presented. In chapter 3, the risk from the exchange rates change from 16 major currency pairs will be examined. Based on the historical empirical result, we can have a general idea that for which currency under which situation, one can use gold either as a hedge or as a safe haven. Chapter 4 then examined the risk as well as extreme negative return from the stock market, and how the investors can hedge these using educated investment strategies with gold. The major contribution from this chapter is the investigation into the latest COVID-19 crisis, which severely affected the global financial market. The research targets have been focused on the United States, Germany, and China. We will see how the stock markets in these three countries have been affected and whether gold can be used to hedge this kind of extreme negative downturn. And the last chapter concludes.

Chapter 2

Gold Market Price Spillover between COMEX, LBMA and SGE

2.1 Introduction

IN this chapter, gold prices' return and volatility spillover between the main markets from New York, London and Shanghai has been investigated. Specific contract prices from the Commodity Exchange Inc. (COMEX), London Bullion Market Association (LBMA) and Shanghai Gold Exchange (SGE) were utilized. Results suggest that even with the increasing market influence of SGE, it still remains an isolated market, COMEX and LBMA maintain their dominant positions and act as the net spillover spreaders in the world gold market with almost equally strong market impacts. This chapter has been published as a journal paper on *Journal of Economics and Finance*.[35][1]

2.1.1 Background

Gold is one of the most homogeneous goods in the world. Due to it's fairly ideal preservation of value and easy storage, gold has been traded globally among exchanges and banks, both as a spot and/or future, as a commodity, and a financed asset. Three major gold trading centres are London, New York and Shanghai.[9]

Established in 1933, Commodity Exchange Inc. (COMEX) is the oldest among the three markets studied in this research. COMEX merged with the New York Mercantile Exchange (NYMEX) in 1996 and then joined the CME Group in 2008. Being the division responsible for metals trading, COMEX is no longer a separate institution but a primary futures and options market for trading metals such as gold, silver, copper and aluminium.

Established in 1987, London Bullion Market Association (LBMA) is a wholesale over-the-counter market for the trading of gold and silver. LBMA took over the London Gold Fix operates by the ICE Benchmark Administration (IBA) since 19. March 2015 and set the benchmark price twice daily (at 10:30 and 15:00 London BST) in US Dollars and is also available in a further sixteen currencies (indicative for settlements).

The youngest market in this paper is the Shanghai Gold Exchange (SGE). Despite its short history (founded in 2002), SGE has already become the largest commodity exchange in the People's Republic of China for trading in precious metals (gold, silver and platinum). Furthermore, the daily trading volume for gold and silver is at the second highest in the world and in 2017, exceeded the Shanghai Future Exchange (SHFE) .

[1]Journal of Economics and Finance, 44-4, October 2020, pp 810-831.

2.1.2 Motivation and research question

Take a panoramic view of the overall situation of the global precious metal exchanges. COMEX is still first with respect to trading volume in gold and silver. SHFE and Tokyo Commodity Exchange (TOCOM) are shrinking significantly since 2016, while Shanghai Gold Exchange (SGE) has climbed to second position in the world rankings. With the emerging market power in Asia, especially the internationalisation process of the Shanghai Gold Exchange (SGE), trading liquidity during the Asia hour has been increased significantly[9]. Meanwhile, LBMA remains relatively stable as a dominating world OTC market[39]. This new world ranking inspires the motivation for researching the latest markets interaction between the first three ranking exchanges, namely COMEX, LBMA and SGE. When SGE started its internationalisation in 2015, expectations increased over this newly emerged market. Chairman of Swiss-based refining group MKS, Marwan Shakarchi once presented his hypothesis to Reuters in early 2016 when SGE launched a Yuan-denominated gold benchmark on 19 April 2016:"(China) is a market of 1.2 billion people and simply cannot be neglected. I am convinced that in the future we won't say China is at a premium or discount to London, but vice versa"; however, even though the Chinese domestic market participants can begin their trading with local currency Chinese Yuan (CNY), the world players may not accept or even take consideration of this newly-developing market. Voice had been made from the side of SGE, expressing the concern that an adjusting process would be time-consuming, and not going to happen in the near future.[1]

Because of the short market history of SGE and the limitations of the existing econometric model, no research, to the best of the author's knowledge, has been done about the gold market daily price volatility spillover including SGE till now. Hence, in this paper, the author would like to a) use a proper method to investigate the market impacts between the current top three markets being introduced in section 2.1.1 and b) examine the dynamic trend of the interactions between these three markets, check if there has already been changes that have taken place or whether any signs can be defined from the recent observations. The result of this research might be helpful for the concerning exchanges to take a review of the strength and market impact in the recent years and develop a qualitative overview of the main market situation and trend during sequential initiatives and changes, either made by themselves or by their competitors and/or partners.

2.1.3 Literature reviews

The attributes of gold have been studied by a considerable amount of literature. Apart from those which focused on the industrial sector and jewellery sector (about mining and fashioning technique), we direct our attention to the monetary attributes of gold in this subsection. Worthington and Pahlavani (2007)[43] provided solid evidence to prove the widely held view that an investment in gold can serve as an effective inflationary hedge. Later Ciner, Gurdgiev and Lucey (2013)[8] examined the correlation between stocks, bonds, gold, oil and exchange rates using data from United States and United Kingdom. They found that gold can be regarded as a safe haven against exchange rates in both countries, which highlighted its role in the monetary assets.

With the world gold markets becoming more open and easily accessible, the interconnection between markets spurred researchers' interest to find a proper econometric method to quantify the connection strength as well as the direction of the spreading. Diebold and

Yilmaz (2009)[11](henceforth DY09) first examined the different spillover behaviours between return and volatility using data from equity markets and coined the term connectedness using the Vector Autoregressive Regression model. They exhibited difference between return and volatility by measuring the time-varying and time-variation spillover intensity. According to Diebold and Yilmaz (2009, 2012, 2014), such a volatility connectedness can be treated as "fear connectedness" expressed by the traders during different market conditions and is particularly crisis sensitive[12]. In their 2012 research[10] (henceforth DY12), they further improved the model from DY09, so that it is no longer sensitive to the VAR order by replacing the Cholesky decomposition, and is able to detect the direction of the connectedness flow (the so-called "directional spillover"). In the technical sense, DY12 can be treated as a robust version of DY09, which applied the decomposition approach from Koop, Persaran and Potter (1996)[23] and Pesaran and Shin (1998)[32]. Additionally, Baruník and Křehlík (2018)[2] realised that a long-term-effect shock has high power at the low frequencies, and thus they separated the long- and short-term connectedness by applying the frequency bands in order to mimic the spillover movements between 1 to 4 days as well as 4 days to a longer period.

According to the fact that most of the gold trading volume is still settled in London, Lucey, Larkin and O'Conner (2014)[27] applied the method from Diebold and Yilmaz (2009) and studied the spillover effect of the spot gold prices between four markets, namely: LBMA, COMEX, SHFE and TOCOM. Results showed that SHFE as a newly emerged market has rarely any effect on the other three. However, Lucey et al.(2014) only researched the future markets and applied Garman and Klass (1980)[16] approach for the volatility spillover estimation. Evidence from Rosenberg et al.(2006)[38] has shown, that in the foreign exchange future and spot markets, the latter one has the dominant information share. On the other hand, the Garman and Klass (1980) approach has been shown to underestimate the volatility because it ignores the overnight jump.[2] Furthermore, their application of DY09 only provided an overall insight of the return or volatility for the multiple markets as a whole, lacking exact directional spillover patterns between the specific markets due to technical restrictions. Addressing the directional spillover patterns is exactly the major contribution of this research paper.

2.1.4 Organisation of this chapter

The goal of this chapter is to determine the strength of the market impacts among three markets by examining their interactions, i.e. receive/give spillover from/to each other, in both qualitative and quantitative senses. This chapter has been organized as follows: Section 2.2 provides detail on the methods we are going to apply for estimating the spillover, section 2.3 introduces the data and the processing procedures to provide descriptive statistics of the sample data, section 2.4 presents the main results, and section 2.5 offers a conclusion.

[2]See Yang and Zhang (2000). The Journal of Business, volume 73, number, p481, "Therefore. ignoring opening jumps will underestimate the volatility."

2.2 Methods

DY09 is the first research developing a model based on VAR (vector autoregressive model) framework and investigating the volatility spillover between different assets by Diebold and Yilmaz. When several assets (or equities) from different countries affect each other (i.e., have spillover effects on each other), DY09 can detect the total volatility among all those assets, define how much volatilities in the fluctuation are actually caused by the spillovers between them. However, as the author Diebold and Yilmaz later in their 2012 research[10] coined, there are two main methodological drawbacks. Namely that a) DY09 depends fairly strong on the variable ordering because of the Cholesky identification applied for a VAR decomposition, and b) DY09 can only address the *total* spillover among all the assets being estimated. In practice, one might be more interested in a separated directional spillover from a specific asset to another specific one. In DY12, the authors followed the general idea of DY09 and computed the total overall spillover index and an unconditional full-sample static average spillover table. Their innovative initiative was using the decomposition from Koop, Pesaram and Potter (1996)[23] and Pesaran and Shin (1998)[32] (henceforth KPPS) in order to avoid the sensitivity of the variable ordering caused by the Cholesky approach they previously used in DY09. Since the result from DY12 no longer depends on the VAR ordering, we can treat DY12 as a more robust version of DY09 which fills the gap of DY09 and an advanced model being able to detect the *direction* of the spillover between every each single assets.

Thus, in this section, DY09 is first introduced until the "overall spillover index" is reached. Thereafter, new improvements have been contributed by DY12, from where we turn to the method of DY12 and present all formulae for the further directional spillover estimation.

DY09 investigated the connectedness using VAR and first created the concept of "spillover index". For a two-variable vector of stationary first-order series x_t, it can be written as:

$$x_t = \Phi x_{t-1} + \varepsilon_t \tag{2.1}$$

where x_t is a vector of either returns or volatilities, here x_t is a 2×1 vector and Φ is a 2×2 parameter matrix. Expression (2.1) can be represented in the following form:

$$(I - \Phi L)x_t = \varepsilon_t \tag{2.2}$$

$$\Phi(L)x_t = \varepsilon_t \tag{2.3}$$

$\Phi(L)$ is a 2×2 matrix polynomial in L. Then the equation can be written as:

$$x_t = \Theta(L)\varepsilon_t = A(L)\mu_t \tag{2.4}$$

where $\Theta(L) = (I - \Phi L)^{-1}$ and $A(L) = \Theta(L)Q_t^{-1}$. Q_t^{-1} stands for a unique lower triangular Cholesky factor of ε_t , with μ being defined as $\mu = Q_t \varepsilon_t$ and $E(\mu_t \mu_t^{'}) = I$. One can show that the one-step-ahead Wiener-Kolmogorov linear least-square forecast as:

$$x_{t+1,t} = \Theta x_t \tag{2.5}$$

with a corresponding one-step-ahead error vector:

$$e_{t+1,t} = x_{t+1} - x_{t+1,t} = A_0 u_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix} \tag{2.6}$$

Thus the covariance matrix can be written as:

$$E(e_{t+1,t} e'_{t+1,t}) = A_0 A'_0 \tag{2.7}$$

The advantage of using this approach is being able to split the forecast error variances into two parts, namely the one-step-ahead error for $x_{1,t}$ as $a^2_{0,11} + a^2_{0,12}$, and $a^2_{0,21} + a^2_{0,22}$ for $x_{2,t}$. By doing this, one can be informed on which proportion of the error variance has been contributed by the shock to itself (in a 2-variable case, this can be x_1), the so-called *own variance shares*, or by the shock to the others (x_2 in this case), the *cross variance shares*, which is also the *spillover* we want to examine. The total forecast error variation is defined as:

$$a^2_{0,11} + a^2_{0,12} + a^2_{0,21} + a^2_{0,22} = trace(A_0 A'_0) \tag{2.8}$$

The spillover as a percentage ratio to the total forecast error variation leads to the formula of the *spillover index* for the basic first-order two-variable case:

$$S = \frac{a^2_{0,12} + a^2_{0,21}}{trace(A_0 A'_0)} \times 100 \tag{2.9}$$

Analogously the case of p^{th}-order N-variable VAR with H-step-ahead forecast *spillover index* can be immediately deduced as:

$$S = \frac{\sum_{h=0}^{H-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{N} a^2_{h,ij}}{\sum_{h=0}^{H-1} trace(A_h A'_h)} \times 100 \tag{2.10}$$

However, there are certain limitations to the use of this method from DY09. Firstly, the variance decomposition resulting from the Cholesky factorisation leads to a strong dependency on the ordering of the variables. The second methodological limitation comes when one has more than 2 markets and would like to detect the *directional* spillovers. With DY09, only a total spillover is identified. By exploiting an order-invariant variance decomposition raised by KPPS, DY12 produced a new approach based on the general idea from DY09. An H-step-ahead forecast error variance decomposition being denoted by $\theta^g_{ij}(H)$ for $H = 1, 2, ...$ has the following representation:

$$\theta^g_{ij}(H) = \frac{\sigma^{-1}_{jj} \sum_{h=0}^{H-1} (e'_i A_h \Lambda e_j)^2}{\sum_{h=0}^{H-1} (e'_i A_h \Lambda A'_h e_i)} \tag{2.11}$$

$$where\ e_i = \begin{cases} 1 & i^{th}\ element \\ 0 & otherwise \end{cases}$$

e_i is a selection vector which equals 1 for the i^{th} items and 0 otherwise. Λ stands for the variance matrix for the error vector ε and σ_{jj} represents the standard deviation of the error term for the j^{th} equation. Realising that each entry of the variance decomposition matrix can be normalised by the row sum as: $\tilde{\theta}^g_{ij}(H) = \frac{\theta^g_{ij}(H)}{\sum_{j=1}^{N} \theta^g_{ij}(H)}$ with $\sum_{N}^{j=1} \tilde{\theta}^g_{ij}(H) = 1$ and

$\sum_{N}^{i,j=1} \tilde{\theta}_{ij}^{g}(H) = N$ by construction, we then have the expression for *total spillover*, which is the KPPS analogue based on the DY09 total spillover as formula (2.10):

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{2.12}$$

Thus in DY12, the following exclusively further spillovers have been deducted:

Directional volatility spillover ***received*** *by market i* ***from*** *all other markets j*:

$$S_{i.}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j\neq 1}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{2.13}$$

Directional volatility spillover ***transmitted*** *by market i* ***to*** *all other markets j*:

$$S_{.i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j\neq 1}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{2.14}$$

Net volatility spillovers ***from*** *market i* ***to*** *all other markets j*:

$$S_{i}^{g}(H) = S_{.i}^{g}(H) - S_{i.}^{g}(H) \tag{2.15}$$

Net pairwise spillovers ***between*** *markets i and j (from i to j)*:

$$\begin{aligned} S_{ij}^{g}(H) &= \left(\frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{j,k=1}^{N} \tilde{\theta}_{jk}^{g}(H)} \right) \times 100 \\ &= \left(\frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{N} \right) \times 100 \end{aligned} \tag{2.16}$$

In the following sections, those formulae will be applied to the data introduced in section 2.3 for return and volatility specifically. The results will be shown in section 2.4 in the form of tables as well as rolling-window dynamic plots.

2.3 Data

Daily data which includes open, close, high and low information for COMEX, LBMA and SGE has been applied from 23. November 2012 to 15. August 2018.

Within COMEX, gold (product ticker GC) has been traded with 100 troy ounces contract size. The minimum tick is $0.10 per troy ounce. For one tick, the dollar value is hence 10$. Trading hours are from Sunday to Friday, 5:00 pm till 4:00 pm the next day depends on the North American Central Time Zone (CT). For each trading day, there is only one hour break from 4:00 pm to 5:00 pm. Contracts are only monthly signed within 23- or 72-monthly period for Feb, Apr, Aug & Oct or Jun & Dec respectively. In order to compare the gold future prices from COMEX with other spot price series, “forwards Panama adjusted price roll on last trading day" (GC1)[40] has been used from Quandl.[3]

LBMA daily gold price data is provided by Bloomberg Terminal. ICE Benchmark Administration (IBA) is the current operator of the LBMA price setting. The trading is 24 hours and the prices are set twice daily at 10:30 am and 3:00 pm London BST in US Dollar and 16 other currencies adjusted at the spot exchange rate as indicative prices for settlements only. In this paper we use the afternoon setting benchmark in US Dollar as the closing price for the node of one day.

For SGE, we are going to use the spot deferred contract Au(T+D) first introduced by Shanghai Gold Exchange in 2004. Au(T+D) allows the traders to postpone their contract made on t^{th} day by d ($d \geq 0$) day(s) through a deferral payment, which only amounts to 10%(as margin level) of the contract value. We also note that Au(T+D) is not a future contract, but a special type of spot contract. Gold futures have fixed delivery dates, while a position of Au(T+D) can always be held without a fixed delivery date. Furthermore, Au(T+D) has night trading hours, which brings another advantage to the trading flexibility. The reason for choosing this contract instead of using the pure spot contract AU9999 from SGE is for its contract attributes, it can avoid the incentive of man-made manipulation. Having no boundary for daily volatility, the price of AU(T+D) contract reflects more about the true spot value balanced by real demand and supply from the market, unlike the settlement price for AU9999, which is typically anchored to the daily LBMA fixing. Besides, Au(T+D) also has the largest trading volume among all gold contracts in SGE during our sample period.[4] Data is traced from Wind Financial Terminal. The trading unit is 1kg with Yuan/gram as the unit of quotation and the minimum tick is 0.01 Yuan/gram. Trading hours have been separated into three periods: 9:00 to 11:30 am, 1:30 to 3:30 pm, 8:00 to 2:30 am (next day).[5]

The continuously compounded return or *log return* will be calculated using daily close-to-close price through the following approach.

$$r_t = \ln(1 + R_t) = \ln \frac{P_t}{P_{t-1}} = p_t - p_{t-1}$$

where $p_t = \ln(P_t)$

By using the log return, one can easily achieve a normalisation and avoid the originating from price series of unequal units and/or quoting currencies. Gold being traded in COMEX and LBMA are both quoted in US Dollar, the only omitted external changing variable is the exchange rate between US Dollar and Chinese Yuan. Since gold is highly homogenous, the possibility of arbitrage does not incentivise the investors due to the law of one price.

[3] This method is sometimes also called "first-true method". By rolling the price forwardly from the oldest history contract to the latest one, one achieves a smoothed contract price series without jumps due to the maturities. The price of the oldest contract will therefore be the "true" as the rolling base of the series, thus the name "first-true method". Original data and this method are provided by Stevens Analytics.

[4] Au(T+D) trading volume amounts to 34.43% of the total gold trading volume in 2017.

[5] There have been sequential changes in margin level and trading hours. The latest information in December 2019 indicates a 6% margin ratio and a longer trading hour with two periods: 9:00 - 15:30 and 19:50 - 2:30 (next day)

Volatilities have been obtained by applying the Yang-Zhang[44] measurement fully using daily open, close, high, low information. Yang-Zhang measurement also takes the overnight jumps and volatility drift into considerations. An once-difference have been taken on it afterwards to reach a stationary time series.[6] The formula is as follow, where notations h, l, o and c stand for logged daily high, low, open and close respectively:

$$\begin{aligned} Volatility_{Yang-Zhang} &= \sigma^2_{YZ} \\ &= \sigma^2_{overnight\ volatility} + k\sigma^2_{open\ to\ close\ volatility} + (1-k)\sigma^2_{RS} \end{aligned}$$

where $k = \frac{0.34}{1.34+\frac{N+1}{N-1}}$

$$\sigma^2_{overnight\ volatility} = \frac{1}{N-1}\sum_{i=1}^{N}\left[ln(\frac{o_i}{c_{i-1}}) - \overline{ln(\frac{o_i}{c_{i-1}})}\right]^2$$

$$\sigma^2_{open\ to\ close\ volatility} = \frac{1}{N-1}\sum_{i=1}^{N}\left[ln(\frac{c_i}{o_i}) - \overline{ln(\frac{c_i}{o_i})}\right]^2$$

σ^2_{RS} refers to the Rogers and Satchell (1991)[37] volatility with the following expression:

$$\sigma_{RS} = \sqrt{\frac{1}{N}}\sqrt{\sum_{i=1}^{N}\left[ln\left(\frac{o_i}{c_{i-1}}\right)\right]^2 + \frac{1}{2}\left[ln\left(\frac{h_i}{l_i}\right)\right]^2 - [2ln(2)-1]\left[ln\left(\frac{c_i}{o_i}\right)\right]^2}$$

After omitting the first 5 observations which have been used for generating the Yang-Zhang volatility and eliminating the entries where the market is not opened, 1351 observations remain. The descriptive statistics for both returns and volatility are provided in Table 2.1 and 2.2.

TABLE 2.1: Descriptive statistics, daily log return, 20. Nov. 2012 - 15. Aug. 2018

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
COMEX	1,351	−0.0003	0.009	−0.094	−0.005	0.004	0.044
LBMA	1,351	−0.0002	0.009	−0.095	−0.005	0.005	0.046
SGE	1,351	−0.0002	0.008	−0.071	−0.005	0.004	0.044

Table 2.1 is the daily log return of the three markets. With 1351 observations, the mean values for returns are all slightly negative, with similar standard deviations. Minimum returns from COMEX and LBMA are lower than SGE, while their first, third quantile and maximum values are quite close to the others. This similarity is highlighted in figure 2.1: it shows that the three stationary return series have been performing in immensely similar patterns over time. This fact also meets the expectation, given that gold as a product has an exceedingly high homogeneity.

[6] There is no overnight jump for the COMEX since it runs 24 hours around the clock. LBMA closes for only one hour with slight jumps most of the time. In contrast, there is always a gap for the SGE since the closing time is much longer than the other two.

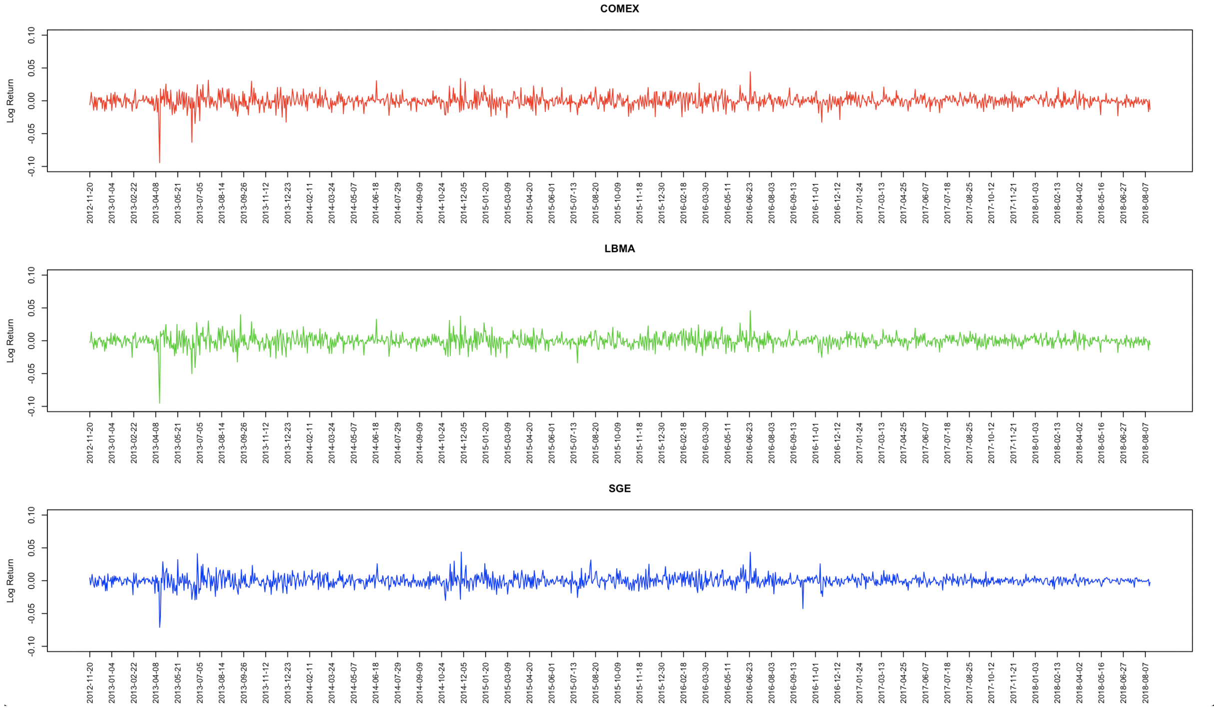


FIGURE 2.1: Daily log returns, 20. Nov. 2012 - 15. Aug. 2018

TABLE 2.2: Descriptive statistics, daily Yang-Zhang volatility, once-differenced, 23. Nov. 2012 - 15. Aug. 2018

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
COMEX	1,351	−0.00004	0.003	−0.030	−0.001	0.001	0.030
LBMA	1,351	0.00001	0.003	−0.035	−0.001	0.001	0.035
SGE	1,351	−0.00004	0.005	−0.050	−0.001	0.001	0.060

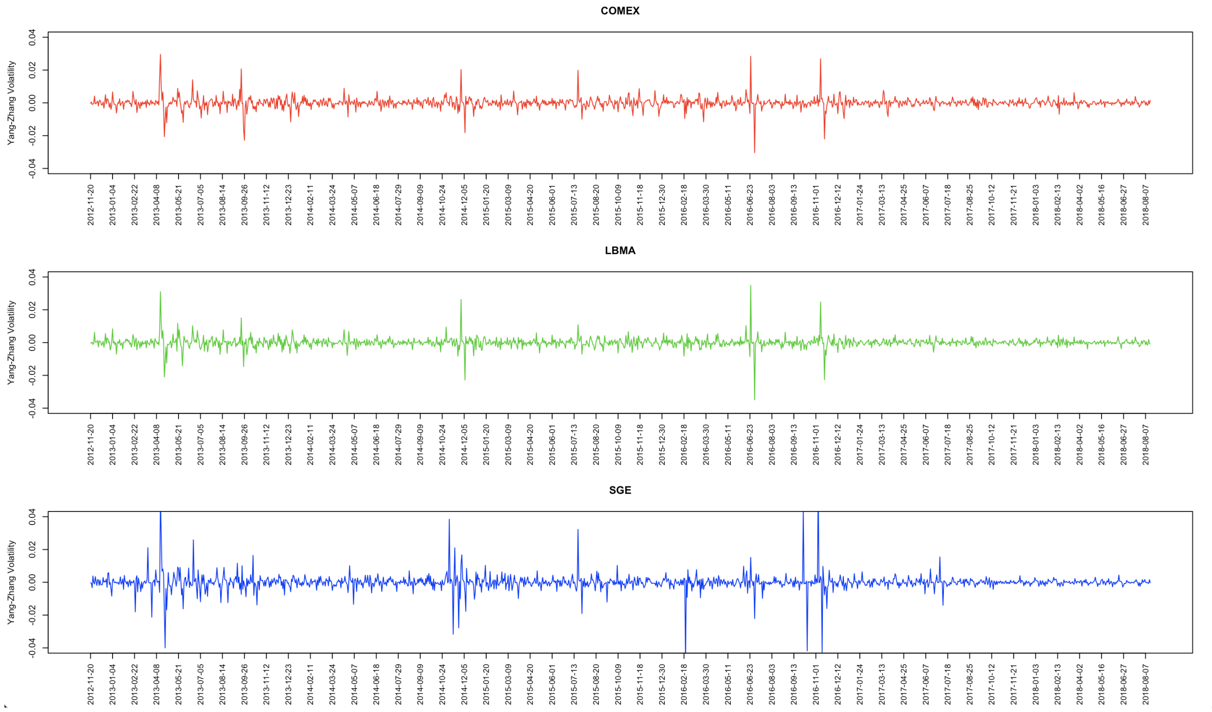


FIGURE 2.2: Daily Yang-Zhang volatility, 20. Nov. 2012 - 15. Aug. 2018

Table 2.2 describes the Yang-Zhang volatility of the three markets. LBMA is the only market that has a slightly positive mean value whereas both COMEX and SGE are insignificantly negative on average. SGE has a larger standard deviation compares to COMEX and LBMA. With the same interquartile range (all three series have -0.001 and 0.001 as the first and the third quarter), both SGE's minimum and maximum values are further from mean than the other two markets.

