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# Dynamic spillovers and linkages between gold, crude oil, S&P 500, and other economic and financial variables. Evidence from the USA

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A B S T R A C T

This paper focuses on the price determinants of gold, and on the challenges associated with gold's safe haven property. Specifically, it analyses the interlinkages and the return spillover effect among gold, crude oil, S&P 500, dollar exchange rate, Consumer Price Index (CPI), economic policy uncertainty and Treasury bills, by employing a Vector Autoregression (VAR) and the spillover index of Diebold and Yilmaz (2012), Diebold and Yılmaz (2014). Monthly realized return series, covering the period from 2nd of January 1986 to 31st of December 2019 are used to examine the short-run linkages, and the return spillovers rolling-window estimates in analyzing the transmission mechanism in a time-varying fashion, respectively. Our findings identify gold as a strong dollar hedge, while crude oil and Treasury bills appear to drive inflation; they also indicate strong spillover effects between exchange rate and gold returns. In general, co-movement dynamics display state-dependent characteristics. Both total and directional spillovers increase significantly during market turbulence caused by severe financial crises such as the Global Financial Crisis (GFC) of 2007–2009 and the European Sovereign Debt Crisis of 2010–2012. Net spillovers switch between positive and negative values for all these markets, implying that the recipient/transmitter position changes drastically with market events. Economic policy uncertainty, stock market returns, and crude oil price returns are the main transmitters, while Treasury bills and CPI are the main return shock recipients. Gold and exchange rate act both as receivers and transmitters over the sample period.

## 1. Introduction

In a period of increased turbulence, as reflected indicatively on the impact of China's geopolitical risks on gold and oil (Li et al., 2021), a new question persists. Are traditional assets, like gold and commodities, still better safe haven investments than alternative assets, like for example Bitcoin (Shahzad et al., 2019a) Within this context, and provided that the answer is still hovering, at least in terms of considering Bitcoin along with gold, and commodities, as safe havens for various stock indices (Wu et al., 2019; Ji et al., 2019; Bouri et al. 2020), it is important to review and investigate the determinants of traditional asset classes. Furthermore, it is crucial to measure and monitor the spillover effects across markets and asset classes in a time-varying fashion.

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By focusing on macroeconomic and financial fundamentals,[1] we revisit the traditional assets, including gold and crude oil that have been perceived as the two main representatives of the large commodity markets (Zhang and Wei, 2010; Le and Chang, 2011) that change over time (Bassil et al., 2019; Bouri et al., 2019; Balcilar, et al. 2021).[2] The US dollar depreciation, along with a persistently and historically low level of inflation, close to zero interest rates, the oil supply manipulation by the OPEC, considerable geopolitical events, and the historical record highs of Standard and Poor's 500 index (S&P 500),[3] are interweaved in such a way that they are not simply interlinked but seem to be co-determined as well (Burdekin and Tao, 2021; Li et al., 2021). Thus, as it is widely documented, we initially observed crude oil and gold prices surging from 2002 until the first half of 2008, and we subsequently moved to an era of increased uncertainty, complexity, and broader turbulence.

Speculators and traders aim to profit on short term price changes, while gold hoarding finds ground in loss minimization. Being highly marketable and liquid (Reboredo 2013a; Reboredo and Ugolini, 2017; Zhang et al., 2021), gold, similarly to cryptocurrencies, brings no return apart from the expectation of price appreciation, since the goal of selling or keeping it for a future sale yields a price difference to investors.[4] Investors, who choose gold, largely rely on their expectations of market developments, current and prospective price of gold, gold demand, and expected return on gold versus other comparable gains (e.g. Gokmenoglu and Fazlollahi, 2015; Kumar, 2017). On the other hand, Baur and Lucey (2010) underline capital gains, and political and economic circumstances crucial to the flight-to-quality behavior of investors (Chan et al., 2011). The factors driving financial assets, such as gold and oil, and their spillover dynamics and interdependence remain areas that are widely debated and researched (e.g., Van Hoang et al., 2016; Kanjilal and Ghosh, 2017; Murach, 2019; Beckmann et al., 2019; Bhalotra et al., 2020; Kang et al., 2021; Gao et al., 2021).

Therefore, the key question of our analysis, is whether the variables under investigation maintain a neighboring trend, and up to what degree each variable could be explained by the dynamics of the others in a time-dependent way. The existing literature focuses on the impact of uncertainty on macroeconomic and financial variables (Chuliá et al., 2017; Gupta et al., 2018; Gabauer and Gupta, 2020; Ma et al., 2021; Zhang et al., 2021), on the uncertainty spillovers across countries and markets (Castelnuovo et al., 2017; Kang et al., 2021), and on the potential contagion effects, i.e., global investors and traders imitating each other's trading strategies under increased uncertainty (Papavassiliou, 2014; Guidolin et al., 2019; Al-Yahyaee et al., 2019; Demiralay and Golitsis, 2021). On the contrary, the analysis of the dynamic dependencies to capture various pairwise and dynamic spillovers, between more variables is still limited. This analysis is even more meaningful by exploring not only the relationship between gold and stock returns (Boako et al., 2019; Triki and Maatoug, 2021), but also by including the EPU, for an extended period of time for the USA. Thus, we aim to capture the short-run "causal" influences that exist among them, and the various transmission channels, by investigating if the variables are shock transmitters or/and shock recipients in a time-varying manner. This is essential since a better understanding of the existing interlinkages and the dynamic spillovers could counterbalance the uncertainty and the evident turbulence which is currently reflected for example on a 'sentiment–based' cryptocurrency-market (Corbet et al., 2020; Demiralay and Golitsis, 2021)[5] and the broader financial, economic, and geopolitical environment (Li et al., 2021).