Figure 2.2 illustrates all three stationary volatility series. Volatility clustering can be identified from all three dynamic series, namely "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes".[7] LBMA and COMEX share more similarity in the volatility pattern. Distinctions of SGE are reflected in two aspects. Firstly, SGE has a fluctuation at the same slots as the other two but with different scales, for example in April 2013, December and June 2014 as well as November 2016. The second aspect can be concluded as an exclusive fluctuation unique to SGE, for example in February 2016 and June 2017. These differences may be caused by partial shocks burst only in one market, however with different international influences to the others. Fluctuations from 2013 April may come from the announcement made by North Korea that a plutonium-producing reactor plan had been restarted. During November 2014, the Asia-Pacific Economic Cooperation (APEC) Leaders Meeting took place in Beijing, China from 5th to 11th, and later from the 15th to 16th, the G20 Leaders Summit was held in Brisbane, Australia. This can, to some extent, explain an early emerged fluctuation in China, then a later one in the other two markets. The large downward shock only occurred in the Chinese market in 2016 February might be the result of a continuous appreciation of the Chinese Yuan against the US Dollar, onshore CNY created a record of the largest increase

[7]The term "volatility clustering" has been first noted by Mandelbrot (1963)[28], this quotation also comes from the same resource.

since 2005 while offshore CNY rose 704 basis points from February 8th to February 12th. In June 2016, the shock caused by the British voters' decision to withdraw from the EU in a referendum on 23rd, happened simultaneously to the three markets, thereof LBMA had the largest fluctuation, then to COMEX, and SGE was affected the least. A grand shock exclusively in the Chinese market happened in October 2016, this was because since October 1st, 2016, the Chinese Yuan has been officially included in the International Monetary Fund's Special Drawing Rights (SDR) currency baskets, becoming one of the official reserve currencies of the International Monetary Fund. Then in the beginning of November, the election of US president affected the three markets at the same time.

2.4 Result

The results will be divided into four parts. First, we consider unconditional spillover, in which we summarise an average spillover index for the whole time period. Later we examine the dynamic variation using the rolling window estimation as the time progresses. The rolling window results will be divided into three parts: overall, gross directional and net directional.[8]

2.4.1 Unconditional full-sample spillover tables

We first treat the entire data sample from November 2012 to August 2018 as a whole and generate the following tables using the DY12 approach for both return and volatility in each of the three markets.

TABLE 2.3: Return spillover, 20. Nov. 2012 - 15. Aug. 2018

Return spillover using DY12	From (Percentage)			
To (Percentage)	**COMEX**	**LBMA**	**SGE**	**Contribution from others**
COMEX	51.12	42.14	6.75	16.29
LBMA	42.48	51.93	5.60	16.02
SGE	30.59	35.90	33.51	22.16
Contribution to others	24.36	26.01	4.11	Spillover Index 54.48

Tables 2.3 and 2.4 are the so-called spillover tables for return and volatility respectively, which describes an "input-output decomposition" of the spillover index.[9] The ijth entry estimates the percentage forecast error variance which has been contributed from the ith market and transferred to the jth market.[10] Entries on the diagonal indicate the proportion

[8]During the computation, the author has the set the correlation between variables (markets) no equal to zero, by not manually setting the off-diagonal in the covariance matrix be zero, since one can not assume that three markets are fully-independent from each other.

[9]This term has been coined by Diebold and Yilmaz(2009) and Diebold and Yilmaz(2012).

[10]The results for return spillover are based on the vector autoregressions with 1 order and 10-day-ahead forecast errors. As being mentioned in Diebold and Yilmaz (2009), the total spillover results are not sensitive to the order of the VAR or the choice of the forecast horizon.

TABLE 2.4: Volatility spillover, 23. Nov. 2012 - 15. Aug. 2018

Volatility spillover using DY12	From (Percentage)			
To (Percentage)	**COMEX**	**LBMA**	**SGE**	**Contribution from others**
COMEX	55.48	39.46	5.06	14.84
LBMA	38.96	55.57	5.47	14.81
SGE	16.56	17.43	66.01	11.33
Contribution to others	18.51	18.96	3.51	Spillover Index 40.98

of return or volatility forecast error variances of themselves. The off-diagonal entries remaining in each row or column thus sum up to the spillover index among those markets.[11] Using the difference between "Contribution to others" and "Contribution from others", the net directional spillover can also be derived.

First consider the return spillover table 2.3. For all three markets, the forecast variance errors mainly come from themselves, 51.12% of COMEX, 51.93% of LBMA, 33.51% of SGE. While SGE has a smaller percentage of self-spillover, it receives a larger contribution (22.16%) of the total spillover from other markets.[12] This disparity is even larger when we look at their "Contribution to others". Both COMEX and LBMA create around a quarter of the total spillover to the others, while SGE has only a small contribution of 4.11%. More than half of the return forecast error variance in total is caused by the spillovers between markets, mainly contributed by COMEX and LBMA. Combining both contributions, a conclusion can be made, that whereas COMEX and LBMA are net spillover givers, SGE is purely a spillover receiver.

The volatility spillover table 2.4 is obviously different from the situation of the return spillover in the column of "Contribution from others". In the case of volatility spillover here, approximately 40% forecast error variance comes from the spillovers, in which almost three quarters from COMEX and LBMA, whereas SGE receives in this case less spillover than the other two markets (11.33%). Nevertheless, when we examine the "Contribution to others" row, SGE still spreads less spillover than COMEX and LBMA. The largest value (66.01%) in this table is the percentage volatility forecast error variance of SGE being descended from its own innovation. This indicates, SGE is more self-dependent in the sense of volatility than in terms of return (table 2.3). Subtract the "contribution from others" from "contribution to others" we have the net spillover. As in the previous case, SGE is a net receiver and the other two are spillover spreaders.

DY09 mentioned, that the spillovers for return and volatility are distinguished from each other. In both cases, whether in return or volatility, the same observation can be concluded as a relatively much weaker frequency connectedness as well as market power of SGE compared to the other two markets. With the main part of its forecast error resulting from its own innovation, SGE receives a lot of shock affections from the others. On the other hand, the innovations taking place in SGE have a weaker transmission power to

[11] Different from the Diebold and Yilmaz(2009) or Diebold and Yilmaz(2012), the percentage value here is the proportion of the whole three markets, not the proportion in the specific market of this row or column.

[12] 22-16% is remained by summing up 30.59% from COMEX and 35.90% from LBMA and divided by 3.

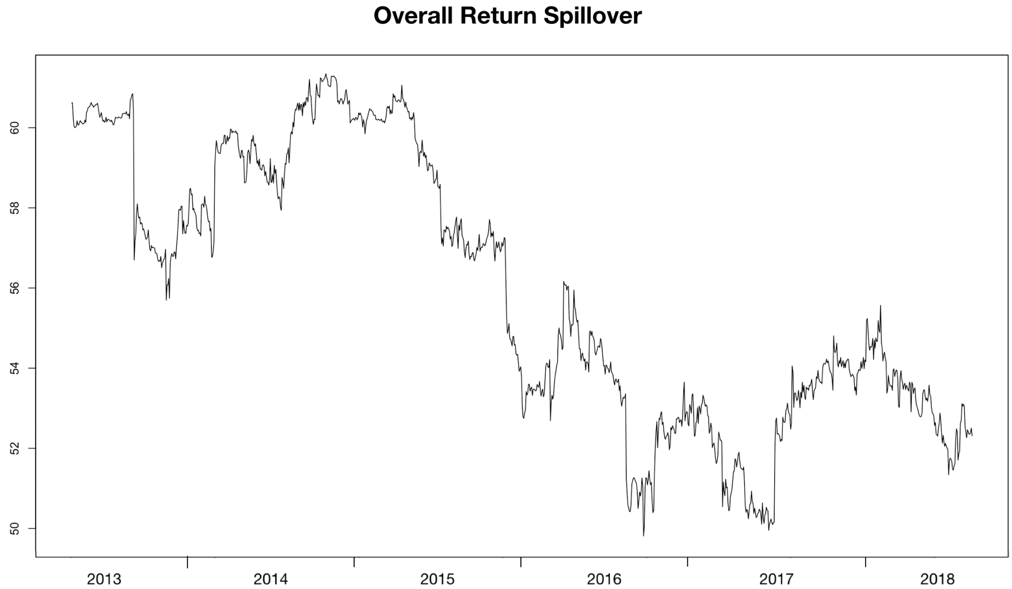


FIGURE 2.3: Total return spillover, three markets, 20. Nov. 2012 - 15. Aug. 2018

COMEX and LBMA.

All in all, LBMA and COMEX are performing dominating roles with the strongest interlinkages between them. However the argument from Lucey et al.(2014)[27] that "Shanghai is very *disconnected* from the other markets with 98.7% of its forecast error variance coming from itself" no longer holds from a later estimation in this research.

2.4.2 Conditional dynamic overall spillover rolling window plots

A serious weakness with the full-sample spillover tables, however, is the missing fact that many dynamic transforms have taken place during the time horizon. Simply treating the total sample as a whole and only examining the average would not be adequate to capture the changes and dynamic movements of the spillover pattern within the sample period. In the following estimation, the rolling window dynamic patterns of 200 days and 10 days ahead are plotted.[13]

Figures 2.3 and 2.4 depict the dynamic variations of overall spillovers for return and volatility respectively (of which the averages are simply the numbers at the lower right corner of tables 2.3 and 2.4). First consider the overall return spillover. The value started from over 60% at the beginning of our sample period in 2013, then a sudden drop from mid-late 2013 till mid-2014, the lowest value during this drop fell even below 56%. Afterwards, the overall return spillover rose again and exceeded the initial 60% till early-2015.

[13]Plotting results are based on the VAR of orders 1 and 5 for return and volatility respectively. As it has been proved in the DY12, the overall spillover plot is not sensitive to the choice of the order of the VAR or the choices of the forecast horizon.

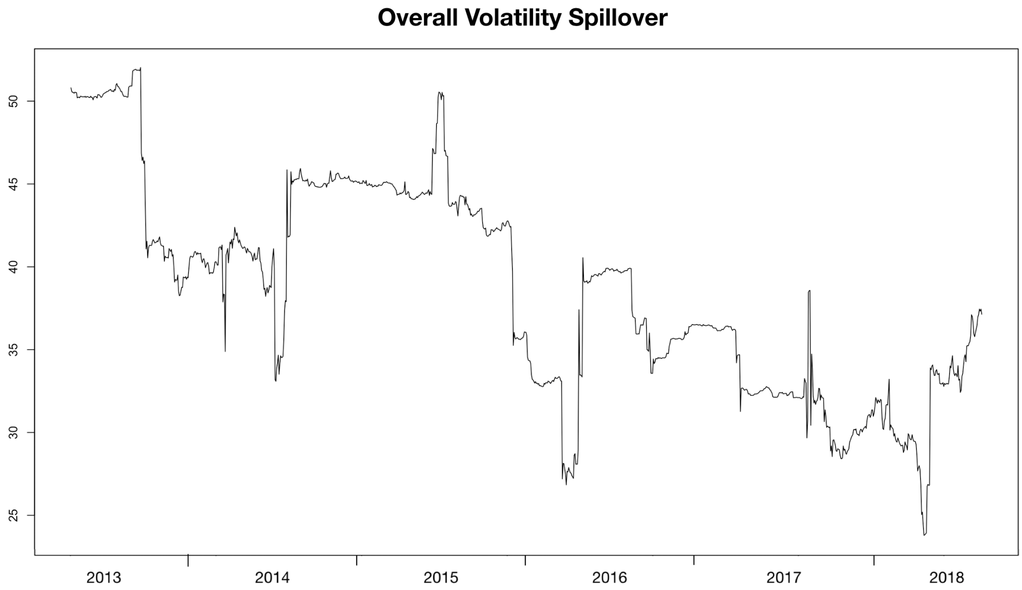


FIGURE 2.4: Total volatility spillover, three markets, 23. Nov. 2012 - 15. Aug. 2018

Then after two cyclical downward-moves in 2016, the overall return spillover hit bottom during the second half of 2016, with the value even lower than 50%. From end-2016 till early-2017, overall return spillover was modestly stronger than 52% but plunged again in the first half of 2017. From mid-2017 till the end of our sample period, the value remained between 52% and 54% most of the time.

The volatility plot shown in figure 2.4 has a much smoother fluctuation than the return plot with similar movement patterns. The overall volatility spillover was slightly above 50% at the beginning of the sample period, which indicates, in the early half of 2013, more than half of the variance forecast error comes from the spillover. Then it suddenly slid to 40%. After a deep sink at mid-2014, it climbed back to approximately 45% and remained at that level for most of the time until end-2015. The second drop appeared at early 2016, overall volatility spillover fell underneath 30% level and bounced back again for a short time afterwards. From early-2016 till mid-2018, the overall trend for volatility spillover was a downward movement. The nadir took place in 2018 with a value even lower than 25%. Finally, a small upward trend can be observed before the end of our data sample.

2.4.3 Conditional directional return spillover dynamic rolling window plots

Directional *from* return spillover

The directional *from* return spillover plot (figure 2.5) describes the return forecast variance error resulting from receiving the spillovers from other markets. Among the whole data period, the spillover received by SGE is always larger than for the other two markets, even its lowest value (around 18%) in early to middle of 2017 was just about the upper boundaries of the percentage spillovers received by COMEX and LBMA during the five years. Yet

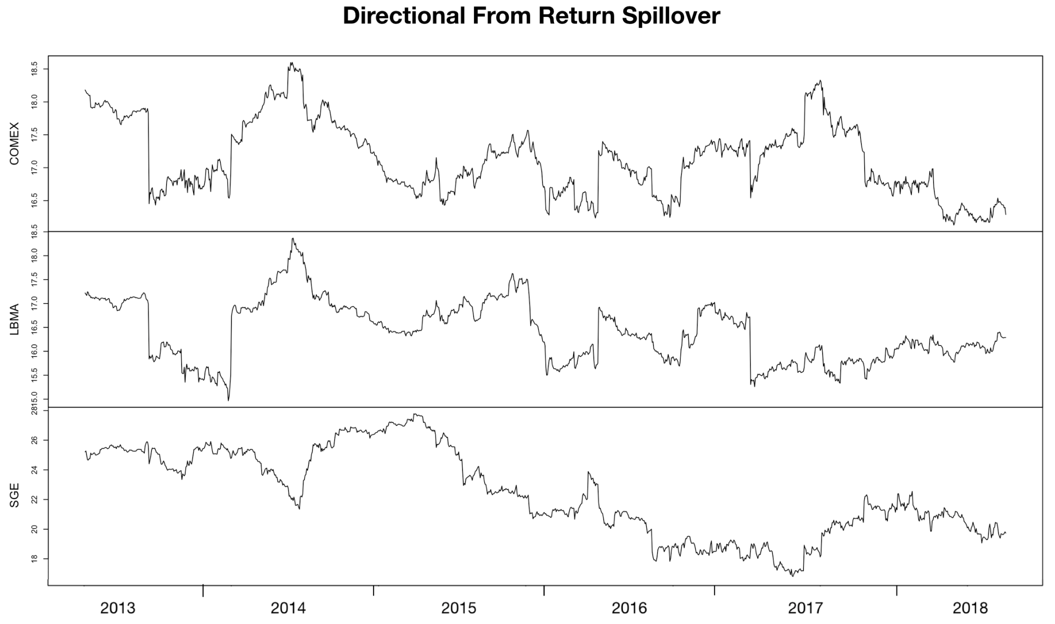


FIGURE 2.5: Directional from return spillover, three markets, 20. Nov. 2012 - 15. Aug. 2018

the overall trend demonstrates a slowly decreasing receiving of SGE. The same downward trends also appeared in COMEX and LBMA and became more obvious since 2016.

Directional *to* return spillover

The directional *to* spillover plot is illustrated in figure 2.6. With the same vertical axis ranging from approximately 15% to 18.5% of COMEX and LBMA in the *from* plot, they have in this case both stronger spillover spreading abilities, which were mainly between an interval from 20% to 30%. Two stages can be easily identified from the plot, namely before and after 2016. The return spillovers before 2016 were most of the time above 24% for COMEX and 26% for LBMA. Then a downturn occurred subsequently. Both of them had an all-time-low concurrently during the middle of 2016. SGE had a positive spillover jump up to 10% from time to time. Nevertheless, this influence from SGE is not at all comparable to either COMEX or LBMA.

Net return spillover

Subtracting the *from* values from the *to* results leads to figure 2.7 of *net* return spillover. Value intervals from the ordinate axis provide the roles all three markets are playing, i.e. COMEX and LBMA are the spillover net givers while SGE is a spillover net receiver. But since the dynamic plotting was getting less negative with time, the market influence of SGE among the three was also slightly growing. We might expect a positive net spillover soon.

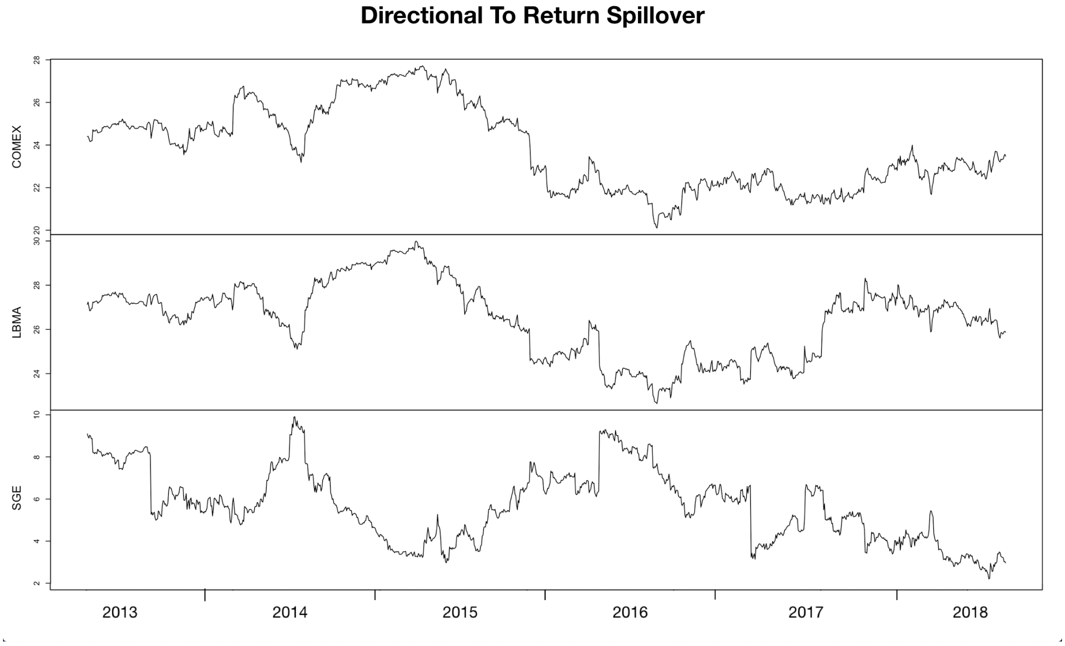


FIGURE 2.6: Directional from return spillover, three markets, 20. Nov. 2012 - 15. Aug. 2018

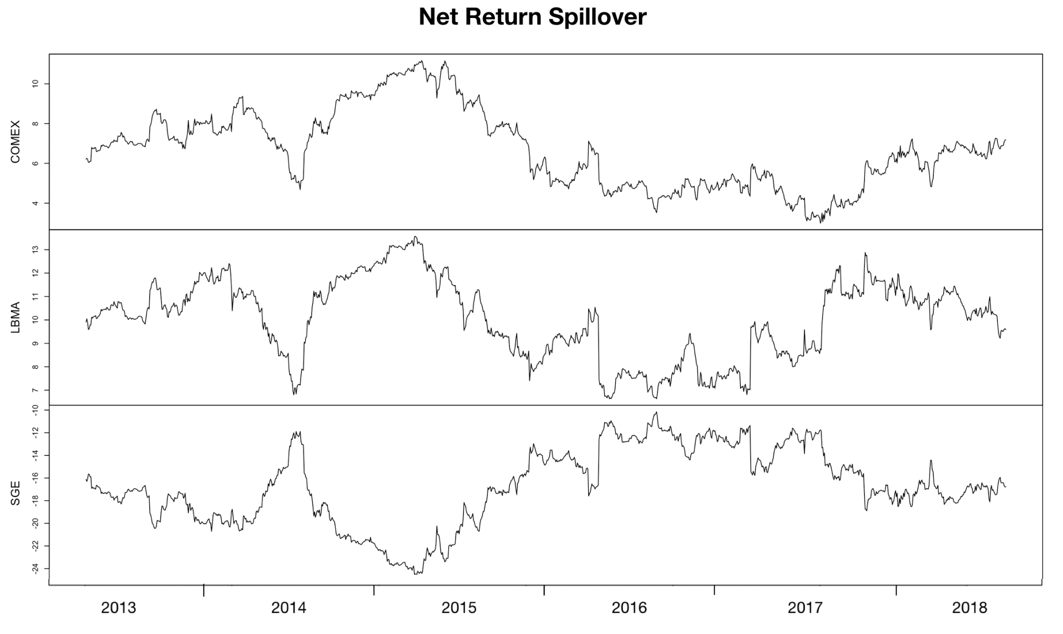


FIGURE 2.7: Net return spillover of three markets, 20. Nov. 2012 - 15. Aug. 2018

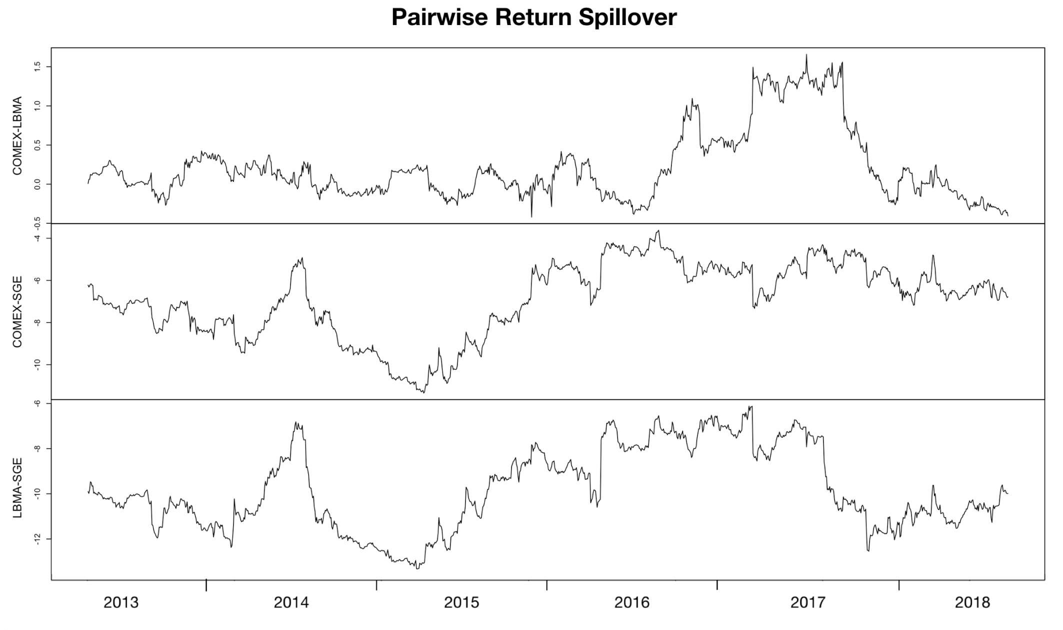


FIGURE 2.8: Pairwise return spillover of three markets, 20. Nov. 2012 - 15. Aug. 2018

***Pairwise* return spillover**

In addition to treating all three markets as a whole, spillover between the pairs i.e. COMEX and LBMA, LBMA and SGE as well as COMEX and SGE was also considered. The pairwise spillover plot enables us to investigate the relationship between only two markets as if all the others do not exist. The first row in figure 2.8 shows the spillover strength from LBMA to COMEX, which was mainly close to zero with slight fluctuation before mid-2016. From late-2016 till almost end-2017, LBMA transferred a series of spillover to COMEX. The reason might be Brexit in 2016. Apart from that occasion, the spillover between COMEX and LBMA were evenly matched. However, the relationship between SGE and either COMEX or LBMA is entirely disparate. The second row presents the net spillover from SGE to COMEX. Remarkably, the whole dynamic rolling estimation results are lying in the negative dimension, from -4% to -12%. It began with a 6% return spillover from COMEX to SGE, then this spillover effect turned stronger in a stepwise fashion until early-2015. After that, the effectiveness of return spillover of SGE pushed the percentage back to approximately -5% and remained at that level without other large change. Till the end of the sample period, there is no sign of a positive spillover from SGE to COMEX. Finally, the last row describes the relationship between SGE and LBMA, which is also an one-sided spillover transmission from London to Shanghai, the percentage scale was floating -6% to -14%. The pattern was similar to the one between SGE and COMEX before mid-2017. From then on, COMEX-SGE pairwise spillover remained around -6% while a stronger tendency of a percentage spillover higher than 10% from LBMA to SGE appeared in the LBMA-SGE pairwise pattern.

2.4.4 Conditional directional volatility spillover dynamic rolling window plots

As Diebold and Yilmaz (2009) mentioned, spillover intensity is indeed time-varying and the nature of the time-variation is strikingly different for return and volatility. Using a dynamic rolling window plot, it was already shown that static tables cannot fully summarise the dynamic of spillover pattern. Now we move to the spillover plots of volatility and examine the latter argument.

Directional *from* volatility spillover

As for the return estimations, one first generates the directional *from* volatility spillover in figure 2.9, which illustrates the spillover received by the respective market on the ordinate from the other two markets. In general, COMEX and LBMA receive more volatility spillover (both scales are from around 10% to above 16%, and lie above 15% for most often) than SGE (scale from 5% to approximately 20%, but the major part lies underneath the 15% line). Different from the previous cases, volatility dynamics are not as volatile as the returns'. Apart from minor-inconsistencies at some specific time points, it stays fairly constant during most of the time. This is the first point which distinguishes from the return spillover. The big change was quite similar to the return estimation, namely a lower stage after the beginning high level spillover from late-2013 till mid-2014. Then, COMEX jumped back to its previous high-level of approximately 15%, LBMA also went back to a flat level slightly lower than the first high stage. In contrast to them, SGE didn't bounce back, the spillover strength decreased slowly even when there was another low at mid-2014 and small spike mid-2016. Finally, after several steps, SGE reached its nadir in 2017, the spillover was even lower than 5% during late-2016 and the first two-thirds of 2017. On the other hand, COMEX and LBMA did not have an obvious medium trend. After their second spillover plateaux from mid-2014 to late-2015, another large decrease followed in early-2016, which lasted only for a short period and both spillover strengths jumped back to their previous level directly afterwards. The third drop in COMEX and LBMA appeared in 2017 (from approximately 15% to 11%) while for SGE it was an accompanying upheaval. The biggest reason for this change was a sudden rising exchange rate of the Chinese Yuan during the end of August till mid-September 2017.

Directional *to* volatility spillover

Figure 2.10 illustrates the directional *to* volatility spillover. One still observes similar pattern from COMEX and LBMA, in which both have spillover range between 12% to 24%, whereas the SGE's spillover keeps in single digits, even close to zero for most of the time. For COMEX and LBMA, a slightly decreasing trend can be identified, but for SGE, there is no clear movement tendency.

Net volatility spillover

Again we use the difference between "directional to" and "directional from" to compute the "net volatility spillover", which is shown in figure 2.11. Here we observe a mirror spillover pattern between SGE and the other two markets. While both COMEX and LBMA experience a decreasing phase between mid-2015 and early-2018, there was an inversely increasing stage for SGE. However, this "increasing stage" in the net spillover of SGE is

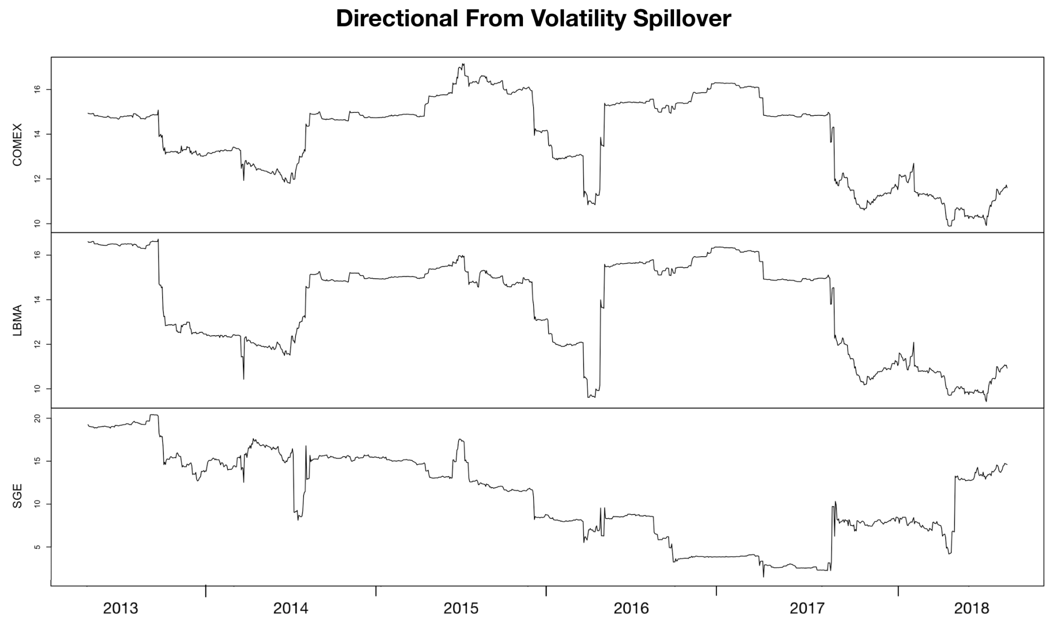


FIGURE 2.9: Directional from volatility spillover, three markets, 23. Nov. 2012 - 15. Aug. 2018

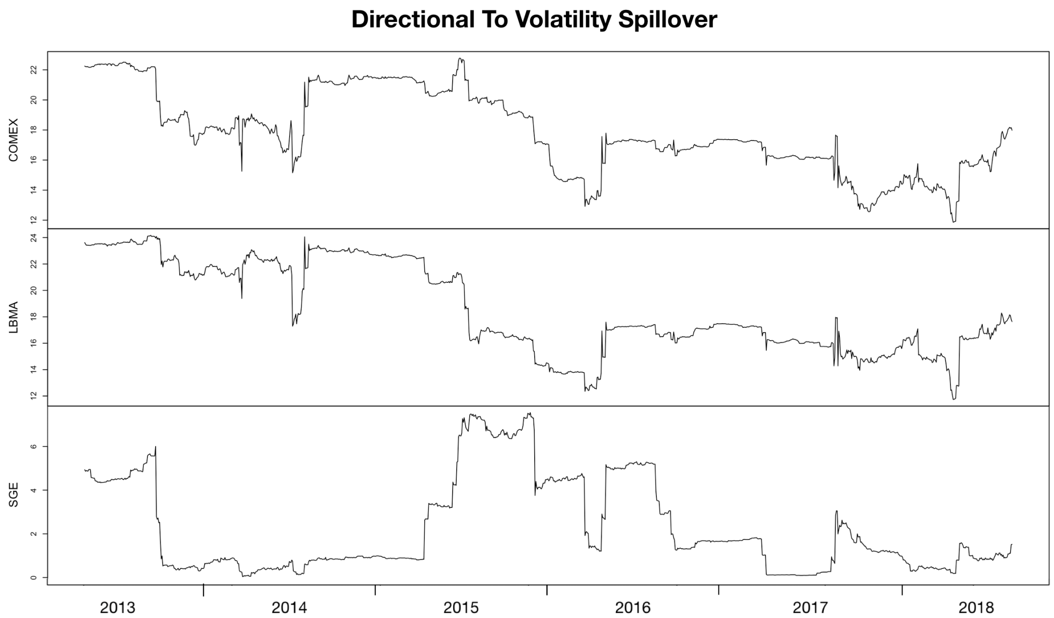


FIGURE 2.10: Net volatility spillover of three markets, 23. Nov. 2012 - 15. Aug. 2018

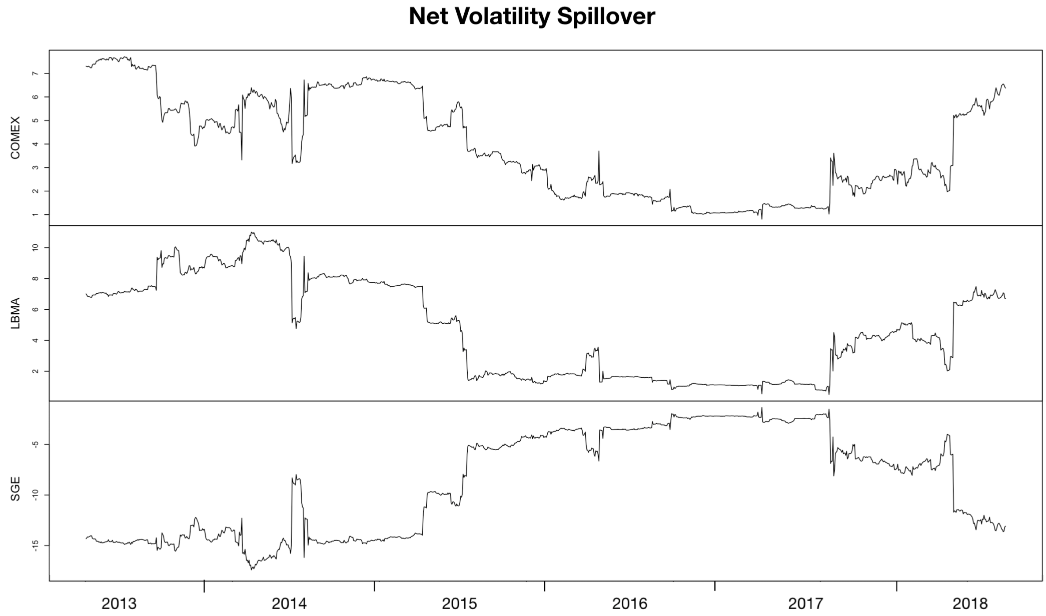


FIGURE 2.11: Net volatility spillover of three markets, 23. Nov. 2012 - 15. Aug. 2018

actually a "less negative stage" after all. The total net volatility spillover for SGE stays entirely in the negative dimension. Just as in the case of return spillover, COMEX and LBMA are the net spreaders among the three markets while SGE plays the role of a net receiver.

Pairwise volatility spillover

Finally, figure 2.12 examines the pairwise spillovers between any two of the three markets. As can be observed from the first plot window, COMEX and LBMA were again mostly even with the volatility spillover staying around 0 within most of the time period. The spillovers from COMEX and LBMA to SGE have similar patterns. However, the pairwise spillover between LBMA and SGE is marginally stronger than the one between COMEX and SGE. During mid-2015 and late-2017, SGE pushed both spillovers from COMEX and LBMA fairly close to zero, probably due to the internationalisation of SGE during that period.

2.5 Conclusions

In this chapter, the spillover strength between COMEX, LBMA and SGE was examined using the method from Diebold and Yilmaz (2012). Both static, as well as dynamic results, prove that the spillover strength of SGE is still comparably minor, and SGE as an emerging exchange remains isolated as compared to COMEX and LBMA. Nevertheless, through the dynamic rolling-window plot, an increasing spillover can be observed since mid-2015, when SGE started its internationalization: however, there does not appear to be any definite signs of SGE becoming as strong as the other two older markets in the short term, and the current situation is far from building a tripartite confrontation between those three

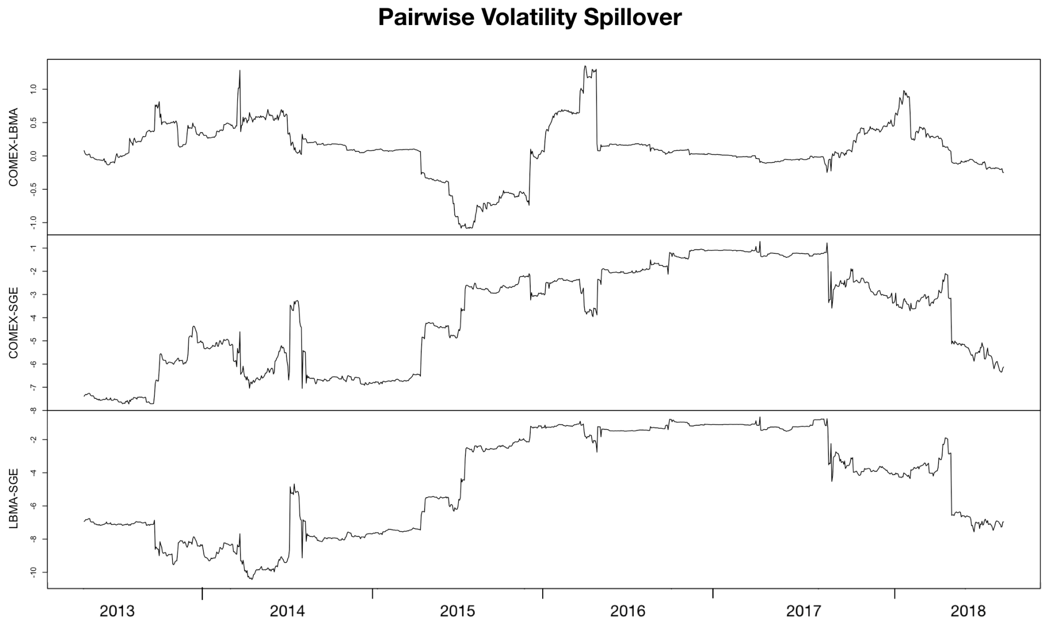


FIGURE 2.12: Pairwise spillover of three markets, 23. Nov. 2012 - 15. Aug. 2018

exchanges. COMEX and LBMA are still the dominant spillover players in the gold markets presumably because of their stronger invest confidence which is based on their more solid foundations, longer trading windows as well as larger trading volume.

Chapter 3

Gold hedging against Exchange Rate

3.1 Introduction

IN this chapter, the author investigates the hedge relationship between Gold and seven major currencies (Euro, British Pound, Australian Dollar, Canadian Dollar, Japanese Yen, Chinese Yuan, Indian Rupee). By pricing both gold and currencies in U.S. Dollar, a general hedging position for gold against currencies can be defined. Furthermore, the author also takes a deeper look at the extreme situation, namely the hedging performance of the gold during extreme exchange rate fluctuation.[1]

3.1.1 Background

The history of gold is almost as long as the history of mankind. Way back to 3000 B.C., gold was first recognised in ancient Egypt. Since then, it has been intertwined with the development of human beings. For its dazzling brilliance, gold has become the material of choice for the ruler of all countries. With the evolution of society, mankind has gradually left the era of self-sufficient and entered a new era of commodity economy. When humans needed coins as a medium of trading to make buying and selling easier, gold naturally became the best choice and started gaining its currency attribution even today. In November 1973, U.S.President Nixon announced the formal cancellation of the gold dual price system. The price of gold no longer exists in the official price. All gold prices are determined according to the free supply and demand of the market. Without the intervention of the government, the price of gold was truly expressed and fully recognised by the market. In the early 1980s, the Reagan administration of the United States repeatedly pulled the relationship between the U.S.Dollar and gold in an attempt to restore the gold standard. However, since the U.S.Dollar bill issuance rate far exceeds the growth rate of the U.S.gold reserve, it has not been able to set the restoration of the gold standard, this also reflects a flaw of the gold standard. Since then, gold's status in the international is not as good as it used to be. In a world where banknotes prevailed nowadays, gold participates no longer in transaction payments, the role turned into a precious metal affected by market supply and demand. While losing its glory as a currency in circulation, gold still owns its main attributes of a non-fiat currency as well as of a commodity and financial equity.

[1] The research topic in this chapter has been inspired by Dr. Guanpin Lu from Shanghai Gold Exchange. There is still a version under construction for journal submission. In this chapter, only the parts done by Xinyi Qian alone have been included.

3.1.2 Motivation and literature

Being treated as an excellent credit zero-interest bond, the hedging function of gold has been investigated and modelled by a huge amount of researchers all over the world for ages. For the purpose of researching in this chapter, we broadly divide the gold purchaser into two roles: investors and households.

Investors are profit seekers. They invest in gold as financial assets in order to gain profit from it. From their perspective, the roles of gold will be treated as a hedge against stock and bond market uncertainty during normal time in general; a safe haven against extreme market failure or geopolitical shock in abnormal time; a direct investment for industrial use.

Households are value holders. They don't expect extra gains from the financial markets, but only after optimal storage of value during normal time against long-run inflation and exchange rate change or during extreme time against the strong devaluation of their domestic currencies or hyperinflation in geopolitical turmoil in the short run.

According to the types of gold purchasers, recent pieces of literature can also be divided into two directions. Part of the literature nowadays puts emphasis on the formal aspect and investigates the hedge and/or safe haven function of gold in the financial market against other assets. Baur and McDermott (2010)[5] found evidence that the investors' behaviour of turning to gold as a safe haven only exists in the developed markets, but not in the emerging ones. Their qualitative test results among 13 countries clearly lead us to the fact that the roles of gold are diverse in different countries or markets. Gold can be used (at most) only as a weak safe haven for some emerging markets while in the developed markets, investors would turn to gold to survive during the short-run market shocks. For these multi-characters gold is playing, there are also investigations simply emphasising on defining the real role of gold. Baur and Lucey (2010a)[4] made detailed definitions for hedge and safe haven and analysed the correlation between gold, stocks and bond.[2] The estimations were made for developed countries U.S., U.K., and Germany. The result was that gold is a short-lived hedge as well as safe haven against stock market uncertainty.

Generally, there is also plenty of literature studies the relationship between gold and currencies from the perspective of households. Capie, Mills, and Geoffrey (2005)[7] coined, there are two senses of gold's hedging functions, namely internal and external. The internal hedges channel works when gold can be used to hedge against the domestic purchasing power of the currency(i.e. gold price rises with the increasing of the domestic CPI.). While an external hedge is the one against the exchange rate change. (i.e. gold price drops when there is an increase in the exchange rate between the domestic currency and foreign currency.)

Among the existed literature, the U.S. Dollar is the most studied target currency. The external hedging was examined in Capie et al.(2005) for the U.S. Dollar against British Sterling and Japanese Yen. The result was that gold is indeed an external hedge against

[2] In their research, they distinguished the hedge and safe haven by their function conditions. A hedge is simply uncorrelated or negatively corrected with other financial assets or portfolio on average while safe have has the same feature during extreme times of market stress or turmoil.

the U.S. Dollar from 1971 till 2004, with an inelastic property in both the short- and long-run. Joy (2011)[21] applied a dynamic conditional correlation model applied 16 major exchange pairs with U.S.Dollar and found that gold is an external hedge against exchange rate change for U.S. Dollar, it can also work as a weak external safe haven and the effectiveness of hedging is continuously increasing over time. Also Pukthuanthong and Roll (2011)[34] can be considered as research about external hedging. They pointed out that the relation between gold and U.S. Dollar is different from the relation between gold with other currencies. Indeed, gold has a much stronger negative correlation with the U.S.Dollar, but its (weaker) relations with other currencies should not be neglected. Existing literature also studies the character of external hedge of gold for U.S.Dollar, Reboredo (2013)[36] started from the view of risk management and found empirical evidence to support the external hedge function of gold against U.S.Dollar on average as well as in abnormal time (as a safe haven).

On the other hand, Ghosh, Levin, Macmillan, and Wright (2004)[17] used a theoretical model and applied monthly data from 1976 to 1999 to prove also an internal hedging function of gold against inflation. They suggested a sizeable short-run co-movement in the gold price and the general rate of inflation in the short-run and stated that gold can be regarded as a long-run inflation hedge. At the same time, the term "safe haven" had been raised in order to describe gold as a zero-beta asset, which could hold its value when there is stormy weather in the stock market. Wang, Lee and Thi (2011)[42] investigated the internal hedge of gold against inflation in the U.S. and Japan from 1971 to 2010. They pointed that the correlation between the U.S.Dollar and gold also indicates a causality that the long-run inflation in the U.S. tends to increase the gold price. However, this hedging correlation is only partially effective in Japan.

3.1.3 Research question

To the best of our knowledge, there is no existing paper studied the hedging function of gold against currencies including the Chinese Yuan, and no research has applied the same data sample for comparing the currencies and gold as two assets priced by the same unit.

The main research target of this chapter is to investigate the role, that gold is playing in several countries including China in the sense of hedging specific domestic currencies. We want to find out whether gold is able to hedge against a currency, to what extent does it hedge, and in which situation. We take Euro, British Sterling, Australian Dollar, Canadian Dollar in order to compare our result to the previous sounding ones, and also take Chinese Yuan, India Rupee, and Japan Yen as a frame of reference.

From the external view, we would like to examine whether gold can be applied as a cross hedge for specific currencies.[3] We know that gold is the most typical anti-Dollar currencies. Meanwhile, one can not find a clear, suitable hedge for currencies other than U.S. Dollar. Therefore, we raise the research question to find out some currencies which have a cross hedge relationship other than U.S. Dollar. Furthermore, we want to investigate whether it is a cross hedge in general and/or if it also/only works as a safe haven during extreme times.

[3] A cross hedge is used to define a positively correlated asset that has similar price movement.

3.1.4 Definitions

Here we first state the major definitions of a role that the gold can play in this research:

Hedge

A hedge can be managed when two assets have *negative correlation* of the price movement between each other. The most ideal hedge would be that two assets 100% inversely correlated with each other.

Cross Hedge

A cross hedge can be managed when two assets have *positive correlation* of the price movement between each other. Individuals can just take opposing positions in both of the assets in order to reduce the holding risk. Even this correlation does not equal one, a hedge position can be created by the correlation coefficient, proving that their prices move in the same direction.

Safe Haven

An asset can play the role of a safe haven for another asset if the formal has *no correlation or negative correlation* during an abnormal situation such as extreme market fluctuation or strong currency valuation change due to geopolitical turmoil.

3.1.5 Organisation of this chapter

This chapter will be organised as follows. Section 3.1 presents the general ideas of the research motivation and relevant literature. Section 3.2 brings the method we applied for investigation, which has been divided into two parts for mean model and variance model. We introduce the data and its descriptive statistics in section 3.3. The estimation results in the form of tables and plots will be presented in section 3.4. Section 3.5 concludes.

3.2 Method

We are going to fit the model in two steps. In the first step, an autoregressive distributed lag (ADL) will be used to fit the mean model, thus one can split the residual and keep a demeaned stationary time series as the determinable part and the residual as indeterminable part, also known as "innovation". This innovation part will be modelled as the second step (variance model) using integrated generalised autoregressive conditional heteroscedasticity (iGARCH) model.[4]The reason why we do these two steps fitting is because of the attribution of those financial series. As can be observed from the section 3.3 and table 3.1, all the series have the features of typical financial series. We also know that most financial series have volatility clusters known as heteroscedasticity. Even the single variable $\Delta gold$ demonstrates the attribution of a financial series. We are interested in the main cause of the variation between different gold-currency series, whether the decisive factor lies in the mean model or the variance one. Later we can prove the main cause can be found in the mean model and the volatility cluster in the series is almost the same for all

[4]Different GARCH classes had been tested in order to achieve the best fit. Here one simply writes GARCH for demonstration.

seven currencies, so the decisive role of the indeterminable part was largely played by the volatilities in gold per se.

3.2.1 Mean model: Autoregressive Distributed Lag (ADL)

The ADL model has first been introduced by Pesaran et al.(2001)[33], in order to model the simultaneous as well as lagged effect of multiple stationary variables on one of them. We consider the percentage change of gold price, which can be observed from two parts, the first part is a linearly correlated mean of the dependent variable, which can be explained by the intercept, its own history values, another lagged series, and the innovation.

An ADL model suitable for our research target takes the following form:[5]

$$\Delta g_t = b_0 + b_1 \Delta g_{t-1} + b_2 \Delta g_{t-2} + b_3 \Delta x_t + b_4 \Delta x_{t-1} + b_5 \Delta x_{t-2} + a_t \tag{3.1}$$

$$a_t = \sigma_t \varepsilon_t \tag{3.2}$$

Using G_t or X_t to represent the gold price (quoted by U.S. Dollar) or exchange rate (currency in the price of U.S. Dollar) in level, g_t and x_t stands for gold or currency price in natural logarithm. After once-difference, we get Δg_t and Δx_t. The interpretation of equation 3.1 can be stated as: the percentage change of gold price of the day t, depends on an intercept (trend), its own previous change, and the change of a currency.

If the change of the gold price is positively correlated with the change of a currency (since they have been both priced by U.S. Dollar), we can say that gold can be used as an external cross hedge of that currency. The higher the correlation coefficient, the better the hedge effect can be. Even when they are not one to one identical to each other, a proper hedge position can still be created depends on the correlation coefficient.

One advantage of using once differenced natural logarithm is that the estimated parameter can be interpreted as elasticity coefficients. The parameter b_3 from equation 3.1 reflects the simultaneous elasticity of percentage change on currency to gold.

3.2.2 Variance model: integrated GARCH (iGARCH)

The volatility innovation will be modelled by a specific GARCH model which has the best fit for the regression pairs individually. Since Engle first developed the basic GARCH model in 1982, the whole family has more than 180 members nowadays. The integrated GARCH model (also known as iGARCH) has been developed by Engel and Bollerslev (1986)[15] in the same year when the standard GARCH has been developed. In the next section, iGARCH will be applied for the variance model and has been proved by information criteria to have the best fit among the major GARCH forms[6].

We assume the ADL regression residual of equation 3.1 follows a GARCH(1,1) process, which can be written as follows.

[5] The lag order has been tested. For all the cases, the maximum number of lag is two.

[6] We have tested standard GARCH, exponential GARCH, GJR-GARCH, family GARCH, and component standard GARCH. Also, the number of the GARCH parameter order of 1 has also been optimised by Bayesian information criteria.

$$a_t = \sigma_t \varepsilon_t \qquad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{3.3}$$

where ε_t is an independent identically distributed random series with mean zero and variance equal to 1. By imposing the restriction that the persistence of the shock equals to 1 ($\hat{P} = 1$), we simply have parameter β_1 in this case of iGARCH(1,1) as $1 - \alpha_t$. Thus we have the iGARCH model as:

$$a_t = \sigma_t \varepsilon_t \qquad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + (1 - \alpha_t) \sigma_{t-1}^2 \tag{3.4}$$

where the assumption of ε_t remains unchanged. The fitting results will be presented in section 3.4.

3.2.3 Distributed quantile regression

In order to define if an asset has a safe haven attribute of another, Baur and Lucey (2010)[4] improved the original ADL model and developed the quantile variable based on Capie et al.(2003)[7]. Using this model we can estimate the partial correlation between the dependent and (only) the independent variables fall into the extreme quantile. An improved regression following this idea takes the form as follows:

$$\Delta g_t = b_0 + b_1 \Delta g_{t-1} + b_2 \Delta g_{t-2} + b_3 \Delta x_t + b_4 \Delta x_{t-1} + b_5 \Delta x_{t-2} + b_6 \Delta x_{t(q)} + a_t \tag{3.5}$$

while most of the item in equation 3.5 are the same as 3.1, one extra component in the regression, namely $\Delta x_{t(q)}$ stands for the asymmetries of both positive and negative extreme percentage changes of the currency price (exchange rate against U.S. Dollar), the parameter b_6 thus estimates the effect of this extreme currency price change. q can take the value of 1%, 2.5%, or 5%. The whole item works as a quasi-dummy variable, when the value of x_t lies in the q percentage tail (either positive or negative end) of its distribution, we keep the value of that entry. For those values that fall in the main middle $1 - 2 \times q$, we set the value of that entry equals 0.