The aim of the current study is twofold; once we review the contemporary research on the price determinants of gold, and outline the challenges associated with gold's safe haven properties, we apply-two distinct econometric methodologies, a Vector Autoregression (VAR) and the spillover index of Diebold and Yilmaz (2012), Diebold and Yılmaz (2014), to test the time-series linkages of various economic and financial variables in the short-run. This is done once on a unified time frame, and then by running rolling-window estimates to analyze the transmission mechanism in a time-varying fashion. Thus, along with a traditional econometric approach, like the VAR, which provides a single average parameter, we test and subsequently compare if stable spillover dynamics are unrealistic or not, given that the ecosystem of financial markets could be constantly changing due to structural reforms and financial crises.

The country chosen to examine these relationships is the USA, since this is the country that determines both directly and indirectly the aforementioned variables by being simultaneously, the strongest economy globally. What is also unique within this case is that especially since the 2008 collapse of Lehman Brothers, gold, and the dollar exchange rate, seem to be more turbulent, responsive, and interlinked to other variables compared to the past. Thus, it is important to test the determinants and the drivers of the regional/global variables, which act not only as safe havens -providing potential hedging and diversification opportunities too - but also as "knobs" within the various financial and monetary transmission channels that modify economic reality. To address the above we use a data set spanning from January 2, 1986 to December 31, 2019, having a total sample of 408 monthly observations (the start date is selected due

[1] According to Bianchi (2020), in the case of cryptocurrencies, they do not affect market activity neither in the short nor in the long run; their short-term market activity seems to be primarily driven by sentiment. The inclusion of the term structure of interest rates and inflation expectations does not affect market activity, and there is only a mild, and not statistically significant, correlation between returns on cryptocurrencies and returns on traditional asset classes.

[2] This holds at least for the pre-COVID-19 pandemic period. For the post-COVID-19 period, see indicatively Ji et al. (2020).

[3] Subsequently, in terms of understanding mainly the drivers of the prices of gold and crude oil, along with the stock market index of Standard and Poor's (S&P 500), and given that there is a lack of a solid theoretical model in the area of investigation, we focus on the following variables: the exchange rate (the trade weighted US dollar index against major currencies), inflation (consumer price index), the US economic policy uncertainty index (EPU), and the interest rate (the three month Treasury bill, i.e. the secondary market rate).

[4] Reboredo and Ugolini (2017), having studied quantile causality between gold commodity and gold stock prices, found consistent evidence of causality running from gold stock returns to gold prices.

[5] Demiralay and Golitsis (2021) provide evidence that the macro-financial factors, such as gold, oil, exchange rate, stocks, and corporate bonds, are not significant drivers of the cross-cryptocurrency co-movements, while Corbet et al. (2020) studying the dynamic correlations between Chinese stock exchanges, gold, and Bitcoin, support that investors preference towards gold raises concerns about the final status of cryptocurrencies.

to data availability). We use a rolling estimation window of 40 months and a 10-step-ahead forecast horizon for the variance decomposition. We repeat the analysis with different choices of the rolling estimation window and forecast horizon steps, i.e., increasing and decreasing them up to 50 % of the fixed choices. The untabulated results imply that qualitative results stay similar, which supports the robustness of the results.

Our empirical results demonstrate the following important findings. First, a robust Vector Autoregressive model is effective in capturing the existing short-run time-series effects; including the prevailing ones like the dollar depreciation which in the short-run increases the gold price, the drop of S&P 500 that increases EPU, the crude oil that decreases Inflation, the Treasury bill that decreases Inflation as well, and vice versa. Second, within the Vector Autoregressive approach, we proceed with Generalized Impulse Response Functions (GIRFs) and the index of Diebold and Yilmaz (DY) to further analyze and interpret the results in a time-varying way. The main findings from the DY spillover index are the strong spillover effects between exchange rate and gold returns. In general, co-movement dynamics display state-dependent characteristics. Both total and directional spillovers increase significantly during market turbulence caused by severe financial crises such as the Global Financial Crisis (GFC) of 2007–2009 and the European Sovereign Debt Crisis of 2010–2012. Net spillovers switch between positive and negative values for all the markets, implying that the recipient/transmitter position changes drastically with market events. Economic policy uncertainty, stock market returns, and oil price returns are the main transmitters, while Treasury bills and the CPI are the main return shock recipients. Gold and the exchange rate act both as receivers and transmitters over the sample period.

To proceed further, to the best of our knowledge, we are the first to apply a Rolling sample spillover index for several specific factors; such as commodities (gold and crude oil), investment instruments (Treasury bills), macroeconomic variables (inflation, exchange rate), and an unpredictability factor (economic policy uncertainty), for the case of USA, for an extended period of time (34 years; 408 monthly observations); our spillover results provide an overview for the "mean" spillover effects over the entire sample in a time-dependent fashion. Nonetheless, as stated in Diebold and Yilmaz (2009, 2012), the non-time-varying measures do not reflect financial evolution and/or financial crises and, thus, it is important to work with a rolling sample framework and construct time-varying spillover indices. Therefore, we use a 3-year and 4-month (or 40 monthly observations) rolling sample to re-estimate the VAR(1) model on a monthly basis for both returns and logarithmic volatility and produce rolling spillover indices.