3.3 Data and descriptive statistics

Data has been supplied by FastMarkets, using intra-day XAU closing price for the daily gold price. The price is originally quoted in U.S. Dollar with the unit of 1 troy ounce (Oz). The exchange rate has been taken from Yahoo finance. The time range is from May 15. 2006 till May 16. 2018. There were two abnormal extreme fluctuations for Australia Dollar and Chinese Yuan against U.S. Dollar. The first was on 2006 December 25. and the second on 2011 July 18., respectively. These two outliers deviate too far away from the main group and were both caused by irrational behaviours. Because of the sensitivity of the model, we replace these two entries by using the average of the respective currency series.

Figure 3.1 describe the movements for gold and estimated currencies in the original unit. The gold price in U.S. Dollar has been through an upward trend from the beginning of our estimation period (only 687.5 USD on 15. May 2006) till 5. September 2011 with the highest price 1895 for another day then remained at a high level till early 2013, afterward there was a downward trend and the gold price arrived a fluctuating plateau till the end of the data period. Seven currencies also valued in U.S. Dollar have been plotted in order

FIGURE 3.1: Per troy oz gold price in U.S. Dollar (G_t), movement comparisons of gold price and currencies priced in the Dollar (exchange rate against U.S. Dollar, X_t) for Euro (EUR), British Sterling (GBP), Australia Dollar (AUD), Canadian Dollar (CAD), Japanese Yen (JPY), Chinese Yuan (CNY), India Rupee (INR) from 16. May 2006 to 16. May 2019.

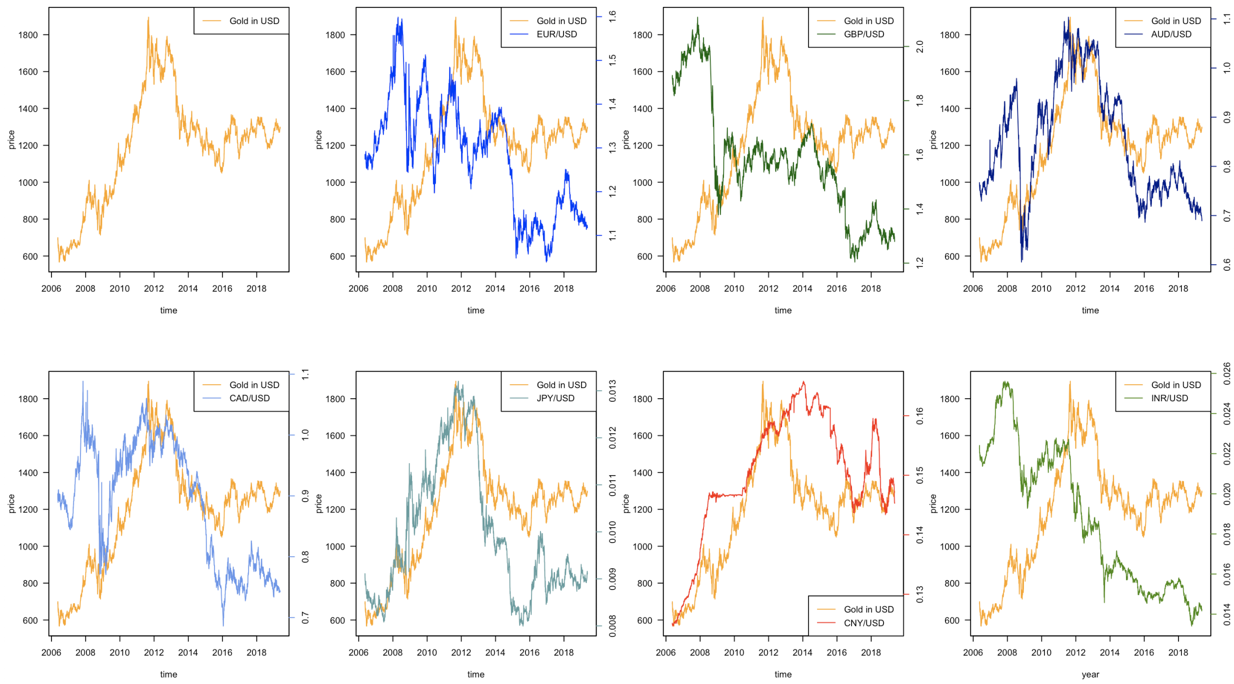
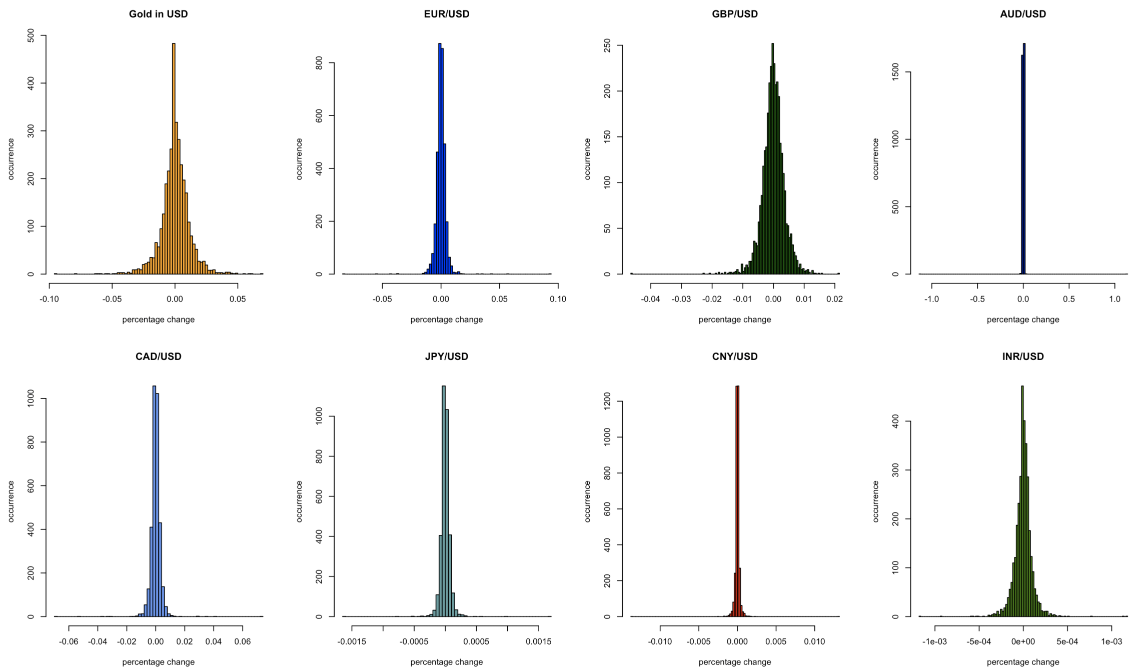


FIGURE 3.2: Distribution histograms of percentage change for Δg and Δx.



to compare the movement with the gold price. By doing this, we make gold and the target currency as two goods being marked by the same unit of measurement. Apparently, we observe highly similar co-movement between gold and three currencies, namely the Australian Dollar, Canadian Dollar, and Japanese Yen. Among the three of them, JPY shares an astonishing similarity with gold, especially during the first half of the period.

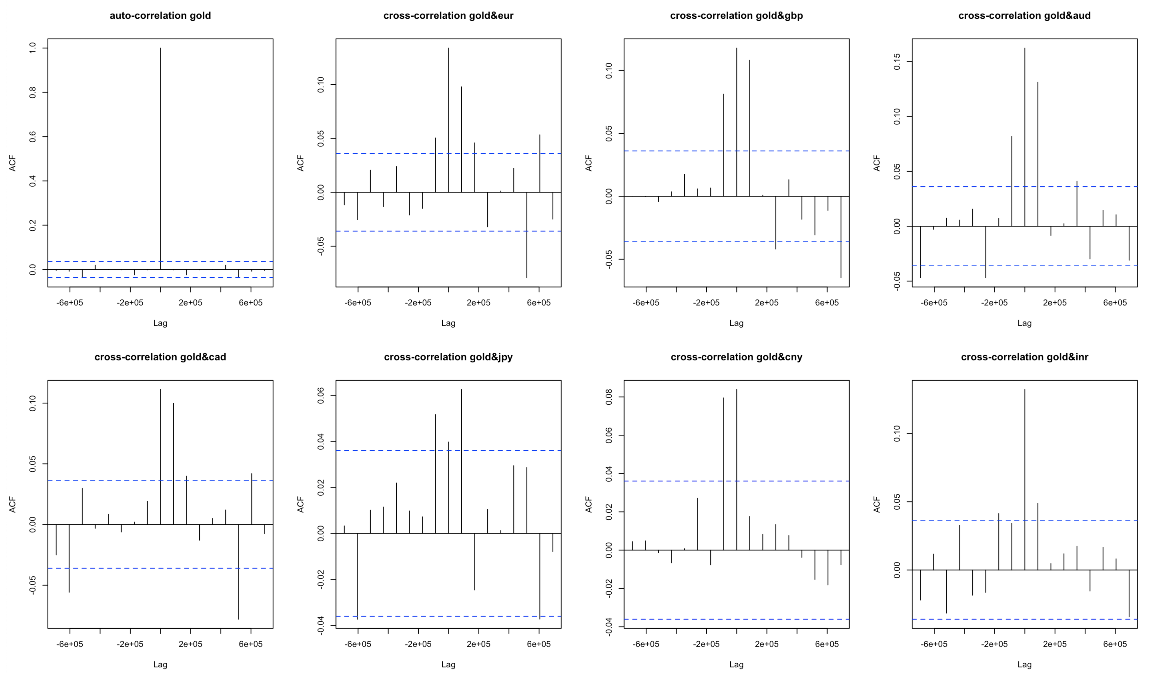
Because of the different numeric levels of the data and large fluctuation, we take the natural logarithm of the data and difference them once. After omitting those entries when either gold or currency has no data, 2953 observation pairs remain with the following descriptive statistics:

TABLE 3.1: Descriptive Statistic of the Data, once-differenced

Statistic	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max	Skew	Kurt
Δ gold	0.0001	0.011	−0.096	−0.005	0.006	0.068	−0.351	6.143
Δ eur	−0.00001	0.005	−0.083	−0.002	0.002	0.092	0.609	107.287
Δ gbp	−0.00003	0.004	−0.023	−0.002	0.002	0.021	−0.311	3.278
Δ aud	0.00001	0.004	−0.030	−0.002	0.002	0.028	−0.513	6.907
Δ cad	−0.00002	0.004	−0.069	−0.001	0.001	0.073	−0.489	107.692
Δ jpy	−0.00000	0.0001	−0.002	−0.00003	0.00003	0.002	0.496	112.240
Δ cny	0.00000	0.0002	−0.003	−0.0001	0.0001	0.002	−0.688	12.191
Δ inr	−0.00000	0.0001	−0.001	−0.00005	0.00005	0.001	−0.051	21.854

As table 3.1 presents, after natural logarithm and once-difference, all the series are very close to zero-mean.Apart from the gold series, all the rest have small standard deviations around the mean, first and third quantiles symmetric with each other. Including gold, most of the series are negatively skewed. Kurtosis of all eight is larger than 3, which indicates a leptokurtic distribution of the typical financial data and the rare existence of the extreme

FIGURE 3.3: Estimated autocorrelation for Δg and cross-correlations between Δg and Δx



values. These facts can also be observed by the distribution histograms in figure 3.2. Currencies with enormous large kurtosis values have in most of the time fairly concentrated entries near the mean and widely spreading rare entries with small frequencies. All eight series have been tested to be stationary by the Adjusted Dicky-Fuller test.

Figure 3.3 illustrates the autocorrelation of Δg and cross-correlation between Δg_t and Δx_t for up to eight lags. Obliviously the once differenced log gold price is fairly efficient and has no significant autocorrelation with neither lags nor leads. It is also not surprising that (a) most of the series have significant positive concurrent correlations, and (b) the dynamic correlations, if exist, are short-lived.

3.4 Empirical results and discussion

3.4.1 ADL estimation result

Table 3.2 summarised the estimation parameters of the ADL regression. All in all, we observe:

a) Non-significant constant for all currencies

This is conspicuous because we have once-differenced stationary series for all the variables, which have a very close to zero mean. A non-zero constant parameter would suggest a drift, this should not be in this case.

b) Different fittings for different currencies

TABLE 3.2: ADL estimation

	Dependent variable:						
	Δ gold						
	Δ eur	Δ gbp	Δ aud	Δ cad	Δ jpy	Δ cny	Δ inr
Δ gold, 1) (b_1)	−0.044**	−0.027	−0.042**	−0.032*	−0.008	−0.012	−0.018
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Δ gold, 2) (b_2)	−0.043**	−0.035*	−0.039**	−0.037**	−0.028	−0.027	−0.034*
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Δ x (b_3)	0.427***	0.381***	0.535***	0.448***	8.118***	4.040***	16.411***
	(0.045)	(0.058)	(0.056)	(0.055)	(2.589)	(0.863)	(2.070)
Δ x, 1) (b_4)	0.415***	0.363***	0.463***	0.471***	10.638***	1.196	8.540***
	(0.047)	(0.058)	(0.057)	(0.057)	(2.674)	(0.867)	(2.107)
Δ x, 2) (b_5)	0.236***	0.031	0.038	0.260***	−0.642	0.648	1.046
	(0.046)	(0.058)	(0.057)	(0.056)	(2.594)	(0.863)	(2.085)
Constant (b_0)	0.0001	0.0002	0.0001	0.0001	0.0001	0.0001	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Observations	2,951	2,951	2,951	2,951	2,951	2,951	2,951
R^2	0.046	0.028	0.048	0.037	0.008	0.008	0.024
Adjusted R^2	0.044	0.026	0.047	0.036	0.006	0.007	0.023
Res. SE (df = 2945)	0.011	0.011	0.011	0.011	0.011	0.011	0.011
F Statistic (df = 5; 2945)	28.462***	16.693***	30.018***	22.760***	4.813***	5.041***	14.599***
Note:							*p<0.1; **p<0.05; ***p<0.01

Parameter R^2 and F Statistic can be traded as indicators of the significance of the regression. Among the seven currencies being estimated, AUD has the largest F-statistic of 30.018, EUR and CAD are also significant and the F-statistic is larger than 20. The GBP and INR are smaller, which are larger than 10. The Currency from East Asia, CNY and JPY have quite a small F-statistic of 4.813, 5.041.Perhaps the large significance of AUD and CAD are from the high cor-relationship of their economy and the commodity markets. Gold is a top Australian export and its elevated price means that the total value of exports has risen accordingly. In investing, the AUD/USD could be used as the proxy to holding positions in gold. Compared with the spent of carrying cost with holding long positions in Gold, long Australian Dollar/U.S. Dollar positions will actually produce net interest payments.

The cor-relationship between the gold price and the Canadian Dollar is also resulting from the economic aspects. It is well known that the Finance department regards the Canadian economy as intimately tied with the U.S.economy and the world economy in general. Thus a greater demand for commodities bodes well for the Canadian Dollar, which is also positively correlated with the Gold price.

The euro is one of the most important alternatives to the U.S. Dollar among fiat currencies (the EUR/USD currency exchange rate is one of the most often traded pairs in the world). This is why there is often a positive link between the euro and gold: both assets are negative correlated with the Greenback. However, the relationship is far from being a perfect correlation, as one can see in Fig. 1. This is because gold is not merely an alternative against the U.S. Dollar, but also against the current monetary system based on fiat currencies. Therefore, in some cases the euro and the Dollar both lose (or gain) ground against gold.

Unlike Australia and Canada, the economy of British is not highly correlated with Gold and Commodity prices. In recent 15 years, British Pound is likely falling into the mire of depreciation. The different trends of Gold and GBP bring the regression with a low F-statistic.

India and China are the top two gold consumer countries. From ancient times to the present, gold performs an important role in Indian life. Nearly 75% of India's saving come from households, of which 66% are in the form of real estate and gold.[7] The love of gold is inextricably linked to the Indian culture. So not surprisingly we have this relationship between Gold and Indian Rupee.

The dependence is also in-negligible between simultaneous Δg_t and Δcny_t. With the increasing global impact of the gold markets in Shanghai, the rising position of the Renminbi in basket of the currencies worldwide, the share of effect for the Chinese Yuan in the gold price system is also inevitably increasing.

c) Lead and lag for dynamic effect

All the currencies have significant simultaneous effects (b_3), which probably means all 7 currencies and gold are linked well in financial markets. The EUR, GBP, AUD, JPY, and INR have a one-step lag with the gold price, which means the gold price could lead those 5 currencies. Perhaps the difference is from the in-dependency of Chinese exchange policy. The EUR, AUD, and CAD have step-2 dependent variables, which means the Gold price

[7] "So Why Do Indian Households Invest So Much In Gold?" by Tim Worstall. https://www.forbes.com/

would lead 2 days of the 3 currencies. This shows the high cor-relationship between gold and the 2 commodities currencies(CAD, AUD) and the reserve currency(EUR).

d) Short- and long-run hedging

Since both dependent and independent variables have been logged and once differenced, the parameter b_3 can be interpreted as the instantaneous effect between gold and specific currency and as an indicator of the concurrent cross-hedge (which does not indicate any causality). Using Euro as an example, a short-run effect means: ceteris paribus, 1 percentile movement in EUR/USD exchange rate (within the EUR/USD distribution) will on average indicates a 0.427 percentile change in the gold price marked by USD in the same direction.

Among the seven currencies being estimated, Indian Rupee had the highest value of 16.411, which (despite even a better goodness-of-fit) is more than double the second-highest Japanese Yen. A one percentile increase in the INR/USD exchange rate is on average accompanied by circa 16 percentile increase in the gold price on the same day, other conditions remain unchanged. Gold has always played an integral role in Indian culture. Nearly 75% of India's saving come from households, of which 66% are in the form of real estate and gold.[8] The love of gold is inextricably linked to the Indian culture. So not surprisingly we have this peculiar result of Indian Rupee.

Meanwhile, Japanese Yen has another reason for being the second high positive correlating currency with gold. Known as a safe-haven currency, JPY has always a low interest rate, a strong net foreign asset position, and a liquid financial market. Researches also stated that the Japanese Yen is one of the few currencies that appreciates against the U.S. Dollar during the market uncertainty in the United State(See Botman et al.(2013)[6]). Another striking observation from the estimation results of Δjpy is that, not like the other currencies, the 1. lag (Δjpy_{t-1})) has a much larger effect on the Δg_t(The effect of the Δcad_{t-1} is only slightly larger than Δcad_t). This result suggests that, all other things remain unchanged, a one percent increase in the JPY exchange rate against USD at period t can indicate more than 10% change in the same direction of the gold price at period $t+1$.

The third highest correlation parameter has been generated from the relationship between the Chinese Yuan and gold. The concurrence positive correlation coefficient reaches 4 percent, which suggests an in-negligible dependence between simultaneous Δg_t and Δcny_t. With the increasing global impact of the gold markets in Shanghai, the rising position of the Renminbi in the basket of the currencies worldwide, the share of effect for the Chinese Yuan in the gold price system is also inevitably increasing.

Apart from the three currencies from Asia, the other four currencies have less than a single-digit positive correlation with the gold price percentage change.

Long-run effect can be calculated by $\frac{b_3+b_4+b_5}{1-b_1-b_2}$ when the corresponding estimated parameters are significant. The "long-run" here we are talking about is not literally long in the time range, but the longest effectiveness can be detected between the currency and gold percentile change. A table of short- and long-run effects has been stated as 3.3. Apart from the Japanese Yen and Indian Rupee, most of the currencies have only a slightly larger

[8] "So Why Do Indian Households Invest So Much In Gold?" by Tim Worstall. https://www.forbes.com/

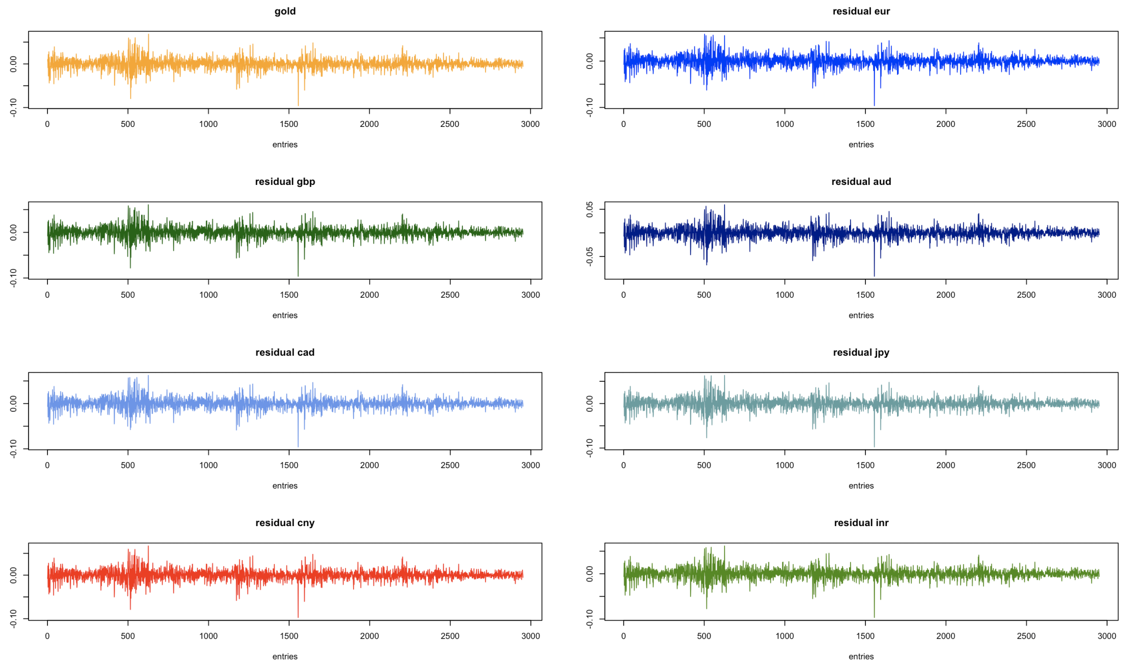


FIGURE 3.4: Differenced log gold price and ADL regression residual of the seven currencies

TABLE 3.3: Short- and long-run effect between percentile movement of currency and gold (both priced by USD)

Short- & long-run effect

	EUR	GBP	AUD	CAD	JPY	CNY	INR
Short-run	0.427	0.381	0.535	0.448	8.118	4.040	16.411
Long-run	0.991	0.712	0.926	1.103	18.76	4.040	24.130

long-run effect than the short ones. For the Chinese Yuan, only concurrent percentile movement can be observed on the gold price. In practice, a larger long-run effect will indicate stronger effectiveness of a delayed investment operation after realising the fluctuation of the currency. For the Japanese Yen and Indian Rupee, if one observed a movement in the currency, there will still exist a time range from one to two days for the individuals to make an investment position in gold in order to hedge the currency fluctuation, and this hedging strength can be fairly high due to the large numeric value of the "long-run effect".

Figure 3.4 illustrates the stationary series of Δg_t and all seven residuals from the first-step ADL regression fitting. After excluding the mean model from the gold $\sim$ currency, the residuals of the fitting have a very similar pattern to the original gold series. In the next step, we fit those residuals in a GARCH variance model.

3.4.2 iGARCH estimation result

Table 3.4 presents the estimation parameter of the variance model. The integrated GARCH has been proved to have the best fit with a generalised error distribution. As we can see,

TABLE 3.4: GARCH estimation

	Dependent variable:						
	eur	gbp	aud	cad	jpy	cny	inr
α_0	0.00000	0.000000	0.000000	0.000000	0.000000	0.00000	0.000000
	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)	(0.000000)
α_1	0.04034***	0.040839***	0.041651***	0.039924***	0.039284***	0.04009***	0.037861***
	(0.003978)	(0.004052)	(0.027983)	(0.003924)	(0.003907)	(0.004041)	(0.003713)
β_1	0.95966	0.959161	0.958349	0.960076	0.960716	0.95991	0.962139
	-	-	-	-	-	-	-
B	1.11238***	1.124650***	1.148820***	1.116888***	1.084711***	1.08838***	1.104454***
$(shape)$	(0.035384)	(0.036051)	(0.056534)	(0.036039)	(0.034833)	(0.035198)	(0.035187)
Note:					*p<0.1; **p<0.05; ***p<0.01		

all the α_0s have a non-significant parameter with value zero, which can be undoubtedly omitted since including or excluding this parameter make no difference to the model output. This also makes sense, since α_0 indicates the mean of the variance model and we have already demeaned the series, this can also be observed from the residual plots of 3.4.

There is neither standard error nor significance statistic for parameter β_1 because as equation 3.4 showed, β_1 has been generated by $1 - \alpha_1$, all $beta_1$ are very close 1, which suggests a highly persistent effect from the last period shock σ_{t-1}.

It is also not hard to realise that the estimation results are quite like each other among the seven currencies. This finding suggest that the main difference between the currencies' attributes have been discovered by the ADL mean model.

3.4.3 Quantile regression result

TABLE 3.5: Quantile Regression for EUR

	Dependent variable:		
	$\Delta gold$		
	$q = 5\%$	$q = 2.5\%$	$q = 1\%$
Δ gold, 1)	-0.040^{**}	-0.041^{**}	-0.042^{**}
	(0.018)	(0.018)	(0.018)
Δ gold, 2)	-0.044^{**}	-0.044^{**}	-0.044^{**}
	(0.018)	(0.018)	(0.018)
Δeur	0.162^{**}	0.299^{***}	0.343^{***}
	(0.079)	(0.073)	(0.066)
Δeur, 1)	0.436^{***}	0.429^{***}	0.431^{***}
	(0.047)	(0.048)	(0.048)
Δeur, 2)	0.240^{***}	0.239^{***}	0.239^{***}
	(0.046)	(0.046)	(0.046)
$\Delta eur_{(}q)$	0.390^{***}	0.207^{**}	0.158^{*}
	(0.095)	(0.092)	(0.090)
Constant	0.0002	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)
Observations	2,951	2,951	2,951
R^2	0.052	0.048	0.047
Adj. R^2	0.050	0.046	0.045
Res. Std. Error (df = 2944)	0.011	0.011	0.011
F Statistic (df = 6; 2944)	26.644^{***}	24.599^{***}	24.252^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01		

Here we present the regression results after applying formula 3.5. Strikingly different safe haven attributes with not only different significance, different numeric values, but even different signs emerge from the individual estimation result from table 3.5 to table 3.11.

Gold can also be used as a cross hedge for Euro in all 5%, 2.5% and 1% extreme percentage change cases as well as for Great Britain Pounds (table 3.5 and table 3.6). For these two currencies, the elasticities of cross-safe haven are smaller, the more extreme the situation goes (further the extreme change lies from zero). This finding suggests us, that during both normal and abnormal time, gold can be purchased as a cross hedge against the exchange rate change of Euro and Great Britain Pounds.

On the other hand, the Australian Dollar, Canadian Dollar, and Chinese Yuan have no significant parameter for the q quantile variables among all cases (see table 3.7, table 3.8 and table 3.10). Gold plays the role of a cross hedge for those three currencies only in the normal time but these hedging attributes disappear during the extreme situation.