This study contributes to the growing literature of spillover effects. Apart from examining, the spillovers effects, we consider both return and volatility spillovers identifying possible similarities or differences in their patterns. Specifically, this study provides rolling sample spillover indices which cover a long period starting from the mid-1980 s, where the financial sector and capital markets in US and Europe attested a period of substantial expansion. This period includes, apart from the financial booms of the 1990 s and the dot-com bubble of 2001, the 2007–2009 global financial crisis and the Debt economic crisis, which preoccupied initially Southern Europe and turned onto a European Debt Crisis between 2010 and 2012. The study concludes on 31 December 2019, when the WHO China Country Office was informed of cases of pneumonia of unknown etiology (cause) detected in Wuhan City, Hubei Province of China. We therefore examine the spillover effects during periods of both exogenous and endogenous shocks in the USA.

Furthermore, according to our results on the time-dependent return and volatility spillover indices, we provide strong evidence that both returns, and volatility spillovers intensify during periods of financial or economic stress, as expected. However, our empirical findings indicate some additional points that should be stressed. First, both indices are rather volatile and there is no clear evidence in terms of whether an upward or downward trend exists during the entire sample. Notwithstanding, we could split the sample in four periods; from 1986 to 1997 the trend is a downward one, from 1997 to 2008 is upward, from 2009 to 2015 downward, and from 2015 and onwards, an upward one again. Second, the European sovereign debt crisis did not increase the level of spillover effects more than the period following the Lehman Brothers collapse, meaning that the financial crisis was more severe than the fiscal one when taking contagion into consideration (in terms of the level of the index, the peaks are observed in 1992–93, 2001–02, and in 2008, while the troughs are evident in 1995–96, and 2003). Third, on average, the spillovers in the 2008 to 2012 period are greater compared to the rest of the periods, including the 2002–2005 spillover effects (which is the period of the post dot-com boom, i.e., the early years of the Eurozone and the 2003 Iraq Invasion), indicating that even strong idiosyncratic shocks can only trigger above average temporary increases in spillovers.

These findings have specific policy implications. A policy maker should expect strong spillover effects among the financial markets in the USA and short-termed increases during unexpected shocks. The next interesting step, from a policy making perspective, is to identify and monitor the directional spillover effects across various classes of markets. This will enable policy makers to locate possible sources of imbalances and propagation channels in the financial system, to control or even predict, through early warning indicators, contagion effects across markets or countries, which, in their turn, might lead to financial instability and economic contraction (In, 2007).

Subsequently, to insist further on policy implications, by understanding the responsiveness of gold - along with the other variables under study - to uncertainty shocks, and the spillover effects that it can cause, policy makers must channel and smoothen these spillovers through, for example, monetary policy conduct. More specifically, the stock market being a net transmitter of volatility, along with the CPI and the TB (the net receivers), shows the importance of the smooth functioning of the money market for the stability of the financial system, since it can contribute considerably to the increase of volatility and thus induce uncertainty, in other aspects of the financial system. Therefore, regardless of its smooth functioning history, and to the degree that the TB could act as a proxy of the interbank rate, the financial crisis, among the rest of the crises, has taught both policy makers and academic researchers that interbank markets should not be neglected (Holthausen and Pill, 2010). Finally, by capturing these interactions, along with their dynamics, especially under a rolling time-window, we provide insights not only to policy makers and scholars but investors as well, who can then enhance their hedging strategies and the diversification of their portfolios.

The rest of the paper is organized as follows. Section 2 offers an extensive review on the literature concerning mainly gold's prices, behavior, and relations to the proposed variables. Section 3 discusses the methodology and data employed for the empirical part. Subsequently, we present the empirical findings and analysis in Section 4, where the limitations of the study are also briefly explained, followed by suggestions for further research. Conclusions and interpretations are brought forward in Section 5 of the paper.

## 2. Literature review

The GFC of 2007–2009 and the European Sovereign Debt Crisis of 2010–2012 and their aftermath, brought once again under the spotlight how assets can act as safe havens for investors who want to secure their portfolios. The ripples of the GFC which started in the USA with the collapse of Bear Sterns and the subsequent collapse of Lehman Brothers were quickly transmitted to the European Monetary Union (EMU). It took Europe almost a decade to start moving forward after a prolonged period of uncertainty due to the unstable foundations of the EMU. After the unexpected turn of recent events though, linked with the outbreak of the recent pandemic due to COVID-19, the study of safe haven assets emerges once more as essential for economists and investors, and thus demands further exploration.

Gold has acted as a reliable and authoritative source of value almost throughout human history. The “barbarous relic”, a term coined by Kriz (1952), has caught wide public attention due to its movement, trends, and overall behavior of its price, especially during the last decade. Gold’s importance is underlined by its industrial application in various sectors (Baur and McDermott, 2010; Sari et al., 2010), while it is heavily used as a medium for exchange, store of wealth, hedge tool (Worthington and Pahlavani, 2007; Bialkowski, 2015), and portfolio diversification purposes (Capie et al., 2005; Ciner et al., 2013; Baruník et al., 2016). The specifics of the gold market, its inherent value as a precious metal and currency, its non-responsive supply side, and the counter-cyclical elements of the significant investment demand for gold, particularly in times of economic turmoil, promote the theory that gold acts as a store of value, or even more as a safe haven, in times of economic turbulence and/or global uncertainty (Baur and McDermott, 2010; Balcilar et al., 2016).