Interesting finding raises from table 3.9 and 3.11. Gold has a significantly higher negative correlation with the Japanese Yen and Indian Rupee. This negative relation is even the strongest when the exchange rate change at its most extreme 1% return. All the others remain unchanged, there would be on average about 15%(18%) inverse change in the gold price if the Japanese Yen (Indian Rupee) reaches an extreme fluctuation only in the top or bottom 1% of the whole distribution. This indicates plural roles gold is playing for JPY and INR, namely a strong cross hedge in general but at the meanwhile a very defined safe haven during abnormal situations.

A summary table is stated as table 3.12:

TABLE 3.6: Quantile Regression for GBP

	Dependent variable:		
	Δ gold		
	$q = 5\%$	$q = 2.5\%$	$q = 1\%$
Δ gold, 1)	-0.026	-0.026	-0.027
	(0.018)	(0.018)	(0.018)
Δ gold, 2)	-0.035^{*}	-0.035^{*}	-0.035^{*}
	(0.018)	(0.018)	(0.018)
Δgbp	0.175^{**}	0.272^{***}	0.324^{***}
	(0.074)	(0.068)	(0.063)
Δgbp, 1)	0.348^{***}	0.349^{***}	0.352^{***}
	(0.058)	(0.058)	(0.058)
Δgbp, 2)	0.041	0.040	0.038
	(0.058)	(0.058)	(0.058)
Δgbp_q	0.535^{***}	0.397^{***}	0.325^{**}
	(0.120)	(0.130)	(0.152)
Constant	0.0003	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)
Observations	2,951	2,951	2,951
R^2	0.034	0.031	0.029
Adj. R^2	0.032	0.029	0.027
Res. Std. Error (df = 2944)	0.011	0.011	0.011
F Statistic (df = 6; 2944)	17.335^{***}	15.505^{***}	14.687^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

TABLE 3.7: Quantile Regression for AUD

	Dependent variable:		
	Δ gold		
	$q = 5\%$	$q = 2.5\%$	$q = 1\%$
Δ gold, 1)	-0.042^{**}	-0.042^{**}	-0.043^{**}
	(0.018)	(0.018)	(0.018)
Δ gold, 2)	-0.039^{**}	-0.039^{**}	-0.040^{**}
	(0.018)	(0.018)	(0.018)
Δaud	0.520^{***}	0.547^{***}	0.566^{***}
	(0.074)	(0.067)	(0.063)
Δaud, 1)	0.461^{***}	0.464^{***}	0.466^{***}
	(0.057)	(0.057)	(0.057)
Δaud, 2)	0.036	0.039	0.044
	(0.057)	(0.057)	(0.058)
Δaud_q	0.036	-0.040	-0.160
	(0.117)	(0.124)	(0.143)
Constant	0.0001	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)
Observations	2,951	2,951	2,951
R^2	0.049	0.049	0.049
Adj. R^2	0.047	0.047	0.047
Res. Std. Error (df = 2944)	0.011	0.011	0.011
F Statistic (df = 6; 2944)	25.023^{***}	25.024^{***}	25.225^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01		

TABLE 3.8: Quantile Regression for CAD

	Dependent variable:		
	Δ gold		
	$q = 5\%$	$q = 2.5\%$	$q = 1\%$
Δ gold, 1)	-0.032^{*}	-0.032^{*}	-0.032^{*}
	(0.018)	(0.018)	(0.018)
Δ gold, 2)	-0.037^{**}	-0.037^{**}	-0.037^{**}
	(0.018)	(0.018)	(0.018)
Δcad	0.429^{***}	0.467^{***}	0.460^{***}
	(0.084)	(0.069)	(0.066)
Δcad, 1)	0.474^{***}	0.465^{***}	0.466^{***}
	(0.058)	(0.059)	(0.059)
Δcad, 2)	0.260^{***}	0.259^{***}	0.259^{***}
	(0.056)	(0.056)	(0.056)
Δcad_q	0.034	-0.052	-0.040
	(0.112)	(0.113)	(0.118)
Constant	0.0002	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)
Observations	2,951	2,951	2,951
R^2	0.037	0.037	0.037
Adj. R^2	0.035	0.035	0.035
Res. Std. Error (df = 2944)	0.011	0.011	0.011
F Statistic (df = 6; 2944)	18.977^{***}	18.997^{***}	18.980^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

TABLE 3.9: Quantile Regression for JPY

	Dependent variable:		
	Δ gold		
	$q = 5\%$	$q = 2.5\%$	$q = 1\%$
Δ gold, 1)	-0.011	-0.011	-0.011
	(0.018)	(0.019)	(0.018)
Δ gold, 2)	-0.028	-0.028	-0.028
	(0.018)	(0.018)	(0.018)
Δjpy	12.979^{***}	11.752^{***}	12.454^{***}
	(3.341)	(3.198)	(3.061)
Δjpy, 1)	11.514^{***}	11.279^{***}	11.452^{***}
	(2.699)	(2.693)	(2.689)
Δjpy, 2)	-0.574	-0.611	-0.698
	(2.592)	(2.592)	(2.591)
Δjpy_q	-12.233^{**}	-10.493^{*}	-15.007^{***}
	(5.319)	(5.425)	(5.667)
Constant	0.00003	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)
Observations	2,951	2,951	2,951
R^2	0.010	0.009	0.010
Adj. R^2	0.008	0.007	0.008
Res. Std. Error (df = 2944)	0.011	0.011	0.011
F Statistic (df = 6; 2944)	4.898^{***}	4.638^{***}	5.188^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01		

TABLE 3.10: Quantile Regression for CNY

	Dependent variable:		
	Δ gold		
	($q = 5\%$	$q = 2.5\%$	$q = 1\%$
Δ gold, 1)	-0.013	-0.013	-0.012
	(0.019)	(0.019)	(0.019)
Δ gold, 2)	-0.026	-0.026	-0.027
	(0.018)	(0.018)	(0.018)
Δcny	5.167^{***}	4.957^{***}	3.971^{***}
	(1.150)	(1.069)	(0.991)
Δcny, 1)	1.250	1.258	1.193
	(0.868)	(0.868)	(0.867)
Δcny, 2)	0.696	0.704	0.643
	(0.864)	(0.864)	(0.864)
Δcny_q	-2.689	-2.697	0.286
	(1.815)	(1.856)	(2.042)
Constant	0.00002	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)
Observations	2,951	2,951	2,951
R^2	0.009	0.009	0.008
Adj. R^2	0.007	0.007	0.006
Res. Std. Error (df = 2944)	0.011	0.011	0.011
F Statistic (df = 6; 2944)	4.569^{***}	4.555^{***}	4.203^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01		

TABLE 3.11: Quantile Regression for INR

	Dependent variable:		
	Δ gold		
	($q = 5\%$	$q = 2.5\%$	$q = 1\%$
Δ gold, 1)	-0.019	-0.019	-0.020
	(0.018)	(0.018)	(0.018)
Δ gold, 2)	-0.034^{*}	-0.034^{*}	-0.034^{*}
	(0.018)	(0.018)	(0.018)
Δinr	17.849^{***}	19.081^{***}	20.078^{***}
	(2.605)	(2.447)	(2.302)
Δinr, 1)	8.655^{***}	8.677^{***}	8.492^{***}
	(2.111)	(2.107)	(2.103)
Δinr, 2)	1.170	1.348	1.480
	(2.089)	(2.089)	(2.084)
Δinr_q	-3.963	-9.298^{**}	-18.333^{***}
	(4.361)	(4.552)	(5.077)
Constant	0.0002	0.0001	0.0001
	(0.0002)	(0.0002)	(0.0002)
Observations	2,951	2,951	2,951
R^2	0.024	0.026	0.028
Adj. R^2	0.022	0.024	0.027
Res. Std. Error (df = 2944)	0.011	0.011	0.011
F Statistic (df = 6; 2944)	12.303^{***}	12.874^{***}	14.388^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01		

TABLE 3.12: Function of the gold for different currencies

Currency	Cross Hedge	Safe Haven 5% quantile	Safe Haven 2.5% quantile	Safe Haven 1% quantile
EUR	$\bigcirc$	$\times$	$\times$	$\times$
GBP	$\bigcirc$	$\times$	$\times$	$\times$
AUD	$\bigcirc$	$\bigcirc$	$\bigcirc$	$\bigcirc$
CAD	$\bigcirc$	$\bigcirc$	$\bigcirc$	$\bigcirc$
JPY	$\bigoplus$	$\bigoplus$	$\bigoplus$	$\bigoplus$
CNY	$\bigoplus$	$\bigcirc$	$\bigcirc$	$\bigcirc$
INR	$\bigoplus$	$\bigcirc$	$\bigoplus$	$\bigoplus$

$\times$: not suitable $\bigcirc$: suit $\bigoplus$: recommended

3.5 Conclusion

The improvement in the globalisation of the international financial market raises the impact of many currencies besides the U.S. Dollar. In addition to the inverse relationship with the U.S. Dollar, gold is gradually linked to other medium-sized currencies. The main research question of this chapter is to find out the (cross) hedging function between gold and several major currencies in normal as well as abnormal situations. We found that among the currencies being studied, all seven can be applied cross hedge with different hedging strengths. In which, Japanese Yen, Chinese Yuan, Indian Rupee can be a strong cross hedge with gold, especially India Rupee and Japanese Yen. A household can hold those currencies as a hedge during holding the gold or vice versa, using gold to cross hedge the value of those currencies in the normal time. For Euro and Great Britain Pound, gold can be used as a weak cross hedge to diversify the holding risk under both normal and abnormal times. In the aspect of a safe haven, gold does not play the role of it for Australian Dollar, Canadian Dollar, and Chinese Yuan but it is a strong safe haven for the Japanese Yen and Indian Rupee, especially in the very extreme cases when the exchange rate fluctuation reaches the tails of the quantile distribution.

This chapter contributes to the existing knowledge of hedging the exchange rate fluctuation by providing a quantitative numerical result of presenting the exact strength of the correlation between 7 currencies and gold, using the U.S. Dollar as a vehicle currency in order to compare all those 8 assets in the same unit. Moreover, the extreme fluctuations have been assumed to have asymmetric effects by combining both top and bottom quantile together and estimating only the average effect of the two. Further studies will be followed, in which we are going to discuss the positive quantile and the negative one separately.

Chapter 4

Gold hedging against Stock Market

4.1 Introduction

IN this chapter, the author investigates the interaction between gold and stock markets for the United States, Germany and China by examining two factors: gold as a hedge and safe-haven investment to protect against stock volatility, and the volatility transmission by VARMA-GARCH model. General hedge positions have been derived by applying DCC-GARCH. Different patterns and properties have been found in the three countries being studied. Significant differences due to COVID-19 were considered.[1]

4.1.1 Background

There is no profit without risk. This unpredictability is the most enticing feature of the stock market, and as a result, one experiences all the tragicomic associated with bull and bear, profit and loss, joy and regret. The research into hedging the stock market risk has never been stopped since its emergence. The technique of totally avoiding the stock market risk will be as hypothetical as a perpetual motion machine, which, is not the major aim of the relevant research any more. Nevertheless, for the fairly extreme negative stock market fluctuation, many assets can be used as a hedge (including cross hedge) or safe haven in order to reduce risk and minimize losses.

As we all know, the stock market is very sensitive to bad news. Investors have different attitudes toward good and bad news, they tend to be conservative when there is good news, but highly risk averse as soon as bad news occurs. On the other hand, bad stock news is good gold news. Gold is a precious metal which has dual attributes of consumption and investment. To the consumer, gold signals higher social status. To the investor, gold is an asset. The increased demand for gold has always been positively correlated with economic growth. Therefore, its demand is related to risk as well. In addition, the central banks of various countries also hold a certain proportion of gold due to many factors such as hedging the risk of the currencies and stabilising the fluctuation of foreign reserves. It stands to reason that investors also hold gold as an asset to hedge against risks from high inflation due to rapid economic growth or stock market fluctuation and uncertainty due to financial and/or geopolitical turmoil.

4.1.2 Literature review

The stock market is very sensitive to bad news. Most investors are seemingly near-sighted and risk averse, they wait on positive signals but generally panic on signs of disturbance

[1] The original title of this chapter as a research paper is: "What are We hedging against when we are hedging against the Stock Market with Gold ?". It has been written during the first Lockdown in Germany.

or trouble. Veronesi (1999)[41] showed that investors will overreact to bad news even in bull markets, but under-react vice versa (the so-called“uncertainty hedging willingness”). Solid results make it more meaningful to focus on the risk-hedging against stock market volatility in the negative direction. Hood and Malik (2013)[19] examined different hedging strength of many assets including gold, silver, platinum and VIX (Chicago Board Options Exchange’s CBOE Volatility Index) against extreme stock market decline from 1995 to 2010 in US. Their results indicate that VIX is a strong hedge and a strong safe haven at the same time during the sample period. Among precious metals, only gold delivered a hedge and weak safe haven attribute, but not silver or platinum. Basher and Sadorsky (2016)[3] studied the hedging ability of oil, VIX, gold and bond against emerging market stock prices in 23 countries using several GARCH-models and found out that oil serves as the best hedge. Empirical study with fairly robust evidence from India, Pakistan and the United States from 1990 - 2013 by Iqbal (2017)[20] suggests only a weak stock-market-hedging ability of gold. Baur and McDermott (2010)[5] tested the hedging attribute of gold for more than 20 years (1979 to 1999).They verified that gold can be a hedge as well as safe haven only for major European stock markets and US markets, but not for most of the large emerging markets nor for Australia, Canada and Japan. Baur and Lucey (2010)[4] examined the constant and dynamic relationship between gold return and returns of bonds and stocks in the U.S., U.K. and Germany. Their results show that gold is a hedge against stocks and average and a safe haven in extreme stock market conditions.

On the other hand, there is sparse literature that investigates the behaviour in the Chinese market. Arouri et al.(2015)[13] applied a bivariate Vector Autoregressive-Generalized Autoregressive Conditional Heteroscedastic (VARMA-GARCH) model from Ling and McAleer (2003)[26] to estimate the relationship between gold and stock market in China. In their work, various GARCH models were run in parallel. They found that VARMA-GARCH was the superior model for evaluating the volatility transmission between gold and stock market in China from 2004 till 2011. Their results suggested that gold has prediction power for the Chinese stock market and can be used as a hedge as well as a safe haven in China. Interestingly, these results actually contradicted to the formal result from Baur and McDermott (2010)[5].

4.1.3 Research question

The dynamic trend of the hedge/safe haven attribute of gold provides the inspiration of estimating the relationship between gold and stock markets using the latest data. The main research question of this chapter is to find out the hedging attribute of gold against extreme drops of the stock return and capture an insight of the volatility transmission pattern in three markets: United States, Germany and China.

During the estimation and generation of this chapter, the whole world was experiencing difficulties that haven’t been dealt with for a long time. Namely the Coronavirus disease 2019 (henceforth COVID-19), viciously attacked the whole world. At the beginning, there were only a few scattered cases in a Chinese province, but the virus spread rapidly. The corona-virus reached global pandemic status by the spring 2020. The number of infections and deaths is increasing in ferocity. It was really hard for policy makers to balance the trade-off between political, economical, social outcome. Indecisiveness pushed the fear and uncertainty of the financial market on the peak over and over. Facing continuously uncertainty from anti-epidemic measures (such as shuttling down public facilities, boarder closings, restricted travel, social distancing etc.), the financial markets overall have been through a major disruption, which is totally different from any financial crisis caused by financial mechanisms.

The data been collected for this research ranges from 02 January 2015 through 08 May 2020, which covers the period from when the virus was first reported in China, until signs of a recovery were evident in China. For the U.S. market, this period data recorded till the number of newly diagnosed in the United States surpassed 50,000 cases, which effectively marked the starting point of the panic. In Germany, the end of the data was almost the end of the forced quarantine measures in various detailed scales announced by different federal states.

In this chapter, the following questions will be investigated qualitatively as well as quantitatively. 1) Based on the latest data, can we use gold to hedge against stock market declines in US, Germany and China? If yes, under which conditions? 2) What about the conditional volatility covariance and correlation dependency between the three stock markets? 3) How should we build a proper hedging position based on our estimated results? 4) Does COVID-19 affect the model structure? If so, how?

4.1.4 Definitions

We continue to use the definitions from Chapter 3. Here they have been stated again for references:

Cross Hedge

A cross hedge can be managed when the return of two assets, are *positively correlated*. Individuals can just take opposing positions in both of the assets in order to reduce the holding risk. Even if the correlation does not equal one, a hedge position can be created.

Hedge

A hedge can be managed when the return of two assets are *negatively correlated*. The most ideal hedge would be that two assets are 100% inversely correlated with each other.

Safe Haven

An asset can play the role of a safe haven for another asset if the former has *no correlation at all or negative correlation* during abnormal situations such as extreme market fluctuation or strong currency valuation change due to geopolitical turmoil.

4.1.5 Organisation of this chapter

This chapter has been organized as follows. Section 4.1 provides the background, relevant literature, research targets and key definitions. Section 4.2 presents the data with basic introduction, descriptive statistics and graphic illustrations. Models being used in this research will be introduced in detail by section 4.3 and the estimated results from them will be presented in section 4.4. The application of the estimation will be derived in section 4.5. Section 4.6 presents a conclusion and appendix A provides the DCC-GARCH used for the application in section 4.5.

4.2 Data

4.2.1 Data introduction

Daily S&P 500, MSCI Germany and MSCI China indices will be used for the stock markets in United States, Germany and China respectively, all collected at daily frequency from Fusion Media.

The S&P 500 index is a market-capitalisation-weighted index of the 500 largest U.S. publicly traded companies and is widely regarded as the best gauge of large-cap U.S. equities. S&P was officially introduced on March 4, 1957 at a starting value of 386.36 by Standard & Poor. Later in 1966 it was acquired by McGraw-Hill. The current owner of the S&P is Dow Jones Indices which is a joint venture between S&P Global (formerly) McGraw Hill Financial, CME Group, and News Corp, the owner of Dow Jones. S&P 500 index represents the stock market's performance by reporting the risks and returns of the biggest companies in United States. Investors all over the world use it as the benchmark for the global markets, not just the US.

For Germany and China stock markets, we are going to apply MSCI (abbreviation for Morgan Stanley Capital International) index, which is a measurement of stock market performance. The reason why we choose MSCI Germany rather than DAX is because of it's wide range of stock selection as compared to the DAX which contains only 30 stocks and makes it a fairly small index compares to the other global indices. The volatility captured by DAX can be satisfactory during a boom session, but it would be too sensitive in a crisis period. Therefore, MSCI Germany is a better measure for the performance of large and mid cap segments of the German market. With 59 constituents, the index covers about 85% of the equity universe in Germany.[29]

Meanwhile, there is also solid proof that MSCI China captures the Chinese stock market behaviour better than CSI300.[30] The MSCI China A Index is an indicator for the Chinese stock market. This index captures large and mid cap representation across China A shares, H shares, B shares, Red chips, P chips and foreign listings. With 704 constituents, it covers about 85% of the China equity universe. Currently, MSCI China A Index includes Large Cap A and Mid Cap A shares represented at 20% of their free float adjusted market capitalization.[29]

Gold data has been collected from World Gold Council using LBMA (London Bullion Market Association) daily settle. The LBMA daily settlement prices have been used as an important benchmark throughout the gold market for a long time. Prices are quoted in several major as well as minor currencies in units per troy ounce. This benchmark price is fixed twice daily in London using an electronic auction system operated by IBA based on the spot market equilibrium reached by buyers and sellers. The auctions take place at 10:30 a.m. and 3:00 p.m. London time with the final auction result published as the LBMA Gold Price AM and the LBMA Gold Price PM respectively. Auction price is settled in US Dollars and then converted into other currencies including: Australian Dollars, British Pounds, Canadian Dollars, Euros, Onshore and Offshore Yuan, Indian Rupees, Japanese Yen, Malaysian Ringgit, Russian Rubles, Singapore Dollars, South African Rand, Swiss Francs, New Taiwan Dollars, Thai Baht and Turkish Lira. Although the benchmark prices in currencies other than US Dollar are not directly tradeable, the conversion includes the spot exchange rate and brings important information about the market in the country with

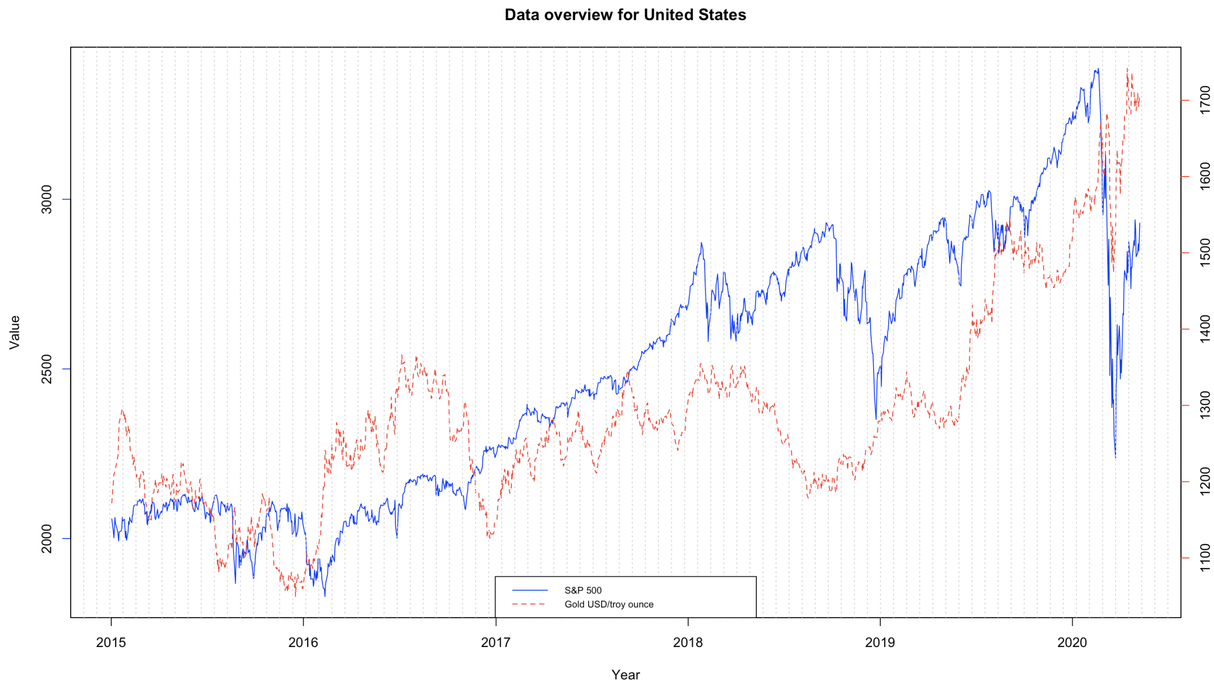


FIGURE 4.1: Daily data for United States, 02 Jan. 2015 - 08 May. 2020

the specific currencies. Since gold is a highly homogeneous product under strict trading regulations, the spot arbitrage opportunity using different exchange rate barely exists. The major gold markets worldwide (for example Shanghai Gold Exchange) also set their daily fixing based on the LBMA benchmark. For the estimation in this chapter, the daily gold price settled in US Dollars converted into Euro and Chinese Yuan (or the so-called: Renminbi) will be applied.

All sample data consists of daily log return time series from 02 January 2015 till 08 May 2020. In order to gain a better inter-country comparison, entries have been omitted when the market in any of the countries was not opening due to different national holidays after the stationary test and calculation for daily log return.

Figures 4.1, 4.3 and 4.5 illustrate the daily level movements for the three markets respectively, in which the left axis shows the value for stock market indices and the right axis for gold price per troy ounce in local currencies. The followings observations were made a) the gold price movements are similar in the three markets, for gold is such a highly homogenous commodity that the same attribute and standard quality can be found in every unit. b) the stock markets have totally different movements. During the research period, S&P 500 has a consistent rise with generally minor dips until COVID-19 caused great uncertainty in 2020. MSCI Germany and China did not show a clear tendency but rather moved up and down. c) From S&P 500 and MSCI Germany, a sharp downturn during the explosion of COVID-19 can be observed, whereas such a shock can not be clearly observed in the Chinese market. These differences can be attributed to the time sequence of the COVID-19 attacking these markets on the one hand. On the other hand, these differences may indicate the qualitative differences in the three markets.

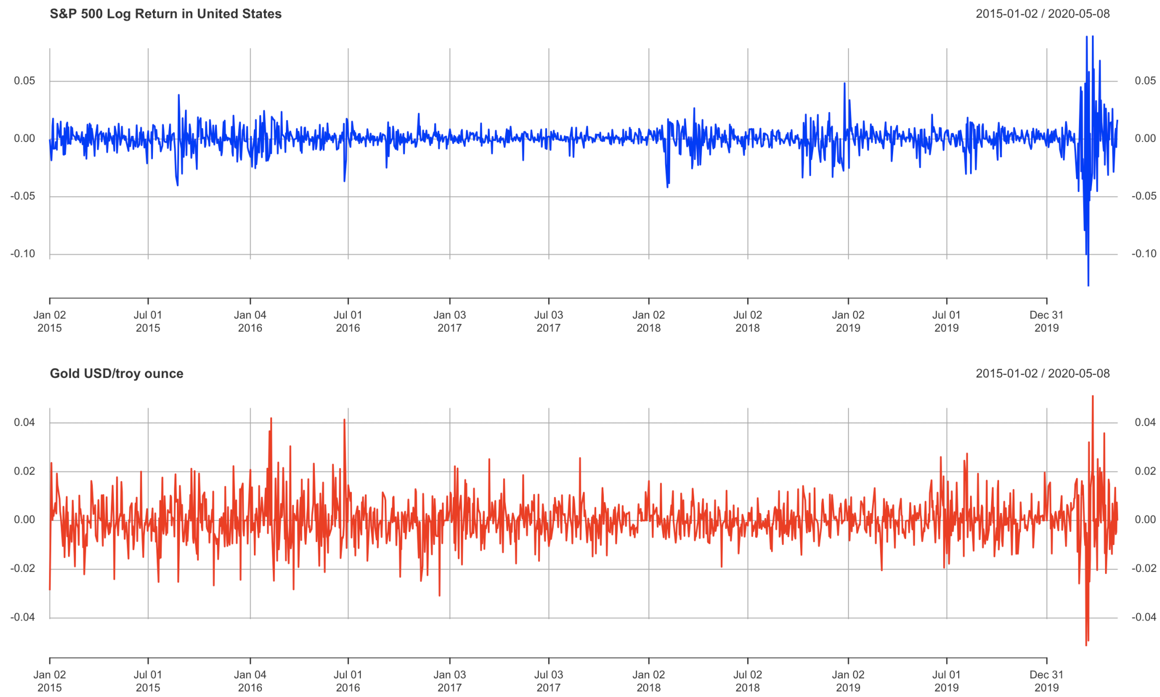


FIGURE 4.2: Daily log return for United States, 02 Jan. 2015 - 08 May. 2020

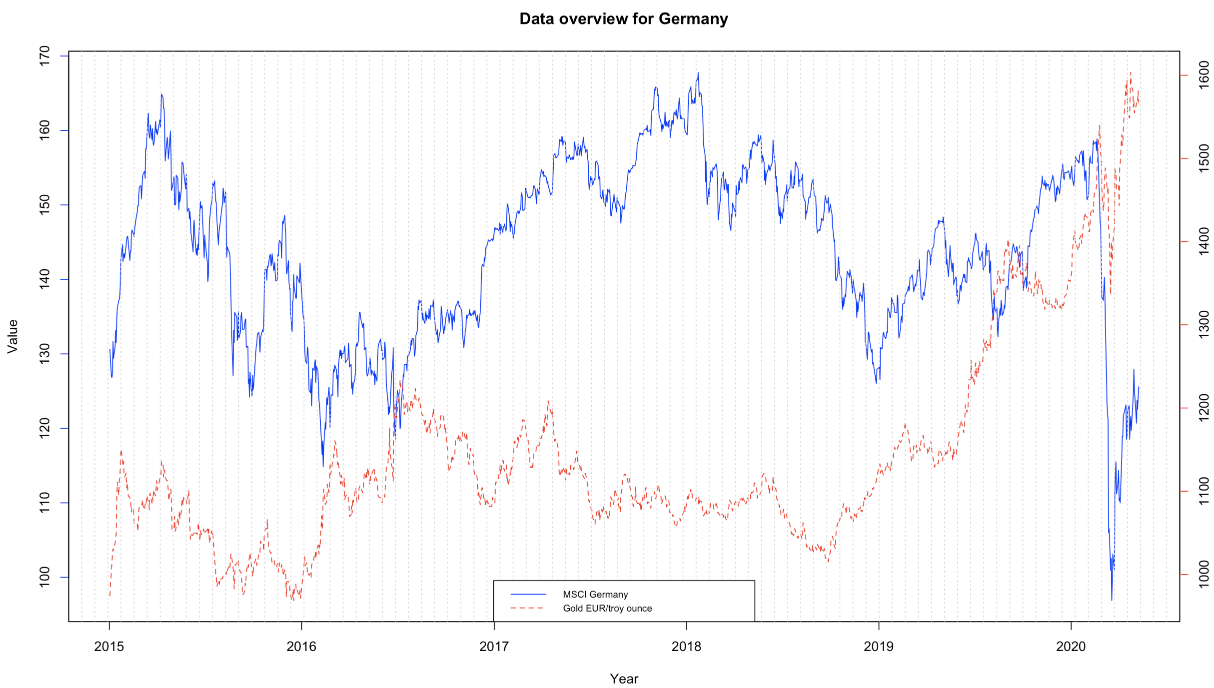


FIGURE 4.3: Daily data for Germany, 02 Jan. 2015 - 08 May. 2020

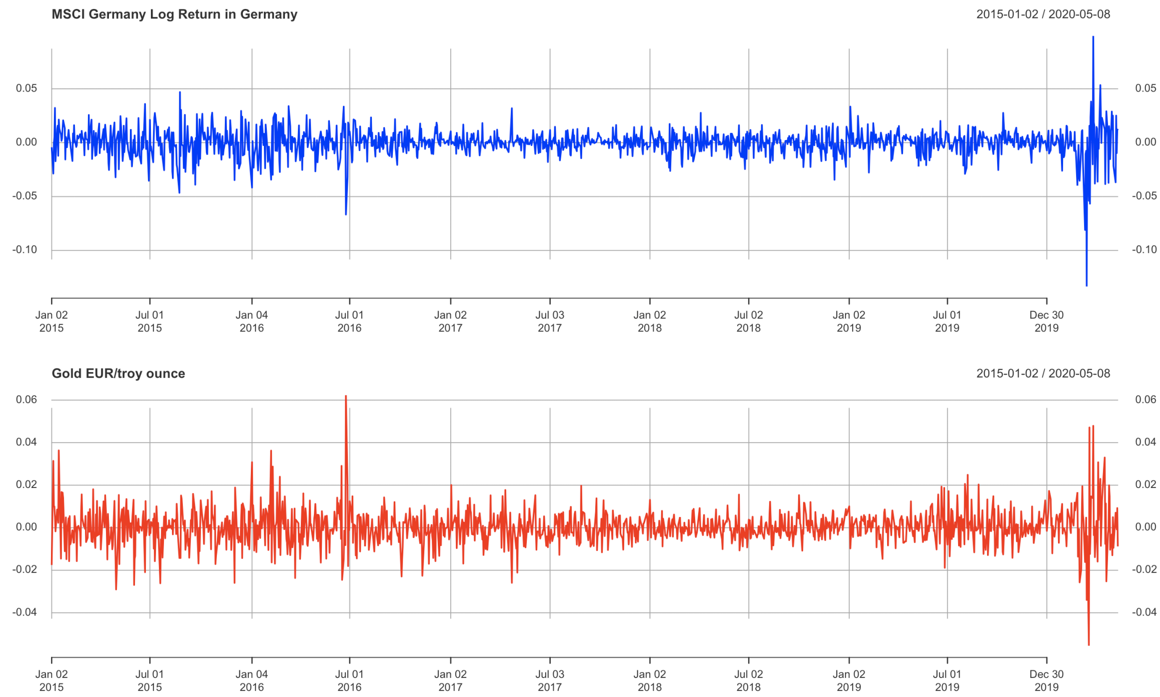


FIGURE 4.4: Daily log return for Germany, 02 Jan. 2015 - 08 May. 2020

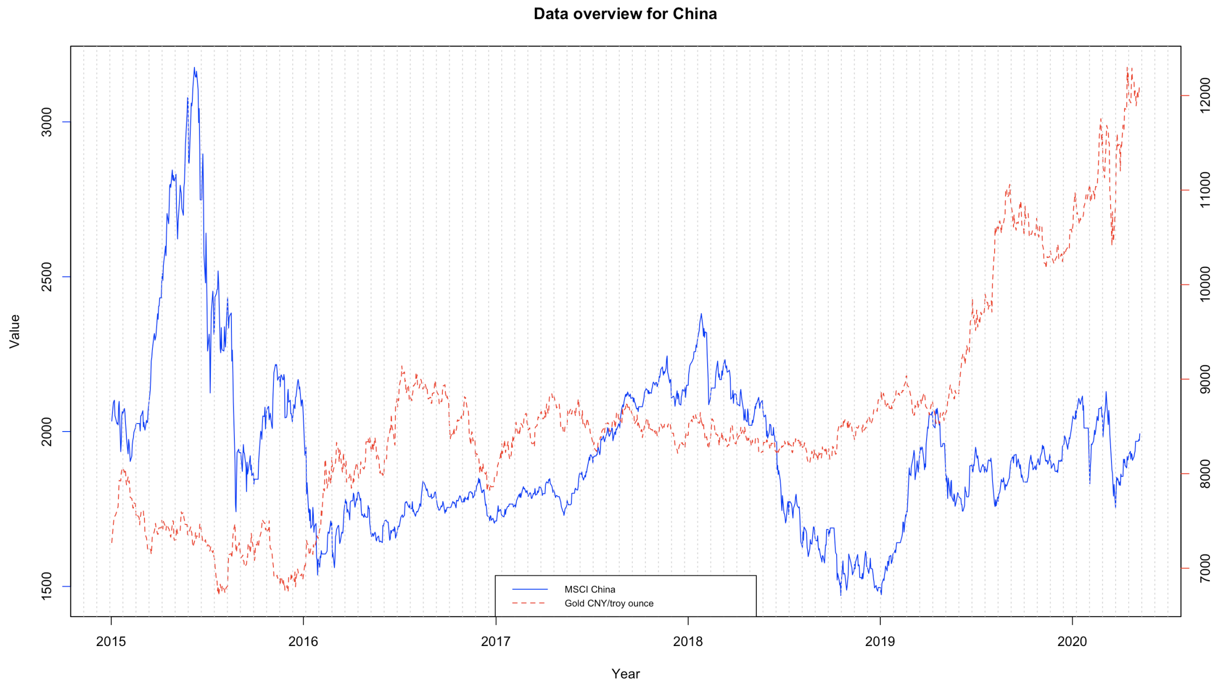


FIGURE 4.5: Daily data for China, 02 Jan. 2015 - 08 May. 2020

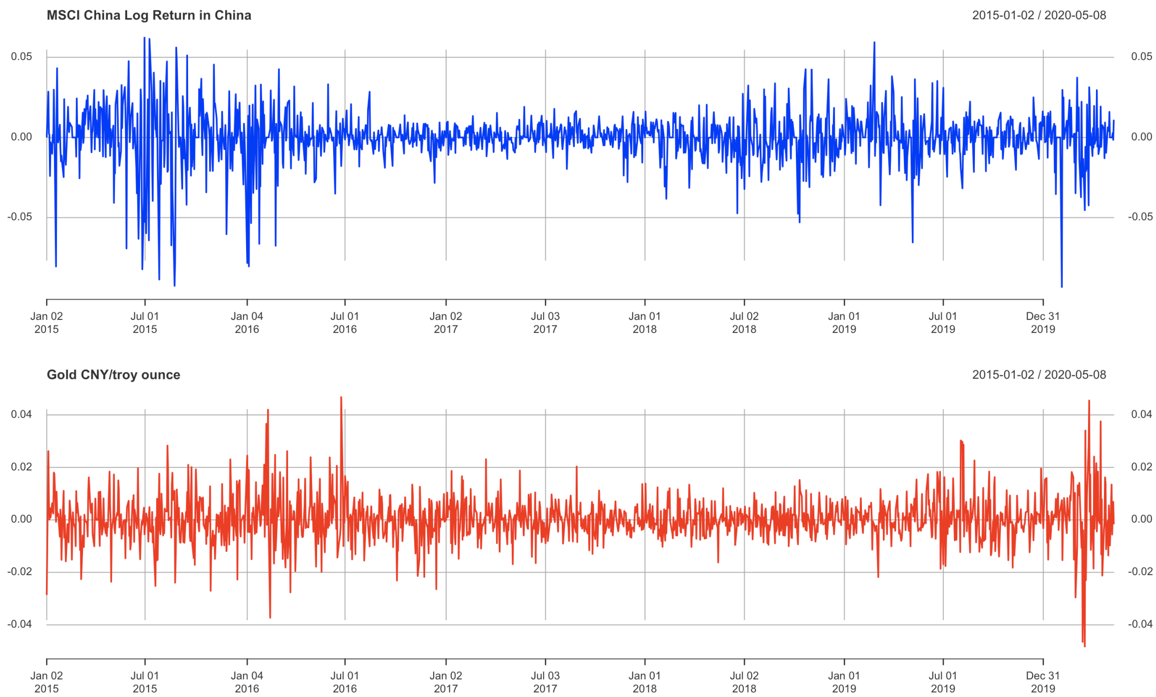


FIGURE 4.6: Daily log return for China, 02 Jan. 2015 - 08 May. 2020

Furthermore, figures 4.2, 4.4 and 4.6 depict the once differenced log return for the corresponding series. By comparing the three volatility plots sets, one can capture the general ideas of the volatility patterns for the three markets. Apart from the COVID-19 period, US and German markets' fluctuations are quite stable and minor for both gold and stock, whereas the Chinese market is much more volatile and clustered during the specific periods, especially mid-2015 and from late-2018 to mid-2019.[2] Combining with the level graph of 4.5, these fluctuations might be explained by the Chinese stock market turbulence happened in June 2015. Directly after the price popping of the stock market bubble on 12. June 2015, the stock market indexes traded in both Shanghai and Shenzhen stock markets experienced a strong sharp drop in the very short term. Only at the beginning of 2016, the Chinese stock market started a modest recovery. In 2018 again, the Chinese stock market suffered a Waterloo-year. While the capital market became more open and the stage of A-share were expanding in that year, an unexplainable extreme reaction caused a turbulence in the index, it dropped from a high point at the beginning of the year all the way to the bottom. Many listed companies have even encountered an equity pledge crisis due to this sharp drop in the stock prices. In November 2018, new regulations were established by the China Securities Regulatory Commission, which created a significant effect and pushed the Chinese stock market into a healthier, more transparent trading environment.

Starting from 2020, all three markets have experienced an unprecedented shock: COVID-19, this can be clearly observed from the plots for U.S. and Germany. This shock is the reason why in this chapter we are going to estimate the data under two periods, namely with COVID-19 (02 Jan 2015 - 08 May 2020) and without COVID-19 (02 Jan 2015 - 31 Dec 2019). Major estimation differences will be presented in later parts of the research. The

[2]There was a volatility shooing for the gold price in Germany around June 2016, very likely due to the Brexit that time.

reason why we didn't just simply make two subsample comparisons is that, the observations for COVID-19 are much too less for our models with many parameters and much too less for leading the GARCH model to convergence (there are only 89 for United States and Germany, and 92 for China during the pandemic period.). Later in section 4.4, we will see how much these small (but extreme) samples can affect the estimation result.

4.2.2 Descriptive statistics

TABLE 4.1: Descriptive statistics for levels

Assets	including COVID-19				excluding COVID-19			
	mean	s.d.	min	max	mean	s.d.	min	max
S&P 500	2487.08	378.03	1829.08	3386.15	2452.64	357.45	1829.08	3240.02
Gold (USD)	1288.70	130.25	1049.40	1741.90	1265.65	99.11	1049.40	1546.10
MSCI DE	143.94	11.78	96.88	167.81	144.55	10.75	114.83	167.81
Gold (EUR)	1143.98	122.67	968.62	1603.48	1121.04	88.38	968.62	1402.83
MSCI CN	1935.30	276.63	1470.66	3176.13	1932.65	285.05	1470.66	3176.13
Gold (CNY)	8609.86	1120.87	6711.23	12298.68	8418.72	878.90	6711.23	11060.49

Note: The descriptive statistics including (excluding) COVID-19 have been generated by 1347(1258), 1351(1262) and 1394(1302) observations for U.S., Germany and China respectively.

Table 4.1 describes the general statistics for the data in level, which corresponds to the figures 4.1, 4.3 and 4.5. In the left half, the full data range from 02 Jan 2015 to 08 May 2020 has been used whereas in the right half, we exclude the COVID-19 and thus only generate the statistics from 02 Jan 2015 to 31 Dec 2019. Comparing the three stock market indices, we can observe some different behaviours. For example, MSCI Germany had it's lowest value (96.88 vs. 114.83) during the epidemic, S&P 500 reached it's highest value (3386.15 vs. 3240.02) during the same period, even the mean has been pushed upwards because of the higher numerical values. At the same time, the Chinese stock market didn't appear to be affected much by the virus. Now we shift our focus to the gold markets. The price of gold has generally increased during the epidemic, which is also in line with the characteristics of gold as a safe-haven asset. At the beginning of the epidemic, when all the market participants were very unclear about the overall COVID-19 development trend, especially this virus cut off the circulation and contact between people, which greatly affected the service industry, tourism and manufacturing industries. Measurements and policies were updating everyday. The intra-sector dependency is as precarious as walking on thin ice. The demand for value preservation in special periods far exceeds the investment in productivity. Gold, as a kind of value-preserving asset, fits this scenario pretty well. No matter which country it is in, the standard deviation of gold during the same period is smaller than that of the stock market indices. This observation compares well with many other relevant data from various time periods and/or markets, due to the monetary attribute of the gold and rigidity against exchange rate intervention.[3]

[3] See Hammoudeh, Yuan, McAleer and Thompson (2010).

TABLE 4.2: Descriptive statistics for returns

Period	Country	US		DE		CN	
	Asset	S&P 500	Gold	MSCI	Gold	MSCI	Gold
Exc. COVID 19	Mean	0.000358	0.000181	0.000124	0.000246	−0.000004	0.000264
	S.d.	0.008476	0.008041	0.010823	0.007537	0.015774	0.007905
	Skew.	−0.524194	0.311375	−0.366957	0.601789	−1.041347	0.421144
	Kurt.	3.831001	2.450386	2.433951	5.473197	6.406866	3.297181
	Min.	−0.041843	−0.030843	−0.066681	−0.029035	−0.092578	−0.037276
	Max.	0.048403	0.041964	0.046967	0.062317	0.062689	0.047009
	ADF	−11.562	−10.911	−11.406	−10.879	−11.415	−10.704
	Lag (BIC)	1	1	1	1	1	1
Inc. COVID 19	Mean	0.000262	0.000257	−0.000032	0.000339	−0.000015	0.000343
	S.d.	0.011772	0.008662	0.012656	0.008185	0.015950	0.008502
	Skew.	−1.025044	0.167100	−1.057170	0.477037	−1.105379	0.265189
	Kurt.	23.149720	4.172311	14.295490	6.864588	6.481998	4.338399
	Min.	−0.127652	−0.051524	−0.133425	−0.055504	−0.093730	−0.048505
	Max.	0.089683	0.051334	0.099027	0.062317	0.062689	0.047009
	ADF	−10.152	−11.551	−10.751	−11.345	−11.78	−11.374
	Lag (BIC)	9	1	1	1	1	2

Note: The descriptive statistics including (excluding) COVID-19 have been generated by 1347(1258), 1351(1262) and 1394(1302) observations for U.S., Germany and China respectively. The null hypothesis of augmented Dickey–Fuller test have all been rejected with statistic significant p-value (0.01).

Table 4.2 is split into two parts, the sub sample from 02. Jan 2015 to 31. Dec 2019. as "excluding COVID-19" in the upper part of the table and the full sample from 02. Jan 2015 to 08. May 2020 as "including COVID-19" in the lower part. Differences between excluding and including COVID-19 can be verified through many aspects. a) The stock market mean return is lower for all three markets if the epidemic period is included (for the German market, it was even a sign change from positive to negative). On the other hand, all gold returns in three markets or rather three currencies have a higher mean including the epidemic. That confirms the theory, that gold as a safe-haven asset gains its value during bad news and turbulent times. b) Despite the different sample sizes, the standard deviations are all higher when COVID-19 period has been included. c) All three stock markets tend to have a negative skewness while gold markets have positive skewness all the time. d) The kurtosis, especially for the stock markets, has extreme fat tails when epidemic has been taken into statistical estimation (23.15 for S&P 500 and 14.30 for MSCI Germany). Combined with return figures 4.1, 4.3 and 4.5, we observe abnormal market dynamics because of the virus explosion, which strengths the analysis needs of dismantling the period and conditionally estimating them.

4.3 Method

In this section, two models will be introduced in order to examine the attributes of gold and the volatility transmission between gold and stock market.

4.3.1 Extreme quantile regression model

The benchmark model proposed by Baur and McDermott (2010)[5] will be first applied to check the hedge and safe haven attribute of gold. The model can be expressed as follows:

$$r_{gold,t} = \mu + \pi_t r_{stock,t} + e_t \tag{4.1}$$
$$\pi_t = c_0 + c_1 D(r_{stock} q_{10\%}) + c_2 D(r_{stock} q_{5\%}) + c_3 D(r_{stock} q_{1\%}) \tag{4.2}$$
$$e_t = \phi_0 + \phi_1 e^2_{t-1} + \phi h_{t-1} \tag{4.3}$$

Equation (4.1) is the multi-variable linear model which captures the linear relationship between stock market and gold with estimation parameter μ as constant and π_t as equation (4.2). Lag length would be selected based on information criteria should they exist.[4] Since the series being studied are financial data, the error term e_t follows a GARCH process which can be described by equation (4.3). However in this model, we will put our research emphasis on equation 2. Dummy variables $D(...)$ in equation (4.2) equal to 1 when stock market return falls into the corresponding extreme negative quantiles (10%, 5% or 1%). Thus, estimation parameter c_0 indicates the normal (cross) hedge strength, c_1, c_2 and c_3 capture the adding-up safe-haven effects. The average 10% quantile safe haven effect can be presented by $c_0 + c_1$, 5% by $c_0 + c_1 + c_2$ and 1% by $c_0 + c_1 + c_2 + c_3$. Applying this model, one can investigate the hedging attribute of gold against stock.

With the help of equation (4.2), the non-linear relationships between gold and stock market extreme negative returns can be captured, which can be used for investors as an investment weather vane for gold hedging against stock index return in general or when stock return falls into different quantiles of the extreme negative return.[5]

4.3.2 VARMA-GARCH model

Furthermore, we also want to investigate the interdependence of conditional variance and correlation between the gold and stock returns, and compare these patterns among the three markets as well as between “including” and “excluding” the pandemic. The VARMA-GARCH model first developed by Ling and McAleer (2003) is an ideal model for this research purpose. Hammoudeh, Yuan, McAleer and Thompson (2010)[18] stated that the VARMA-GARCH model outperforms the BEKK for the statistic significance. Compared to the famous DCC-GARCH model developed by Engle (2002)[14], the two major differences are, a) in VARMA-GARCH, there are cross terms not only in the linear part, but also in the ARCH and GARCH parts, with which we can estimate the volatility transmission mechanism between multiple assets. b) DCC-GARCH model (as it can be defined by its name), estimates the *dynamic* conditional correlation between the series, while in VARMA-GARCH model, only the *constant* conditional correlation can be estimated. This is a shortcoming of this model which, to the best of my knowledge, can not be solved due to technical reasons till the finishing of this thesis. The assumption of a constant correlation will not be sufficient for generating the optimal hedge and portfolio position. That is the reason the DCC-GARCH model is going to be applied to capture a dynamic insights for the investment application. The detailed model presentation can be found in appendix A.1.

[4]Lag length of 1 has been selected for all assets by BIC.
[5]This statement follows Baur and McDermott (2010).

The VARMA-GARCH model by Ling and McAleer (2003)[26] can be presented as following for a two-asset case:

$$R_{i,t} = a_i + b_i R_{i,t-1} + \varepsilon_{i,t} + d_i \varepsilon_{i,t-1} \tag{4.4}$$

$$\begin{bmatrix} r_{s,t} \\ r_{g,t} \end{bmatrix} = \begin{bmatrix} a_s \\ a_g \end{bmatrix} + \begin{bmatrix} b_{s1} & b_{s2} \\ b_{g1} & b_{g2} \end{bmatrix} \begin{bmatrix} r_{s,t-1} \\ r_{g,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{s,t} \\ \varepsilon_{g,t} \end{bmatrix} + \begin{bmatrix} d_{s1} & d_{s2} \\ d_{g1} & d_{g2} \end{bmatrix} \begin{bmatrix} \varepsilon_{s,t-1} \\ \varepsilon_{g,t-1} \end{bmatrix}$$

$$r_{s,t} = a_s + b_{s1} r_{s,t-1} + b_{s2} r_{g,t-1} + \varepsilon_{s,t} + d_{s1}\varepsilon_{s,t-1} + d_{s2}\varepsilon_{g,t-1}$$
$$r_{g,t} = a_g + b_{g1} r_{s,t-1} + b_{g2} r_{g,t-1} + \varepsilon_{g,t} + d_{g1}\varepsilon_{s,t-1} + d_{g2}\varepsilon_{g,t-1}$$

The $R_{i,t}$ denotes the 1×2 matrix of two assets, namely the return of stock $r_{s,t}$ and the return of gold $r_{g,t}$. With such a VARMA(2,1,1) mean model as equation (4.4), we assume that the return of an asset $r_{i,t}$ depends on an intercept $a_{i,t}$, own return history $b_{i1} r_{i,t-1}$, cross return history $b_{i2} r_{-i,t-1}$, concurrent shock $\varepsilon_{i,t}$, past own and cross shocks $d_{i1}\varepsilon_{i,t-1} + d_{i2}\varepsilon_{-i,t-1}$.

$$\varepsilon_{i,t} = h_{i,t}^{1/2} \eta_{i,t} \tag{4.5}$$

$$h_{i,t} = c_i + \sum_{j=1}^{2} \alpha_{ij} \varepsilon_{j,t-1}^2 + \sum_{j=1}^{2} \beta_{ij} h_{j,t-1} \tag{4.6}$$

$$h_{s,t} = c_s + \alpha_{s1}\varepsilon_{s,t-1}^2 + \alpha_{s2}\varepsilon_{g,t-1}^2 + \beta_{s1} h_{s,t-1} + \beta_{s2} h_{g,t-1}$$
$$h_{g,t} = c_g + \alpha_{g1}\varepsilon_{s,t-1}^2 + \alpha_{g2}\varepsilon_{g,t-1}^2 + \beta_{g1} h_{s,t-1} + \beta_{g2} h_{g,t-1}$$

Further we assume that the shock $\varepsilon_{i,t}$ consists of random *i.i.d.* innovation $\eta_{i,t}$ and conditional variance $h_{i,t}$ as shown in equation (4.5). The conditional variance $h_{i,t}$ can be decomposed as an intercept c_i, the short-run persistence of the past shock $\sum_{j=1}^{2} \alpha_{ij}\varepsilon_{j,t-1}^2$ (the so-called "ARCH effect") and the long-run persistence of the past volatilities $\sum_{j=1}^{2} \beta_{ij} h_{j,t-1}$. Such an MGARCH(2,1,1) model is different from the DCC-GARCH model due to the extra cross terms $\alpha_{i2}\varepsilon_{-i,t-1}^2$ and $\beta_{i2} h_{-i,t-1}$, which can not be modelled in a DCC-GARCH model to capture the volatility transmission between the assets.