Reboredo (2013a) explains that gold has distinctive characteristics of acting as an instrument of wealth storage, hedge, and even safe haven in periods of economic turmoil. These distinctive characteristics almost define the entire process of price formation. Gold mining and production have limited impact on its price, even though the resources seem to be virtually depleted. Co-movements with other commodities and their prices are traced within gold, partly in accordance, and in response to similar macroeconomic triggers.

The advent of blockchain and cryptocurrencies in the last decade has secured a place for the latter (especially Bitcoin) to be considered as safe haven assets in periods of economic turbulence and crises. Many studies, by applying various econometric and statistical techniques aim to shed light to the role that cryptocurrencies play as safe haven assets when compared with gold and commodities (Shahzad et al., 2019a; Shahzad et al., 2019b; Wu et al., 2019; Bouri et al., 2020; Ji et al., 2020). Bouri et al. (2020) by using wavelet analysis find that Bitcoin is the strongest safe haven asset followed by gold, and commodities. Shahzad et al. (2019b) state that despite the fact that gold might have lost its edge as the go-to safe haven asset in some countries in the face of Bitcoin’s emergence as an alternative, it is still playing an important role.

Regardless of whether gold is considered as a weak or a strong safe haven asset, it still maintains its strong position for investors seeking to safeguard their portfolios in times of turmoil. Identical results can be found by Shahzad et al. (2019b), and Ji et al. (2020). Especially the latter analysis, focusing on the period after the outbreak of the pandemic associated with COVID-19, verifies that gold is central in investors’ efforts to find safe haven assets to secure their portfolios. One very important finding by Ji et al. (2020), which is in accordance with the existing literature, is that safe haven assets have time and country specific characteristics. We therefore need to be alert to take these into consideration when exploring safe haven assets in different time and country contexts. A common finding between Bouri et al. (2020), Shahzad et al. (2019a), and Shahzad et al. (2019b) is that although Bitcoin seems to be the choice of many investors and is on the rise as an asset that can play the role of a safe haven, it is still faced with skepticism by many investors due to the lack of intrinsic value that characterizes it. This further cements gold’s place as the asset that still plays a crucial role as a safe haven asset. In what follows, we address the interactions between gold and other macroeconomic determinants that the existing literature has focused upon.

### *2.1. Gold and oil*

Sari et al. (2010), Reboredo (2013a) and Tiwari and Sahadudheen (2015) explain how oil prices impact gold prices, partly due to expected rises in inflation, and due to the impact that oil has on economic growth and assets’ values. Investors in this case turn to gold hoping that it will safeguard their wealth. Eventually, oil has influence on gold production costs by exerting upward pressure on gold prices as well (Shahbaz et al., 2017). Institutional investors possess both gold and oil in their respective portfolios, as hedge or diversification tools (Baruník et al., 2016; Beckmann et al., 2017a), while price excitability spillover in the real economy, and in capital markets is another key factor for holding them (Chang et al., 2013; Gokmenoglu and Fazlollahi, 2015; Kanjilal and Ghosh, 2017).

Baffes (2007), Narayan et al. (2010), Reboredo (2013a), Wang and Chueh, (2013), estimate gold responding positively to oil price changes. Others find bi-directional Granger causality between them (Zhang and Wei, 2010; Šimáková, 2011; Bildirici and Turkmen, 2015; Bouri et al., 2017; Kanjilal and Ghosh, 2017). Sari et al. (2010) find a weak long-run equilibrium among spot prices of gold, oil price, and the dollar/euro exchange rate. Baruník et al. (2016) inform of varying behaviors among them, while Bildirici and Turkmen, (2015), and Shahbaz et al. (2017), accentuate the non-linearity of their relationship. Some argue that gold could be used as a hedge against oil price inflationary shocks and that oil prices determine the behavior of the gold market (Le and Chang, 2012; Gangopadhyay et al., 2016). Finally, Lin et al. (2016), and Zhang and Wei (2010) find that financial crises intensify interdependencies between oil and gold and emphasize the value of the US dollar as a crucial factor to the price of oil and gold.[6]

In a rather different strand of literature, Bassil et al. (2019) investigated the long run relationship between the daily prices of oil and gold between 1986 and 2015. Among their findings is that the existence of structural breaks is a strong indication that the magnitude and the sign of the relationship between oil and gold prices may be different across different regimes, which cannot be considered as stable through time. Similarly, Balcilar et al. (2019) studied the dynamic linkages between oil and gold prices for the spot and 1 to 12-month future markets over the period between 1983 and 2016 and concluded that there is no long-run causal link between gold and oil, but instead distinct periods of strong bi-directional or uni-directional causality. The interconnectedness between oil and gold is enriched by Li et al. (2021), who added geopolitical risk (BRICS geopolitical risk) in their analysis and showed, by employing the Diebold and Yilmaz (2012) methodology, that spillovers take place mainly in the short-term initiating from the oil market. In addition, they showed that China's geopolitical risks have the greatest impact on gold and oil.