4.4 Estimation results

4.4.1 Safe haven regression estimation result

Table 4.3 presents the estimation results for the Baur-McDermott (2010) extreme quantile regression model introduced in subsection 4.3.1 with respect to two data periods: excluding the COVID-19 and including it. Totally different statistical results and the hedge/safe haven attributes can be derived from this table. In order to gain an intuitive analysis of the result, an attribute summary has been generated in table 4.4. The hedge coefficient will be taken from the parameter c_0 directly if it is statistically significant. A 10% safe haven is then the $c_0 + c_1$, for 5% we add up $c_0 + c_1 + c_2$, analogously, 1% safe haven coefficient is

TABLE 4.3: Baur and McDermott (2010) extreme quantile regression model estimation

	Excluding COVID-19:			*Including COVID-19:*		
	US	DE	CN	US	DE	CN
c_0	-0.054	-0.022	-0.009	0.085***	0.043*	-0.005
	(0.038)	(0.026)	(0.021)	(0.029)	(0.025)	(0.022)
c_1	-0.082	-0.045	-0.175***	-0.233***	-0.082	-0.133**
	(0.091)	(0.065)	(0.056)	(0.089)	(0.069)	(0.059)
c_2	-0.027	-0.125*	0.123**	-0.003	-0.112	0.128**
	(0.094)	(0.070)	(0.058)	(0.094)	(0.074)	(0.060)
c_3	-0.107	-0.278***	0.014	0.370***	0.263***	-0.039
	(0.114)	(0.085)	(0.042)	(0.062)	(0.056)	(0.043)
μ	0.00004	-0.00003	-0.00001	-0.0001	0.0001	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)
Obs.	1,258	1,262	1,302	1,347	1,351	1,394
R^2	0.017	0.048	0.015	0.040	0.018	0.007
Adj. R^2	0.014	0.045	0.012	0.037	0.015	0.004
Res. SE	0.008	0.007	0.008	0.009	0.008	0.008
	(df = 1253)	(df = 1257)	(df = 1297)	(df = 1342)	(df = 1346)	(df = 1389)
F Stat.	5.462***	15.787***	4.855***	13.820***	6.195***	2.342*
	(df = 1253)	(df = 1257)	(df = 1297)	(df = 4; 1342)	(df = 4; 1346)	(df = 4; 1389)

Note: *p<0.1; **p<0.05; ***p<0.01

TABLE 4.4: Summary of hedge and safe haven attributes of gold for stock

Country	US		DE		CN	
Condition w.r.t. COVID-19	Excluding	Including	Excluding	Including	Excluding	Including
Hedge	-	0.085***	-	0.043*	-	-
	inapplicable	cross hedge	inapplicable	cross hedge	inapplicable	inapplicable
10%	-	-0.148***	-	0.043*	-0.175***	-0.133**
	safe haven	safe haven	safe haven	inapplicable	safe haven	safe haven
5%	-	-0.148***	- 0.125*	0.043*	-0.052**	-0.005**
	safe haven	safe haven	safe haven	inapplicable	safe haven	safe haven
1%	-	0.222***	-0.403***	0.306*	-0.052**	-0.005**
	safe haven	inapplicable	safe haven	inapplicable	safe haven	safe haven

Note: *p<0.1; **p<0.05; ***p<0.01

the summation result of $c_0 + c_1 + c_2 + c_3$.[6] Furthermore we use "-" sign to indicate a statistically insignificant result. Recall the definitions of these attributes, two assets are *hedge* of each other if they have *significant negative correlation* between their returns; if they have *significant positive correlation* between their returns, we define them as *cross hedge*. When the return of one assets has *no significant correlation at all* or *significant negative correlation* during *extreme or abnormal* situation with another, we define the former one as a safe haven for the later.

As can be seen from table 4.4, when excluding the COVID-19 pandemic period, gold can not be used as a hedge against stock index return for the U.S. because the correlation between them is not statistically significant at all. But due to this insignificance, gold can be used as a safe haven for all extreme quantiles return of the stocks. Results are significant if we include the abnormal period due to Corona-virus started from 2020. A much higher adjusted R^2 (0.037 instead of 0.014) indicates a better fit of the model when the COVID-19 observations are included. A significant positive correlation of 0.085 makes gold now a cross hedge against the stock market. The correlation changes its sign significantly when the stock return falls into extreme 10% and 5% quantiles. During which, investors can use gold as a safe haven to avoid the secondary extreme fluctuations of the stock. Nevertheless, when the stock situation turns into the 1% extreme return, gold has a highly significant positive correlation with the stock, by which the safe haven attribute is no longer applicable since the returns of both tend to move in the same direction in average. This change is important for the investors as they might need to re-balance their portfolio holding strategies in response to the different extreme situations.

Situations are much easier in the other two countries. Hedge attributes are also inapplicable in both Germany and China if the pandemic period has been excluded for a statistically insignificant coefficient. When an extreme situation leads to a 10% negative index return of the stock market, gold can be used as a preferable safe haven for having no correlation with return in Germany and a highly significant negative one in China. The safe haven attribute becomes stronger in Germany when the negative index return of the stock markets approaches the extreme. In 1% negative quantile, gold is an optimal safe haven asset for stock with a negative coefficient of -0.403, which is also highly significant in the statistical sense. These estimation results imply a simple investment strategy for holding gold as a safe haven against the stock market abnormal situation before COVID-19 in Germany and China.

However, after the explosion of COVID-19, the attribute of gold divergent in the two countries. The goodness of fit is worse for "including" cases in Germany and China, which indicates that these "including" data are beyond the explanation power of the "excluding" model. With a positive coefficient of 0.043, gold becomes a cross hedge of stock index return, and the safe haven attribute becomes inapplicable due to a continuing weakly significant positive correlation for 10% and 5% extreme negative quantile. The positive correlation between gold and stock becomes even larger and still significant when the stock market approaches the 1% extreme return. Gold can no longer be a safe haven in Germany when Corona-virus changed the situation. The Chinese market, on the other hand, always

[6] A parameter would only be added up if it is with at least * statistic significance. If the adding parameter for a further threshold is not significant, we will continue to use the previous result for the last threshold, e.g. $c_0 + c_1 + c_2 + c_3 = c_0 + c_1 + c_2$ for an insignificant c_3 for 1% safe haven attribute.

has a gold-safe-haven-suitable environment for stock market. The COVID-19 didn't fundamentally change the safe-haven attribute of the gold, only the coefficients are smaller in numerical value when the pandemic period has been included.

The estimation results suggest very different investment strategies for gold hedging stock in these three markets. Another remarkable observation is the difference between "excluding" and "including" COVID-19. The overall sample size is over ten times more than the pandemic samples, and only about 90 observations have been excluded from "including" data for the "excluding" data, however, these minorities have greatly changed the estimation results. In order to have a closer examination of this phenomenon, we are going to investigate the volatility transmission mechanism between gold and stocks for these three markets as well as for the both "excluding" and "including" data samples.

4.4.2 VARMA-GARCH estimation result

Tables 4.5 and 4.6 are the estimation results for the mean and variance parts of the VARMA-GARCH, respectively. The left three columns for both tables are results for the "excluding" and the right three columns for the "including" cases. Different levels of statistical significance have been noted by asterisk signs "*". On the last line of both stock and gold blocks for variance model in table 4.6, the degree of persistence has been computed by $\alpha + \beta$. The closer this value is to 1, the faster the convergence of the corresponding asset to the long-run equilibrium after shock. So this speed of convergence can be used by investors to compare the time they have to wait for a new equilibrium after a shock. In both "excluding" and "including" cases, for both gold and stock, the Chinese market always has the fastest convergence speed. We also see that in United States, the gold series converges much faster than stock one.

The estimation parameters for $\varepsilon^2_{i,t-1}$ are the so-called "ARCH effect", i.e. the parameter α from equation 4.5. An ARCH effect presents if the time series exhibits autocorrelation in the squared series, which implies the conditional heteroscedasticity. The ARCH effect indicates the degree of the short-run persistence or so to say, the news sensitivity to the i_{th} asset. In general, all three stock assets are much more sensitive than the gold assets from the same country during the same data range. This supports the safe-haven attribute of gold for being much more stable than the stock. The risk-tolerant investors who are good at anticipating stock market reactions, and want to profit through the volatility, should choose stock market investment. Those investors who are rather risk averse should prefer the gold market.

The parameters for $\varepsilon^2_{g,t-1}$ in the stock block and for $\varepsilon^2_{s,t-1}$ in the gold block suggest the short-run cross effect of that i_{th} asset on the asset of that block. All 6 parameters for the cross effect from gold on stock are not statistically significant, which means that stock is not sensitive to the news in the gold market. On the other hand, two significant parameters can be found for the cross effect from stock on gold in United States and Germany when COVID-19 is included. So under special conditions, gold markets are also sensitive to the stock-markets news in these two countries.

All estimated parameter for $h_{i,t-1}$ of i_{th} asset are highly statistically significant, but the cross term ($h_{-i,t-1}$ of i_{th} asset) are only significant for stock on gold in United States and Germany including COVID-19. These parameter are the long-run volatility dependence of an asset's time series, it shows how persistent a past volatility in the long run will be. All the gold series have rather high sensitivity to their own past volatility (all parameter value larger than 0.9). The Chinese stock market has the strongest self long-run persistence, the German stock market is the second.

If we compare the α and β values for gold and stock, stock markets have in general a much higher α and a lower β than gold. This means, under the same condition, stock markets are much more influenced by business cycles, whereas gold is more stable and depends more on the long-run economic factors.

In order to have an intuitive insight of the variables we have plugged the statistically significant parameters back into the VARMA-GARCH model equations from subsection 4.3.2. So in subsections 4.4.2, 4.4.2 and 4.4.2, the detailed transmission mechanism for the three countries being studied will be analysed with their corresponding equations.

TABLE 4.5: VARMA-GARCH estimation: mean model

	Excluding COVID-19			*Including COVID-19*		
	US	DE	CN	US	DE	CN
Stock						
Constant	0.000*	0.000	0.001	0.031	0.001**	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$r_{s,t-1}$	0.570**	1.233***	-0.873***	0.619**	-0.984	-0.261
	(0.223)	(0.419)	(0.099)	(0.270)	(0.536)	(0.294)
$r_{g,t-1}$	0.374	1.858***	-0.121	0.326	0.203***	-0.728**
	(0.358)	(0.548)	(0.168)	(0.518)	(0.039)	(0.333)
$\varepsilon_{s,t-1}$	-0.634***	-1.217***	0.897***	-0.676***	0.989*	0.272
	(0.215)	(0.416)	(0.092)	(0.253)	(0.533)	(0.297)
$\varepsilon_{g,t-1}$	-0.336	-1.824***	0.103	-0.284	-0.201***	0.725**
	(0.358)	(0.544)	(0.174)	(0.514)	(0.039)	(0.340)
Gold						
Constant	0.000	0.001	0.000	0.011	0.002*	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
$r_{s,t-1}$	0.078	-0.878*	0.534	0.049	−3.089	0.498***
	(0.367)	(0.453)	(0.423)	(0.476)	(2.021)	(0.039)
$r_{g,t-1}$	−0.412***	−0.975**	−0.497***	−0.383**	−0.257	−0.639***
	(0.154)	(0.394)	(0.124)	(0.162)	(0.535)	(0.193)
$\varepsilon_{s,t-1}$	−0.071	0.888**	−0.516***	−0.057	3.092	−0.484***
	(0.376)	(0.449)	(0.423)	(0.485)	(2.021)	(0.041)
$\varepsilon_{g,t-1}$	0.439***	0.955**	0.494***	0.404**	0.271	0.614***
	(0.153)	(0.391)	(0.130)	(0.162)	(0.534)	(0.194)
Observations	1,257	1,261	1,301	1,346	1,350	1,393
Log Likelihood	−2818.9827	−3108.3872	−3579.7354	−15556.3129	−3455.4420	−3951.6941

Note: *p<0.1; **p<0.05; ***p<0.01

TABLE 4.6: VARMA-GARCH estimation: variance model

	Excluding COVID-19			*Including COVID-19*		
	US	DE	CN	US	DE	CN
Stock						
Constant	0.000***	0.000**	0.000***	0.049***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\varepsilon^2_{s,t-1}$	0.209***	0.087***	0.032***	0.246***	0.116***	0.044***
	(0.029)	(0.022)	(0.007)	(0.033)	(0.021)	(0.009)
$\varepsilon^2_{g,t-1}$	−0.001	0.000	−0.013	−0.002	0.017	−0.014
	(0.013)	(0.020)	(0.011)	(0.013)	(0.024)	(0.010)
$h_{s,t-1}$	0.743***	0.891***	0.967***	0.721***	0.866***	0.957***
	(0.028)	(0.029)	(0.007)	(0.027)	(0.025)	(0.008)
$h_{g,t-1}$	−0.006	−0.005	−0.012	−0.010	−0.030	−0.019*
	(0.017)	(0.031)	(0.013)	(0.019)	(0.037)	(0.011)
$\alpha + \beta$	0.952	0.978	0.999	0.967	0.982	1.00
Gold						
Constant	0.000	0.000	0.000	0.008***	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\varepsilon^2_{s,t-1}$	0.005	0.006	0.001	0.025***	0.016***	0.001
	(0.006)	(0.005)	(0.001)	(0.006)	(0.005)	(0.001)
$\varepsilon^2_{g,t-1}$	0.025***	0.054***	0.016**	0.024***	0.066***	0.040***
	(0.008)	(0.017)	(0.007)	(0.007)	(0.017)	(0.009)
$h_{s,t-1}$	−0.007	−0.005	0.001	−0.026***	−0.014**	0.000
	(0.007)	(0.006)	(0.001)	(0.007)	(0.007)	(0.002)
$h_{g,t-1}$	0.969***	0.932***	0.979***	0.967***	0.911***	0.954***
	(0.010)	(0.023)	(0.008)	(0.010)	(0.024)	(0.012)
Constant	−0.091***	−0.106***	−0.081***	−0.078***	−0.099***	−0.074***
$\alpha + \beta$	0.994	0.986	0.995	0.991	0.977	0.994
Correlation	(0.024)	(0.024)	(0.025)	(0.023)	(0.026)	(0.026)
Observations	1,257	1,261	1,301	1,346	1,350	1,393
Log Likelihood	−2818.9827	−3108.3872	−3579.7354	−15556.3129	−3455.4420	−3951.6941

Note: *p<0.1; **p<0.05; ***p<0.01

VARMA-GARCH result for United States

US: VARMA-GARCH equations *excluding* COVID-19

$$
\begin{aligned}
r_{s,t} &= 0.570 r_{s,t-1} + \varepsilon_{s,t} - 0.634\varepsilon_{s,t-1} \\
r_{g,t} &= -0.412 r_{g,t-1} + \varepsilon_{g,t} + 0.439\varepsilon_{g,t-1} \\
h_{s,t} &= 0.209\varepsilon^2_{s,t-1} + 0.743 h_{s,t-1} \\
h_{g,t} &= 0.025\varepsilon^2_{s,t-1} + 0.969 h_{g,t-1}
\end{aligned}
$$

US: VARMA-GARCH equations *including* COVID-19

$$
\begin{aligned}
r_{s,t} &= 0.619 r_{s,t-1} + \varepsilon_{s,t} - 0.676\varepsilon_{s,t-1} \\
r_{g,t} &= -0.383 r_{g,t-1} + \varepsilon_{g,t} + 0.404\varepsilon_{g,t-1} \\
h_{s,t} &= 0.049 + 0.246\varepsilon^2_{s,t-1} + 0.721 h_{s,t-1} \\
h_{g,t} &= 0.008 + 0.025\varepsilon^2_{s,t-1} + 0.024\varepsilon^2_{g,t-1} - 0.026 h_{s,t-1} + 0.967 h_{g,t-1}
\end{aligned}
$$

By comparing the equations, there is no big difference between "excluding" and "including" COVID-19. In the U.S. market, gold and stock returns are quite independent from each other, for there is no significant cross term in the mean equations. Asset returns for both cases are only affected by its own past return and own shock. For stock market, the past return is a good indicator for the current return (0.570 & 0.619) but a shock will bring negative reaction to the return (-0.634 & -0.676). In the gold market, the return tends to self-adjust and fluctuate around some "true price" ((-0.383). The positive parameters in front of the shock term $\varepsilon_{g,t-1}$ (0.439 & 0.404) indicate that gold loves shock. In the GARCH parts, stock volatility depends partially (0.209 & 0.246) on the own past shock and mainly on the past own long-run volatility (0.743 & 0.721). There is no cross term from gold to stock in the stock variance equations, neither in "excluding" nor "including COVID-19". The gold volatility reacts positively to the stock market shock in short run (both 0.025) and has a strong long-run effect from the own historical volatility (0.969 & 0.967). When we include the pandemic period, we see that stock is more volatile than gold (0.049 vs. 0.008 as constants). The short-run shocks from both stock and gold have equally weak effects on the gold variance. The stock market variance offsets the variance in the gold market (-0.026). From these findings, a conclusion can be made that in the abnormal time due to Corona-virus, volatility transfers from stock to gold, but not vice versa. Gold has a weak absorbing power to the long-run volatility from the stock market and still highly persistence to its own past variance (0.967). This conclusion supports the safe-haven attribute of gold for stock in U.S. for most of the extreme conditions in table 4.4.

VARMA-GARCH result for Germany

DE: VARMA-GARCH equations *excluding* COVID-19

$$
\begin{aligned}
r_{s,t} &= 1.233 r_{s,t-1} + 1.858 r_{g,t-1} + \varepsilon_{s,t} - 1.217\varepsilon_{s,t-1} + \varepsilon_{g,t} - 1.824\varepsilon_{g,t-1} \\
r_{g,t} &= -0.878 r_{s,t-1} - 0.975 r_{g,t-1} + 0.888\varepsilon_{s,t} + 0.955\varepsilon_{g,t} \\
h_{s,t} &= 0.087\varepsilon^2_{s,t-1} + 0.891 h_{s,t-1} \\
h_{g,t} &= 0.054\varepsilon^2_{s,t-1} + 0.932 h_{g,t-1}
\end{aligned}
$$

DE: VARMA-GARCH equations *including* COVID-19

$$
\begin{aligned}
r_{s,t} &= 0.001 + 0.203 r_{g,t-1} + \varepsilon_{s,t} + 0.989\varepsilon_{s,t-1} - 0.201\varepsilon_{g,t-1} \\
r_{g,t} &= 0.002 + \varepsilon_{g,t} \\
h_{s,t} &= 0.116\varepsilon^2_{s,t-1} + 0.866 h_{s,t-1} \\
h_{g,t} &= 0.016\varepsilon^2_{s,t-1} + 0.066\varepsilon^2_{g,t-1} - 0.014 h_{s,t-1} + 0.911 h_{g,t-1}
\end{aligned}
$$

The volatility transmissions are totally different for Germany between "excluding" and "including" COVID-19. The estimation results using data till the end of 2019 indicate that the German stock market return works like an amplifier, it does not just amplify the effect from its own yesterday's stock return (1.233), but also from the gold return (for which the amplification is even stronger with the estimated parameter 1.858). The past returns from both stock and gold reinforce the current stock return. At the same time, the German stock return is rather negatively sensitive to its own shock (-1.217) and even more sensitive to shock in the gold market (-1.824). Comparing the mean equations between "excluding" and "including" cases, we can find a big difference has been made by the Corona-virus in the German market, videlicet, when the pandemic period data from 2020 is included, the gold return becomes independent. It has no cross term from the stock return and is highly efficient for not depending on own historical results. The current return depends only on the current shock. Meanwhile, stock market return loses confidence to itself and starts weakly anchoring the gold return (0.203), it becomes positively sensitive to its own shock (0.989 with only weak statistical significance), but negatively sensitive to the gold shock (-0.201). The return behaviours can be transferred from gold to stock, but not vice versa. The differences in the variance equation for stock and gold between "excluding" and "including" COVID-19 is mainly reflected in the volatility of the gold market. Using data till 2020, we see, that both gold and stock variances depend partially on the short-run *stock* market shock (0.087 & 0.054) and primarily on their own long-run persistence (0.891 & 0.932). When later data has been included, gold market reacts more on the shock from itself (0.066) than from the stock (0.016). Furthermore, it reacts negatively to the stock past variance (-0.014) while remain highly persistence to its own long-run variance (0.911). We conclude that in the sense of variance, the volatility transfers from stock to gold, not vice versa. Since gold starts reacting to the stock volatility in the "including" case, this observation might explain why the safe haven attribute of gold is less predictable when the pandemic data has been included in table 4.4.

VARMA-GARCH result for China

CN: VARMA-GARCH equations *excluding* COVID-19

$$
\begin{aligned}
r_{s,t} &= -0.873 r_{s,t-1} + \varepsilon_{s,t} + 0.897\varepsilon_{s,t-1} \\
r_{g,t} &= -0.497 r_{g,t-1} + \varepsilon_{g,t} + 0.491\varepsilon_{g,t-1} \\
h_{s,t} &= 0.032\varepsilon^2_{s,t-1} + 0.967 h_{s,t-1} \\
h_{g,t} &= 0.016\varepsilon^2_{g,t-1} + 0.979 h_{g,t-1}
\end{aligned}
$$

CN: VARMA-GARCH equations *including* COVID-19

$$
\begin{aligned}
r_{s,t} &= -0.728 r_{g,t-1} + \varepsilon_{s,t} + 0.725\varepsilon_{g,t-1} \\
r_{g,t} &= 0.498 r_{s,t-1} - 0.639 r_{g,t-1} + \varepsilon_{g,t} - 0.484\varepsilon_{s,t-1} + 0.404\varepsilon_{g,t-1} \\
h_{s,t} &= 0.044\varepsilon^2_{s,t-1} + 0.957 h_{s,t-1} - 0.019 h_{g,t-1} \\
h_{g,t} &= 0.040\varepsilon^2_{g,t-1} + 0.954 h_{g,t-1}
\end{aligned}
$$

By examining the mean equations when pandemic data have been excluded, we see that both Chinese stock and gold returns have self-adjusting behaviours (-0.873 & -0.497). Different from the U.S. and German stock markets, the Chinese stock market favours shocks (0.897). If we compare the mean equations between "excluding" and "including", the biggest difference is a) stock market has no statistically significant correlation with its own past return but negatively anchors to the gold past return (-0.728). b) gold return has positive correlation to the stock market past return (0.498) and is averse from the stock market shocks (-0.484). The variance equations don't show many differences between "excluding" and "including" cases. In all variance equations, both stock and gold volatility have small short-run effects from past shock and depend mainly on the long-run past variances. We find cross terms in the mean equations in "including" estimations but not in "excluding" ones. There are both-way return transfers and only a minor long-run variance transfer from gold to stock exclusively in "excluding" cases, which differs from the cases in U.S. and Germany where the long-run variance of gold offsets the stock market volatility (-0.019). There is no short-run shock transfer for all situations in the Chinese markets. This irrelevance, particularly the dependency of gold from stock corresponds to the safe-haven attribute of gold for stock for all the extreme conditions in table 4.4.

4.5 Hedging position

In order to bring the estimation results into application, we would like to provide some basic insights for solving some investment problems. For example an optimal fully invested portfolio holdings subject to a no-shorting constraint can be derived using the approach raised by Kroner and Ng (1998)[24] nested in the DCC-GARCH dynamic (co)variance estimations:[7]

$$
w_{gs,t} = \frac{h_{ss,t} - h_{gs,t}}{h_{gg,t-2h_{gs,t}+h_{ss,t}}} \tag{4.7}
$$

$$
w_{gs,t} = \begin{cases} 0, & \text{if } w_{gs,t} < 0 \\ w_{gs,t}, & \text{if } 0 \leq w_{gs,t} \leq 1 \\ 1, & \text{if } w_{fs,t} > 1 \end{cases} \tag{4.8}
$$

In expression (4.7), $w_{12,t}$ is the portfolio weight of the first asset in one unit investment of two, with which one minimizes the risk without lowering the expected returns.[8] For a $w_{12,t}$ with a value that falls between 0 and 1, a corresponding value shall be assigned to it

[7]The reason has been stated by Kroner and Sultan (1993)[25]. This hedge model has been characterised to be adequate to the dynamics in the second moments of currency price. For this approach, the DCC-GARCH estimation results can be found in appendix A.2.

[8]Here we simply assume a zero return, which fits the definition of "risk-minimising". See Kroner and Ng (1998)[24], section 5, page 839.

according to the upper formula, otherwise it shall be either 0 or 1 according to the lower formula.

For the hedging position, we are going to use the approach raised by Kroner and Sultan (1993)[25] as equation 4.9, in which a "hedging portfolio" has been found by dividing the covariance between two assets by the variance of the target asset one wants to hedge. So a dynamic hedge ratio for holding gold which minimises the risk for holding the stock at time t can be demonstrated as dividing the conditional covariance between gold and stock $h_{gs,t}$ by the variance of the stock $h_{ss,t}$ as follows:

$$\beta_t = \frac{h_{gs,t}}{h_{ss,t}} \tag{4.9}$$

Figures 4.7, 4.8 and 4.9 depict the dynamic changes of these two hedging values for the three countries been studied. The upper part of each figure is the dynamic risk-minimising portfolio weight for gold in one local currency (USD, EUR or CNY respectively) based on approach (4.7). The lower part of the figures illustrate the dynamic risk-minimising hedge position deducted from (4.9) for gold against stock overtime. We present the average value in table 4.7.