### *2.2. Gold and stocks*

Baur and Lucey (2010) were the first to formulate empirically testable definitions of gold as a hedge and a safe haven with regard to financial assets such as stocks. Bouri et al. (2017) corroborate the latter. Basher and Sadorsky (2016), through Generalized Autoregressive Conditional Heteroskedasticity (GARCH), prove that there is negative correlation between commodities and equities, while Baur and McDermott (2010) reveal gold's safe haven property for most developed country stock markets, emphasizing though dependency on economic cycles. Triki and Maatoug (2021) also use the GARCH methodology to study the stock prices and gold, but they add geopolitical risk in the context, showing that during peaceful periods S&P 500 correlates less with gold, while it correlates more during turbulent geopolitical periods, indicating the role of gold as hedging instrument. These findings are further supported by Mitsas et al. (2022). Mensi et al. (2015) show the same for BRICS' stock markets, using vines copulas. Ciner et al. (2013) on the other hand, by estimating dynamic correlation with Exponential GARCH (EGARCH), find that gold does not act as a safe haven for equities from the US. Baruník et al. (2016) argue of heterogeneous correlations between gold and stocks, while Śmiech and Papież (2017), and Iqbal (2017) by using univariate Autoregressive Moving Average (ARMA) and EGARCH, and Dar and Maitra (2017) through wavelet analysis, find gold to be a weak hedge towards stocks during normal market regimes. The same findings are reported by Shahzad et al. (2019a) who explore bitcoin, gold and commodities, reporting all three to be weak safe havens for world stock markets, with gold being the only weak safe haven of the three in developed economies. This is not the case in the USA and China, where commodities and Bitcoin respectively are the weak safe haven assets with gold not exhibiting such status. The implication of gold being the best asset to hedge emerging market stocks, at least after the 2008–2009 recession periods is supported partly by Kumar (2017), with structural Vector Autoregression (VAR) and GARCH suggesting gold is a useful asset to own, one that provides better diversification compared to only-stocks constituent portfolios. Dicle and Levendis (2017), test and compare lead-lag relationships among known safe haven assets in different occasions and find treasuries to be a better safe haven asset than gold. Chen and Wang (2017) estimate dynamic correlation with GARCH, while modelling gold and stocks in China, concluding the hedging effect of gold on China's stock market has strengthened significantly. Shrydeh et al. (2019) though, defy the strong hedging role of gold on stocks and in their study in the post financial crisis period, which employs a VAR-ADCC-BVGARCH model for 2,870 daily observations of US financial market, show that the hedging effectiveness diminishes as the market capitalization increases. Similarly, Beckmann et al (2019b) focusing on Chinese sectorial stocks during the period 2009–2015 find a weak but significant tail dependence between gold and stock returns, which though confirms the hedging role of gold. Getting to another continent and more specifically to Africa and examining the asymmetric linkages between spot gold prices and stocks, Tweneboah et al (2020) indicate the geographical and time heterogeneity in the nexus between gold and stock market indices. Due to that, hedging to stocks can be applied in the medium and long term in Morocco, South Africa and Tunisia, while in Egypt and Ghana, this takes place only in the long run.

### *2.3. Gold and inflation*

Gold is perceived as a safe haven for investors during inflationary crises, and a type of anchor currency, which never loses its purchasing power even when monetary systems erode (Capie et al., 2005; Tully and Lucey, 2007). Due to its durable, physical asset character, gold's property is in line with inflation hedge theory i.e. investment in gold retains its purchasing power by responding to rising inflation through increased returns. Or, as price levels are increasing, the purchasing power of the US dollar is decreasing, thus

[6] Šimáková (2011) applies cointegration and VECM testing; Le and Chang (2012) apply structural VAR, while Reboredo (2013a) uses the copulas approach. A threshold error correction model is analyzed by Kanjilal and Ghosh, (2017), Gokmenoglu and Fazlollahi (2015), Wang and Chueh, (2013). Tiwari and Sahadudheen (2015) use GARCH techniques. Shahbaz et al. (2017), and Bildirici and Turkmen (2015) use nonlinear causality tests and Autoregressive Distributed Lag (ARDL), while Lin et al. (2016) conduct wavelet analysis and Baruník et al. (2016) revisit the DY spillover index.

gold will increase in value, counterbalancing the loss of purchasing power. Research studies on gold/inflation (CPI) relation yield different outcomes. Xu et al. (2021) by employing a Fourier unit root test and by examining all possible structural breaks over both short- and long-term horizons, showed that the purchasing power of gold has been maintained during the last 39 years, denoting that gold is a reliable hedge against inflation in both short and long-time horizons. Shahzad et al (2019c) on the other hand verify a positive significant relationship between gold and inflation in six major countries.[7] Worthington and Pahlavani (2007) find that the gold/inflation relation quickly incorporates macroeconomic and price instability news. Bialkowski et al. (2015) with a Markov regime-switching ADF test, Sharma (2016), and Gangopadhyay et al. (2016), through a VECM approach find gold being a hedge to inflation. Van Hoang et al. (2016), through a nonlinear ARDL test find evidence of gold being an inflationary hedge for specific countries studied (China, France, India) only in the short run, while they are emphasizing the nonlinearity of the relationship and dependence on a country's market development and overall economic condition. In the same line Salisu et al (2019) find that the hedging impact of gold against adverse inflation developments is valid for only 14 out of 32 OECD economies. Wang et al. (2013), on the other hand, apply threshold cointegration techniques aided by error correction to study US and Japan, and claim the relation to be ineffective in the long run, and dependent on circumstantial events/factors. Beckmann et al (2019a) similarly goes against the previous findings and presents evidence that inflation uncertainty is negatively related to gold prices. Tully and Lucey (2007), through a GARCH approach, do not find a significant relationship between gold and inflation.

### 2.4. Gold and interest rates

Economic theory explains the influence of interest rate changes on gold to be in line with expectations about future inflation and the opportunity cost of holding gold. Increasing commodity prices create anticipation of inflation, and thus influence constrained monetary policy by hiking interest rates. Subsequently, interest rates influence the returns of investments, and indirectly affect returns for owners of gold. This, ultimately, leads investors to consider whether they will be moving their funds to the gold market for speculation or preservation reasons, and thus cause fluctuations in gold prices. Wang and Chueh (2013) prove the validity of a long-term relationship between interest rates and gold, while Baur (2011), by regressing multivariate market factors on gold prices, is not able to show meaningful results on interest rates and gold, finding only the dollar to be the strongest determinant of gold's prices. Yildirim et al. (2021) provide evidence for Turkey during the period 2000–2017 which confirms a significant causality association with gold Granger causing interest rate movements. Mensi et al. (2015) by evaluating the usefulness of the three value protectors (gold, Dow Jones Islamic Market World Emerging Markets Index, and *T*-bills) find significant dependence between them, and always recommend these as appropriate hedges. Apergis et al. (2019) examined the transmission dynamics between the real interest rate and gold prices in the G7 during the period 1975–2016 and proved their positive and significant association, showing that gold can be a hedge against real interest rate movements especially during recessions. Finally, Chan et al. (2011) show that US Treasury bonds are a safe haven asset for equity investors during periods of financial markets stress and are therefore a better substitute to gold.[8]

### 2.5. Gold and exchange rate

Notably, gold was a traditional foreign exchange hedge, since it was the standard to which monetary systems were once based – gold's value was simply relative to other currencies and expected to have an inverse relationship to the value of the currency (Capie et al., 2005). Dong et al. (2019) confirm this inverse relationship between gold price and the USD exchange rate with both the Euro and the Pound, denoting that the association becomes more strong when the US currency has a depreciating trend. A particularly important factor to gold now is its denomination in US dollars. The value of the US dollar is determined by the US sovereign monetary policy and is triggered both by the economic conditions in the US and globally. Thus, gold displays the relative strength of the US dollar as a currency, while it serves as a currency itself.[9] Furthermore, Sui et al. (2021) focusing on three different economies (Turkey, USA, and Peru) using quantile-on-quantile regression (QQR) and quantile-on-quantile correlation (QQCOR) models, displayed a hedging aspect of gold against currency movements under specific macroeconomic conditions and dollarization levels. While, Baur (2011), Reboredo (2013b), and Beckmann et al. (2015) through the use of VAR and GARCH models, and Lin et al. (2016) through wavelet analysis, find that the US dollar dominates the gold market, and conclude that the volatility of dollar rates are turning gold into a strong hedge with respect to the movements of its labelled denominator currency. Giannellis and Koukouritakis (2019) studying the G7 countries and by using a two-regime Panel Smooth Transition Regression model, showed that hedging by gold against exchange rate risk appears mainly in times of economic turmoil. The strength of this relationship varies over time according to the findings of Capie et al. (2005) and Wang et al. (2013), with the former applying VAR and GARCH modelling, and the latter TAR. Finally, the gold price volatility and its impact on targeting exchange rate has been modelled by Gevorkyan and Khemraj (2019) showing that the exchange rates anchors are unaffected by intensive volatility of monthly gold returns.

### 2.6. Gold and uncertainty

Theoretically, a positive relationship is expected between the uncertainty measure and gold prices (Baur and McDermott, 2010).

[7] China, India, Japan, France, United Kingdom, and the United States.

[8] Mensi et al. (2015) apply multivariate density modelling through vine copulas, while Chan et al. (2011) adopt a regime switching framework.

[9] What has been coined in literature as "the anti-dollar" (Tully and Lucey, 2007).

Even though the uncertainty factor has been overlooked through the years, Baker et al. (2016) have intensely analyzed and devised a measure of elevated policy uncertainty in the US and Europe. The authors claim that in previous years, the policy uncertainty in US and Europe, which stemmed from the domains of fiscal, regulatory, and monetary policies, contributed to the steep economic decline of 2008–09 and to anemic recoveries later on. Their debate points out to the fact that higher uncertainty influences economic agents' behavior and poses a threat on macroeconomic performance and reductions in output. Thus, in crisis times, when assets' values become ambiguous and investors diminish unnecessary trading, the attractiveness of gold increases, due to its relatively simple market and the fact that it gives investors a greater sense of safety.