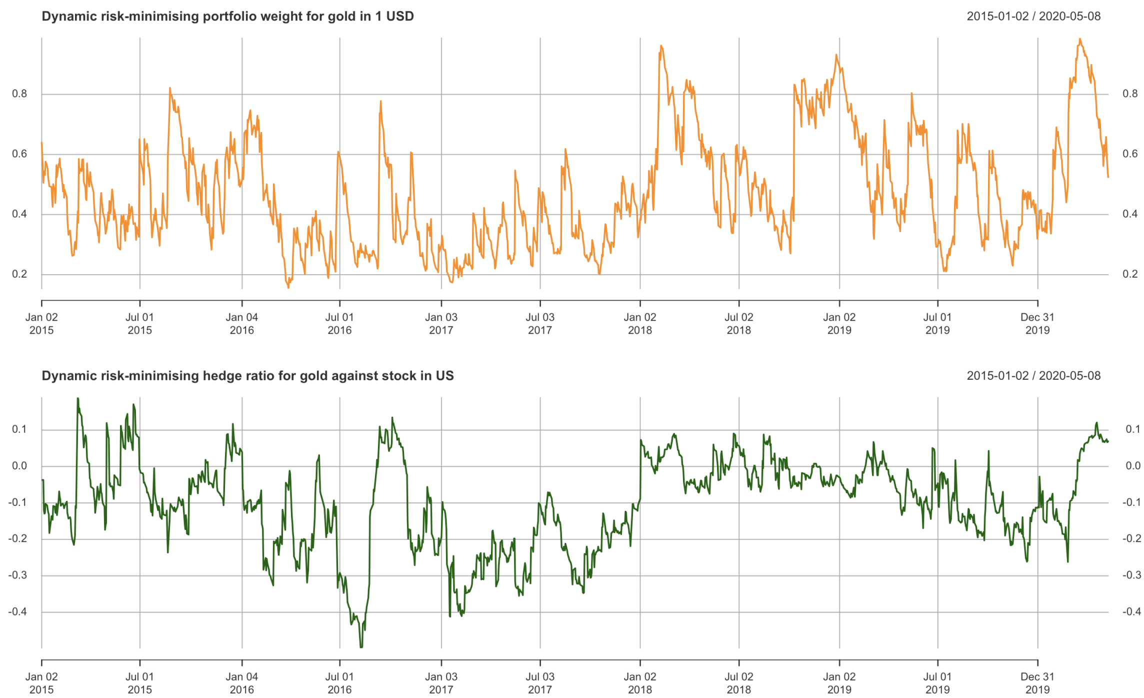


FIGURE 4.7: Dynamic risk-minimising hedging position in U.S., 02 Jan. 2015 - 08. May. 2020

Again we can observe different risk-minimising strategies for the countries being studied and also different weights for particular conditions. After all, investors in these markets have different tolerances for risk and faith in the financial system. Furthermore, COVID-19 generated common yet unique uncertainty to these markets. Various measures taken by the policy makers led to diverse consequences. We are indeed facing something we have never faced before. Not only the investors, but also the markets have to develop and improve through arduous difficulties. This is also a manifestation of the survival of the fittest

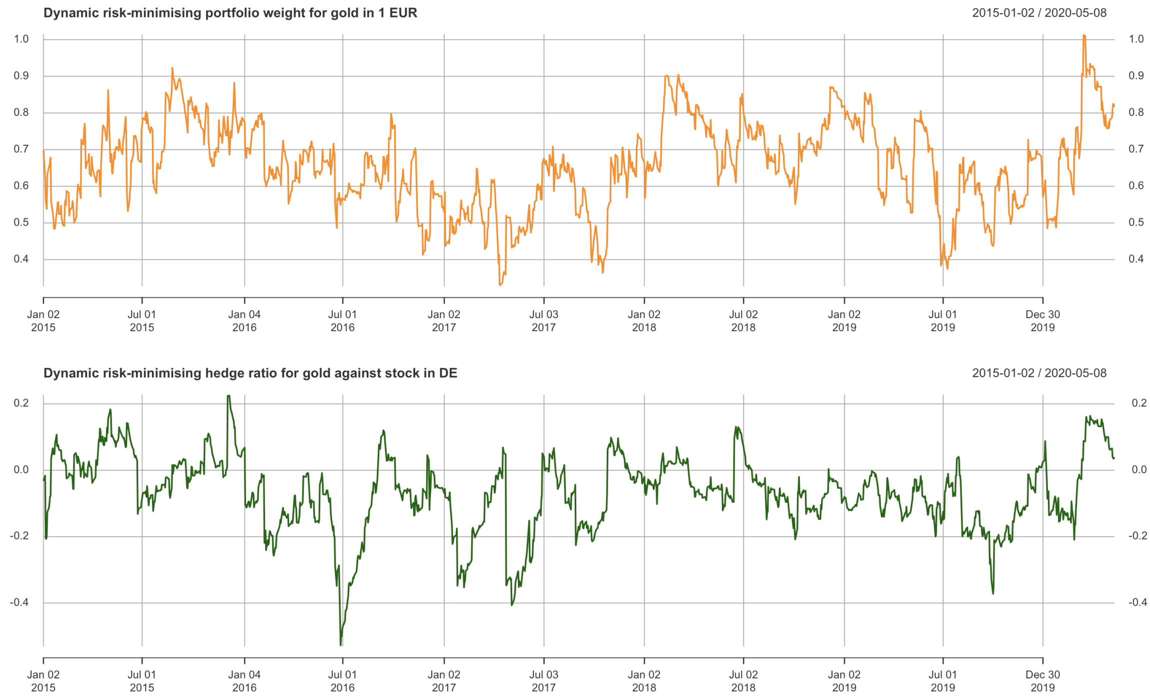


FIGURE 4.8: Dynamic risk-minimising hedging position in Germany, 02 Jan. 2015 - 08. May. 2020

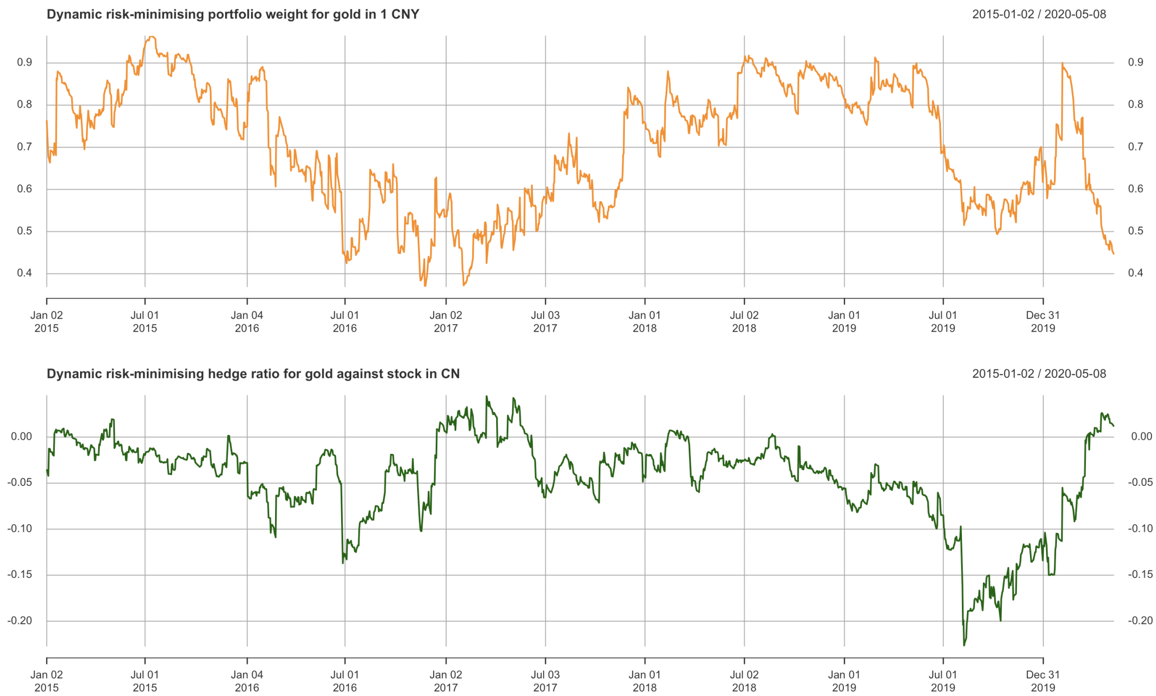


FIGURE 4.9: Dynamic risk-minimising hedging position in China, 02 Jan. 2015 - 08. May. 2020

TABLE 4.7: Average hedge position from DCC-GARCH estimation

	US		DE		CN	
	w_{gs}	β	w_{gs}	β	w_{gs}	β
Excluding COVID-19	0.462	−0.108	0.651	−0.076	0.709	−0.045
Including COVID-19	0.677	−0.036	0.735	−0.005	0.655	−0.049
Total	0.476	−0.103	0.657	−0.072	0.706	−0.045

in the market economy.

4.6 Conclusion

In this chapter, the interactions between the gold and stock markets in the United States, Germany and China have been studied. Due to the particularity of COVID-19 pandemic period being involved, the data has been estimated as excluding as well as including the COVID-19. Three models have been applied in this research. The extreme quantile regression model from Baur and McDermott (2010)[5] has been used to examine the hedge and safe haven attribute of gold for stock. VARMA-GARCH model has been used to investigate the detailed volatility transmission pattern between gold and stock, how the short-run stock and long-run variance affect each other under different conditions. In order to capture an insight for the dynamic hedging application, the traditional DCC-GARCH from Engel (2002)[14] has been applied for deriving the dynamic conditional (co)variance of gold and stock returns to generate the risk-minimising portfolio weights and hedge position based on Kroner and Ng (1998)[24] and Kroner and Sultan (1993)[25], respectively.

Results show that a) the hedge and safe-haven attribute is totally different in the three countries being studied. Including the COVID-19 period also leads two big changes of the estimation results. Hedge and/or safe-haven attribute has different strengths and applicability under virus "condition". b) In general, gold is much more long-run persistent than stock for all three markets and tend to have self-adjusting ability. During abnormal situations, gold can absorb the volatility from the stock market.

Chapter 5

Conclusion

THIS thesis looks into the impact and attributes of gold in the international financial market. Applying the latest mathematical and econometric approach as well as the data from the last decade, the thesis acquired a closer view into the development of the gold market (exchanges) impacts and the hedging attribute of the gold as a financial asset against exchange rate changes and the stock market changes. This thesis has especially highlighted the latest global shock caused by COVID-19, which can not be found in the earlier literature, hence it is also the biggest achievement by this research.

5.1 Summary

Starts with the major three gold exchanges and the price spillover between them, this thesis takes an empirical view into the latest financial market and investigates the hedging function of gold against exchange rate changes and the stock market changes.

From chapter 2, we learned that gold is highly sensitive to geopolitical issues and the volatility caused by regional turmoil can be globally transmitted since gold is a highly homogeneous good that abides by the law of one price almost perfectly all the time. In the meantime, we also observe various market impact from the three exchanges in New York, London, and Shanghai due to both endogenous reasons such as culture, institutional differences, etc. as well as exogenous reasons such as local unsystematic risks, currency shocks, etc.

Insights from chapter 1 bring the research questions in later chapters, namely the regional application of gold as a hedge for the shocks in the exchange rates and stock markets. The results from chapter 3 confirm the regional difference in investing gold as a hedge against exchange rate changes since different currencies have different strengths of link with gold and the U.S. dollar. Investors coming from non-identical currency regions should have their unique investing allocations for gold based on the hedging attributes for the target currency.

In addition to investors' hedging demand for exchange rates, the volatility of the stock market has always been a market where investors hope to minimise risks. Chapter 4 examines this topic not only for the normal cases but also for the latest financial turmoil due to COVID-19. Results suggest that gold has indeed different hedging attributes during different financial situations. Comparing the results with the existing literature, a conclusion can be derived that the hedging attribute of gold is dynamic and reacts also differently under different financial environments. COVID-19 is also a new crisis that never happened before and has merely existed case in moderns times as references. We can see the vulnerability of the international financial market under unprecedented shock and how much does it cost to reconstruct the market back to a self-functioning mechanism. This appeals us to put more effort into the forward- and dynamic-looking research in order to take preventive measures and make more educated, determinative, and consistent political decisions based on the best economic insights.

5.2 External vs. internal

As we have mentioned in subsection 3.1.2, the investors have been divided into "profit-seekers" and "value holders". Chapter 3 studies the hedging attribute of gold for the purpose of value holding while chapter 4 focuses on the investment behaviours of profit seekers. The hedge used by profit-seekers is an external hedge and the one used by value holders is the internal hedge.

In comparison between the researching results from the above-mentioned chapters, the major key information we have found for hedging against exchange rate change is contained in the ADL mean model part, which can be used to describe the movement of the time series and the hedging attribute of gold. Although we have applied the GARCH model on the residuals, the volatility pattern we can capture is from the gold price itself. Gold has an inverse relationship with the currency, but this relationship is rather a trend correlation than a volatility interaction.

On the other hand, the hedging attribute of gold against the stock market can also be revealed by the application of the GARCH models for the volatility heteroscedasticity. This means stock and gold series do not only have a correlation with each other but also have interaction on the volatility level.

This difference might also indicate the effective interval for the external and internal attributes of gold. For an external application such as stock market hedging, the time interval is normally rather short. The stock market can change dramatically within several hours thus force the hedging strategy also being short-term and sometimes even ad-hoc. The internal application is used to hedge against inflation rate change and exchange rate change, which normally follow the policy announcement and react nor that rapidly like the stock market. So the hedging strategy for this application takes the term of the medium towards long.

5.3 Shortcomings and discussions

Financial time series models including VAR, GARCH are the major technique being used in this thesis, the dynamic historical trend has been illustrated based on the historical data. These are all backward-looking analysis which can only be used to interpret the policy/shock transmission mechanism in history yet not powerful enough to make a strong statement for future. This is, however, not only the shortcoming of this thesis but also rather the shortcoming of the methodologies and the truth of the scientific research. Since chapter 2 has been published as a journal paper, the Shanghai Gold Exchange indeed first extended the trading hour and established further globalisation measurements. Further contribution can be made if the spillover impact could be detected once more *after* the new policy. Chapter 4 benefits from the COVID-19 crisis, which is a shock we can not replicate again. Till the finishing of this thesis, the global economy still hasn't recovered to normal, which also leads to the question, whether there exists a true *normal* situation for the international economy. The international financial market is changing all the time, and the normal situation could be just a short stable period before the next shock. Major policy changes, geographical crises can reshuffle the whole market in no time. This urges us to keep the pace up and stick to the latest tendency with a forward-looking attitude, where lies also the charm of this science. Meanwhile, gold as a financial asset with the longest history hence keeps its position of facing the vicissitudes and provides a rather safer wealth-holding power than the other assets. Hereby I end this thesis with a quote from Karl Marx again:

"Gold is now money with reference to all other commodities only because it was previously, with reference to them, a simple commodity."

Karl Marx, Das Kapital, 1867

Appendix A

DCC-GARCH

A.1 Model

The DCC-GARCH developed by Engel (2002)[14] is a widely used well-known model for investigating the dynamic correlation between multiple assets return. Different from the VARMA-GARCH model being introduced in subsection 4.3.2, the conditional variance equation for each asset only follows a univariate GARCH(p,q) process as following (no cross term between the assets in the GARCH part):

$$h_{i,t} = c_i + \sum_{k=1}^{p} \alpha_{i,k}\varepsilon_{i,t-s}^2 + \sum_{s=1}^{q} \beta_{i,s}h_{i,t-s} \tag{A.1}$$

Here we still assume a two-asset case and GARCH(1,1) will be applied for our estimation in this research. So the DCC-GARCH model can be simplified as:

$$h_{s,t} = c_s + \alpha_s\varepsilon_{s,t-1}^2 + \beta_s h_{s,t-1} \tag{A.2}$$

$$h_{g,t} = c_g + \alpha_g\varepsilon_{g,t-1}^2 + \beta_g h_{g,t-1} \tag{A.3}$$

It can be noticed that the ARCH(GARCH) effect term $\sum_{k=1}^{p} \alpha_{i,k}\varepsilon_{i,t-s}^2(\sum_{s=1}^{q} \beta_{i,s}h_{i,t-s})$ in equation (A.1) is different from the ARCH part $\sum_{j=1}^{2} \alpha_{ij}\varepsilon_{j,t-1}^2(\sum_{j=1}^{2} \beta_{ij}h_{j,t-1})$ in the equation (4.6) for the previous VARMA-GARCH model in the subscript. There is no cross term in the DCC-GARCH model, thus $\sum_{k=1}^{p} \alpha_{i,k}\varepsilon_{i,t-s}^2$ only reflects the short-run persistence of an asset's *own* past shock, while $\sum_{s=1}^{q} \beta_{i,s}h_{i,t-s}$ indicates the long-run past volatility persistence of the i^{th} asset itself merely. In such an expression, the two assets in this model are independent from each other in the sense of conditional variance. Nevertheless, the conditional correlation can be estimated dynamically using a matrix expression as the following form:

$$Q_t = (1 - \theta_1 - \theta_2)Q_0 + \theta_1\varepsilon_{t-1}\varepsilon_{t-1}' + \theta_2 Q_{t-1} \tag{A.4}$$

The dynamic correlation matrix on time t Q_t can be decomposed as an unconditional correlation matrix Q_0 with the weight of $(1 - \theta_1 - \theta_2)$, the matrix of shocks $\varepsilon_{t-1}\varepsilon_{t-1}'$ from the last period $t - 1$ with the weigh parameter θ_1 and the last period correlation Q_{t-1} with the weight parameter θ_2. Later in the estimation section, we are going to check if either of the both parameters θ_1 and θ_2 is statistically significant; if so, the null hypothesis of a constant correlation can be rejected and our hedge strategy should based on the estimation result from a DCC-GARCH approach for a better practical effect, for which the dynamic conditional coefficient $\rho_{12,t}$ for 2 assets takes the following form will be used:

$$\rho_{12,t} = \frac{Q_{12,t}}{\sqrt{Q_{11,t}Q_{22,t}}} \tag{A.5}$$

Thus the dynamic conditional covariance matrix for our two assets cases can be deduced as:

$$H_{12,t} = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} = \rho_{12,t}\sqrt{Q_{11,t}Q_{22,t}} \tag{A.6}$$

In section 4.5, the estimated conditional variance $h_{11,t}$ and $h_{22,t}$ and the estimated conditional covariance $h_{12,t}$ and $h_{21,t}$ will be applied to calculate the hedge position for gold against stock for all three markets.

A.2 Estimation result

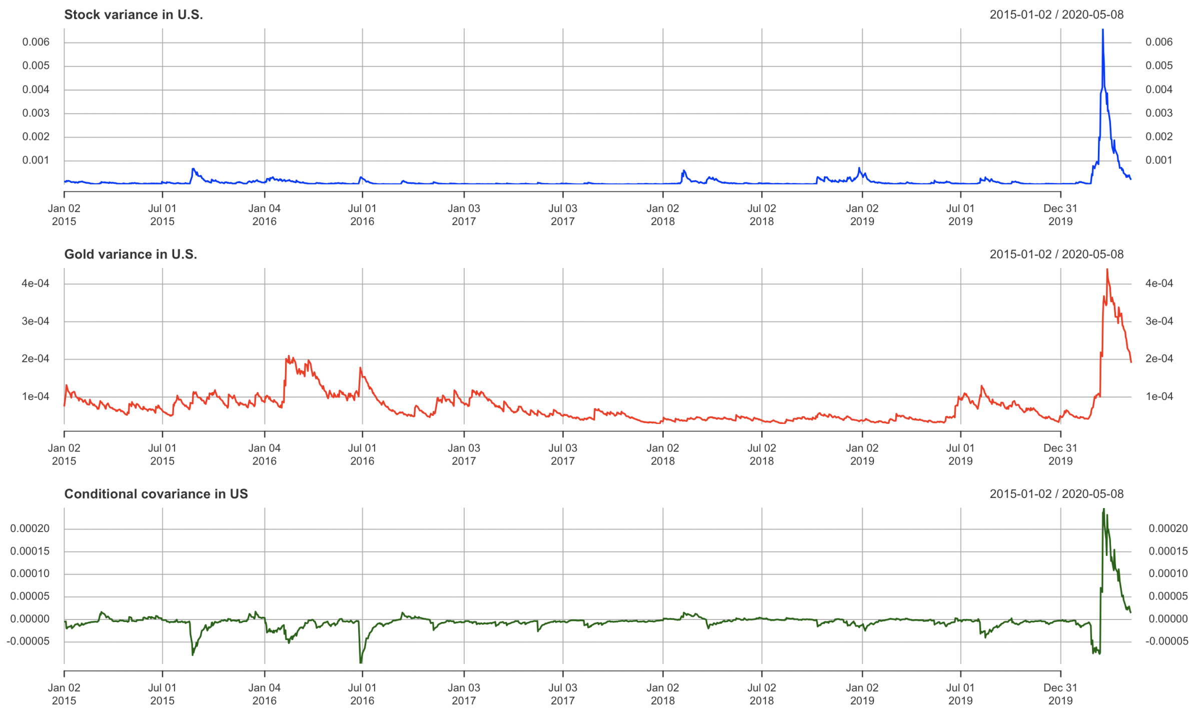


FIGURE A.1: Dynamic (co)variances in U.S., 02. Jan. 2015 - 08. May. 2020

DCC-GARCH has been applied to generate dynamic estimation over the time. Here we provide the correlation the estimation result table and the correlation plots.

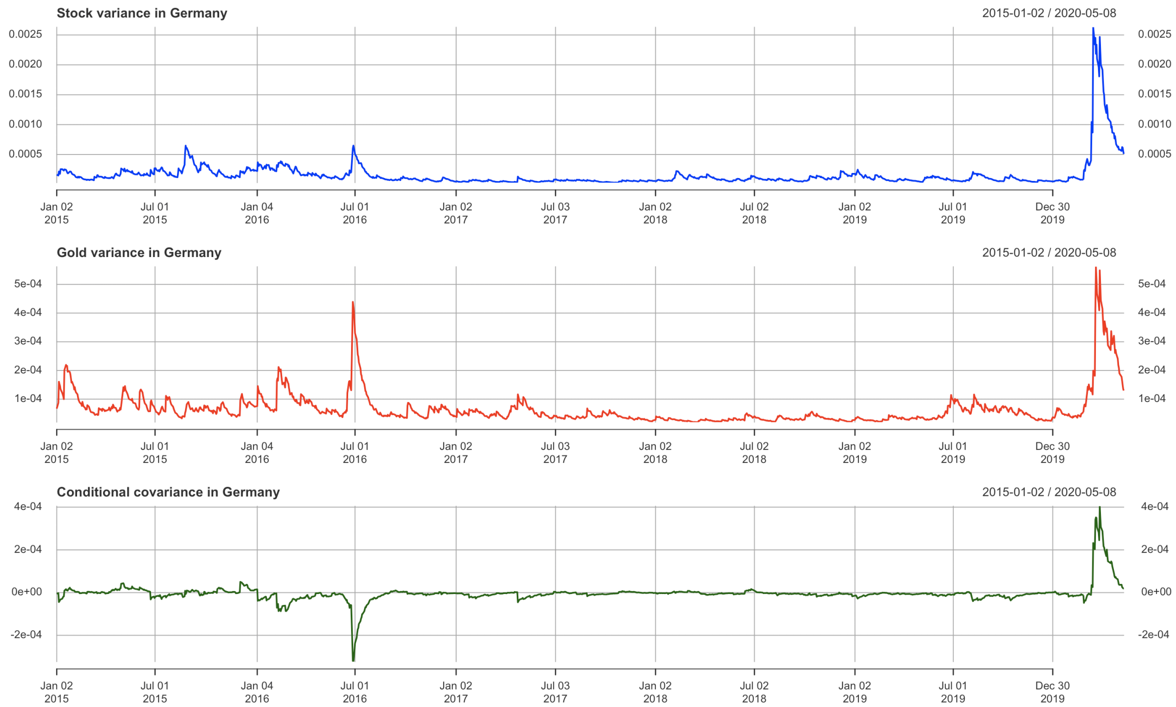


FIGURE A.2: Dynamic (co)variances in Germany, 02. Jan. 2015 - 08. May. 2020

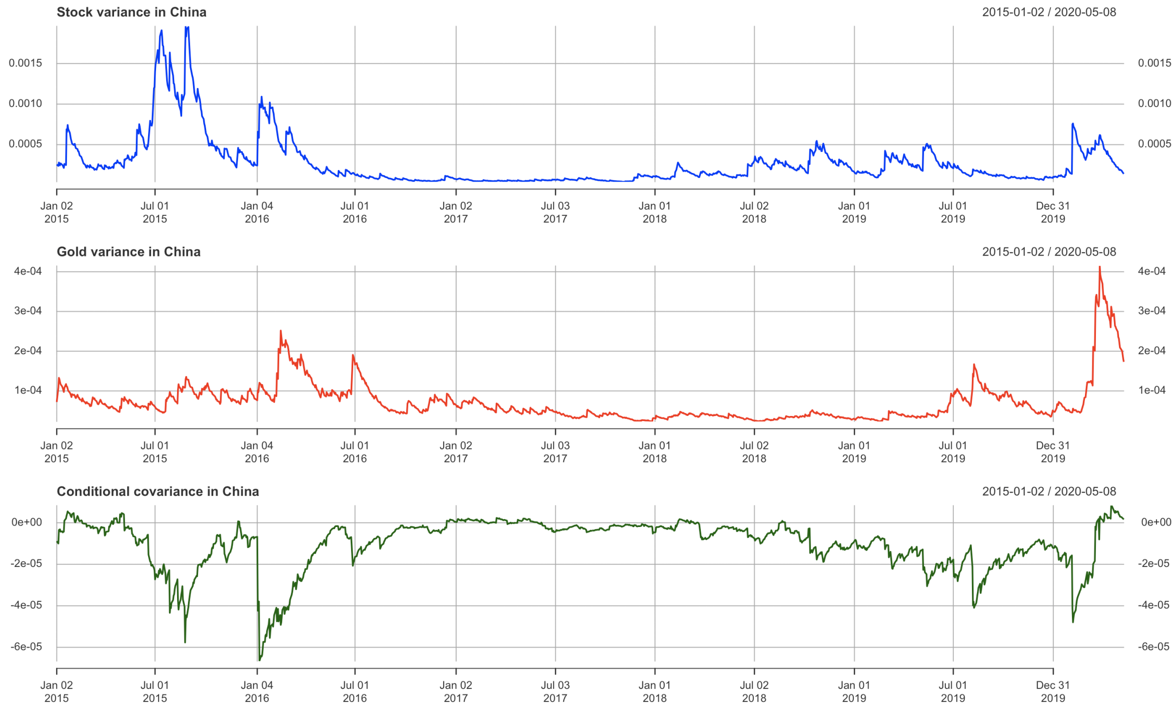


FIGURE A.3: Dynamic (co)variances in China, 02. Jan. 2015 - 08. May. 2020

TABLE A.1: DCC-GARCH estimation result

	US	DE	CN
Stock			
Mean Constant	0.000663***	0.000319	0.000000
	(0.000122)	(0.000621)	(0.000005)
$r_{s,t-1}$	0.744284***	0.834781***	−0.828723***
	(0.105685)	(0.038798)	(0.002394)
$\varepsilon_{s,t-1}$	−0.825165***	−0.871001***	0.828723***
	(0.090347)	(0.012304)	(0.000002)
GARCH Constant	0.000002***	0.000002	0.000002
	(0.000002)	(0.000024)	(0.000011)
$\varepsilon^2_{s,t-1}$	0.187508***	0.096600	0.070662
	(0.047924)	(0.269068)	(0.098534)
$h_{s,t-1}$	0.799704***	0.888146*	0.927711***
	(0.041277)	(0.320009)	(0.091429)
skewness	0.868540***	0.875175***	0.999999***
	(0.041441)	(0.120778)	(0.002589)
shape	5.389108***	1.250329***	0.889012***
	(0.820608)	(0.170417)	(0.168648)
Gold			
Mean Constant	0.000183	0.000161	0.000203
	(0.000208)	(0.000219)	(0.000405)
$r_{g,t-1}$	−0.859796***	−0.972417***	−0.112954***
	(0.067070)	(0.004345)	0.008839
$\varepsilon_{g,t-1}$	0.885174***	0.982176***	0.088216***
	(0.059585)	(0.000337)	(0.013367)
GARCH Constant	0.000001	0.000001	0.000001
	(0.000001)	(0.000005)	(0.000001)
$\varepsilon^2_{g,t-1}$	0.046500***	0.082308	0.047474***
	(0.005789)	(0.073689)	(0.006386)
$h_{g,t-1}$	0.943991***	0.896258***	0.943171***
	(0.007848)	(0.087848)	(0.008858)
skewness	1.061462***	1.027092***	1.048961***
	(0.033090)	(0.040557)	(0.041137)
shape	4.800108***	1.291901***	1.167241***
	(0.583123)	(0.109268)	(0.061825)
DCC parameter			
dcca1	0.028520**	0.035899***	0.009874*
	(0.012143)	(0.009263)	(0.005212)
dccb	0.925244***	0.923802***	0.980231***
	(0.031917)	(0.017761)	(0.012389)
mshape	5.247511***	5.731292***	4.674270***
	(0.397427)	(0.578864)	(0.221485)
Observations	1,347	1,351	1,394
Log Likelihood	9336.44	9080.224	9004.716

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

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