Many researchers claim that in developed stock markets, gold serves as the strongest go-to asset when turmoil and unpredictability are expected, thus, offering protection of portfolio values (Zhang et al., 2021; Balcilar et al., 2016; Beckmann et al., 2017). Still, existing studies rarely incorporate gold prices regression on economic policy uncertainty indicators. Ma et al. (2021) explored the association between economic uncertainty and conditional volatility in the gold futures market (daily data from 16 countries from 1997 to 2019) using Markov regime-switching GARCH-MIDAS models and showed that higher uncertainty leads to higher volatility in the gold futures market, a finding which the authors further verify in the cases of the Global Financial Crisis of 2008 and the European Debt Crisis. Balcilar et al. (2016) analyze only gold prices returns and different uncertainty proxies. Reboredo and Uddin (2016), and Yin and Han (2014) examine the impact of financial stress and policy uncertainty on the price dynamics of energy (crude oil, heating oil and gas) and metals, futures, and other commodities differently, but do not include macroeconomic indicators. Yin and Han (2014) by constructing a multivariate GARCH, find that the relation between the macroeconomic unpredictability and gold prices varies over time. The study of Gozgor et al. (2019) highlights the role of geopolitical uncertainty in affecting gold returns by utilizing a Bayesian Graphical Structural Vector Autoregression model, while Piffer and Podstawski (2018) propose a new instrument to identify uncertainty shocks in a proxy structural vector autoregressive model (SVAR), which is related to the gold price variations. Their results show that the uncertainty events identified by this proxy generate larger and more rapid effects on the real economy, when compared to other approaches of uncertainty shocks identification. Reboredo and Uddin (2016) on the other hand, using stock market volatility indices, do not find crucial significance of uncertainty in determining commodity futures prices. Beckmann et al. (2017) is the only study that considers gold price dynamics against stocks, bonds, exchange rates, and uncertainty measures. Yet, it differs from our study since it includes only macroeconomic and inflation uncertainty proxies, not the indicators itself, while oil is also missing as a factor.

Overall, the GFC of 2007–2009 and the European Sovereign Debt Crisis of 2010–2012, have generated a different reality, which is still financially, economically, and geopolitically active (e.g., Brexit, Syrian war, Libyan war, Nagorno-Karabakh war, Russian Invasion of Ukraine). In such a historical context, and along with the gradual transition from a bipolar, to a unipolar, and currently a multipolar world (Jiang, 2013; Muzaffar et al., 2017; Kelly, 2020) in terms of power distribution at the global level, it is important to study the existing interlinkages and how they affect key global assets (including gold, crude oil, the dollar exchange rate, S&P 500, Treasury bills). This should be done through both a unified time frame, and a time varying one like those applied in this study. Thus, there are dynamic spillovers across the markets that could peak during various financial and non-financial crises, and subsequently this suggests that there are potential contagion effects.

## 3. Methodology and data

### 3.1. Methodology and model specification

We attempt to model and explain the interlinkages between the price of gold, crude oil price, inflation, a stock market index (S&P 500), the three-month Treasury bill rate, the US dollar exchange rate, and the economic policy uncertainty (EPU), by using two distinct approaches. First, we incorporate a Vector autoregressive model (VAR) (see Appendix)[10] and then we proceed with the Diebold and Yilmaz (2012), Diebold and Yılmaz (2014) spillover index which is VAR based.

### 3.2. Spillover indices

Diebold and Yilmaz (2012), DY henceforth, introduce a methodology for measuring spillovers based on forecast error variance decompositions. Their empirical technique is based on the decomposition of the H-step-ahead forecast-error variance for each of the K variables of a K-dimensional Vector Autoregression (VAR) model. The DY spillover indices are estimated based on the generalized VAR which is invariant to the ordering of the variables in the system, unlike the restrictive Cholesky factorization. The generalized forecast error variance decompositions (GFEVDs) split the forecast error variances into shares as own-shocks and cross-shocks, allowing us to obtain total, net, and directional return spillover dynamics.

First, let us consider a covariance stationary VAR($p$) of market returns:

$$X_t = \sum_{i=1}^{p} \phi_i X_{t-i} + \varepsilon_t$$

[10] As discussed below, the DY spillover analysis (2012, 2014) provides results which are generated from Variance Decompositions and Impulse Response Functions, and subsequently, we obtain with it time-varying results, which are opposed to the static IRFs. However, for comparison purposes, in terms of the time-varying versus the static results, we provide the statistic IRFs in the appendix.

where, $X_t$ is a $K \times 1$ vector of returns, $\varphi_i$ is a $N \times N$ parameter matrices and $\varepsilon_t$ is a random error with zero mean and equal variance.

Given that the VAR system is covariance stationary, the above equation can be written in an MA($\infty$) representation:

$$X_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \qquad where \qquad A_i = \sum_{i=1}^{p} \phi_i A_{t-i}$$

Under the generalized VAR model, the H-step-ahead GFEVDs can be written as[11]:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)^2}$$

Each entry of the variance decomposition matrix is normalized by its row sum since the sum of the row elements of the generalized variance decomposition is not equal to 1.

$$\widetilde{\theta}_{ij}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}$$

Total Spillovers Index (TSI) can be calculated as given below using the GFEVDs:

$$TSI(H) = \frac{\sum_{i,j=1,i\neq j}^{K} \widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{K} \widetilde{\theta}_{ij}^{g}(H)}.100\% = \frac{\sum_{i,j=1,i\neq j}^{K} \widetilde{\theta}_{ij}^{g}(H)}{K}.100\%$$

*TSI* measures the total contribution of spillovers among all the markets under consideration. The index ranges from 0 to 100 %, a higher (lower) value of the index shows stronger (weaker) interactions across the markets in the generalized VAR system.

The DY method also allows us to obtain the gross Directional Spillovers Indices (DSI) to measure the spillover from market *i* to all other markets *j* in the system, as well as the spillover from all markets *j* to market *i* as given below.

$$DSI_{j\to i}(H) = \frac{\sum_{j=1,j\neq i}^{K} \widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{K} \widetilde{\theta}_{ij}^{g}(H)}.100\%$$

$$DSI_{i\to j}(H) = \frac{\sum_{j=1,j\neq i}^{K} \widetilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{K} \widetilde{\theta}_{ji}^{g}(H)}.100\%$$

Finally, the net directional spillover index (NSI) from market *i* to all others can be calculated as:

$$NSI_{i\to j}(H) = DSI_{i\to j}(H) - DSI_{j\to i}(H)$$

Based on the *NSI*, we determine the position of the market; positive (negative) value of the net spillover index implies that the market is a transmitter (receiver) of return spillovers.

It is also worth-noting that we run rolling-window estimations to analyze the transmission mechanism in a time-varying fashion. As suggested by Diebold and Yilmaz (2012) the traditional econometric models provide a single average parameter, however, assuming stable spillover dynamics would be unrealistic given the changing ecosystem of financial markets due to structural reforms and financial crises. More specifically, we use a rolling estimation window of 40 months and a 10-step-ahead forecast horizon for the variance decomposition. We repeat the analysis with different choices of the rolling estimation window and forecast horizon steps, i.e. increasing and decreasing them up to 50 % of the fixed choices. The untabulated results imply that qualitative results stay similar, which supports the robustness of the results.

### 3.3. Variables and data description

The selected variables are: gold price, US dollar exchange rate, crude oil price, a stock market index (S&P 500), inflation (CPI), economic policy uncertainty (EPU), and the short-term interest rate (the three-month Treasury bill). All data is retrieved and is publicly available through the FRED database of the Federal Reserve Bank of St. Louis (2020). The sample spans from January 2nd, 1986 to December 31st, 2019, with a total sample of 408 observations. The choice of data with a monthly frequency is based on the grounds that all variables are available on a monthly basis. All variables are transformed in natural logarithms due to their index character or US dollar value, except for the interest rate which takes a percentage form.

Exhibit 1 presents all the variables in terms of the exact variable description, units of measurement, forms, and their official names.

[11] Since VAR and GFEVDs are well established in the literature, we do not present more details here. For further details see the Appendix and please refer to Koop et al. (1996), and Pesaran and Shin (1998).

Exhibit 2 and Exhibit 3 provide the descriptive statistics for the employed variables at level, and the first differenced logarithmic variables respectively,[12] excluding the short-term interest rate, i.e., the three-month Treasury bill (TB), which is in its first difference.[13]

**Exhibit 1.** Brief description of variables.

| Variable | Description | Measure/Units | Form | Official Variable Name | Variable Name Used |
|---|---|---|---|---|---|
| **Gold price** | London Bullion market AM fix | US dollars per troy ounce | Log | GOLDAMGBD228NLBM | GOLD |
| **Exchange rate** | Trade Weighted US dollar Index: major currencies | Index: March 1973 = 100 | Log | DTWEXM | EXC |
| **Oil price** | Crude oil WTI | US dollars per barrel | Log | DCOILWTICO | OIL |
| **Stock market** | Standards & Poor's 500 Index | The stock market index | Log | S&P 500 | SP |
| **Inflation** | Consumer Price Index (All urban consumers - US) | Index: 1982–1984 = 100 | Log | CPIAUCNS | CPI |
| **Uncertainty** | US economic policy uncertainty index | Index | Log | USEPUINDXD | EPU |
| **Interest rate** | 3-Month *T*-Bill Secondary Market rate | Percentage | % | FED US, DTB3 | TB3 |

*Notes*: All data obtained from the Federal Reserve Bank of Saint Louis Database (FRED, 2020). All data is monthly and covers the period 1986/01/02–2019/12/31. CPI is available on a monthly basis and subsequently variables with daily frequencies are modified to monthly ones (using the aggregation method of averages).

**Exhibit 2.** Descriptive statistics of variables at level.

| | GOLD | EXC | OIL | SP | CPI | EPU | TB3 |
|---|---|---|---|---|---|---|---|
| **Mean** | 701.1286 | 88.68533 | 44.17735 | 1153.922 | 184.4656 | 100.3418 | 0.031661 |
| **Median** | 417.3474 | 89.08404 | 31.18612 | 1128.205 | 182.2000 | 89.68290 | 0.030650 |
| **Maximum** | 1780.648 | 120.1897 | 133.8800 | 3230.780 | 258.4440 | 253.9187 | 0.088200 |
| **Minimum** | 256.1977 | 69.06084 | 11.34727 | 211.7800 | 108.7000 | 38.20903 | 0.000100 |
| **Std. Dev.** | 453.8574 | 10.01046 | 29.14822 | 710.3382 | 43.40979 | 41.30387 | 0.024652 |
| **Skewness** | 0.800796 | 0.217632 | 0.865434 | 0.764291 | −0.040648 | 1.205516 | 0.202263 |
| **Kurtosis** | 2.092180 | 2.799815 | 2.611647 | 3.051004 | 1.775395 | 4.307216 | 1.833304 |
| **Jarque-Bera** | 57.61702 | 3.901978 | 53.49432 | 39.76580 | 25.60654 | 127.8722 | 25.92195 |
| **Probability** | 0.000000 | 0.142133 | 0.000000 | 0.000000 | 0.000003 | 0.000000 | 0.000002 |

**Exhibit 3.** Descriptive statistics of first differenced logarithmic variables.

| | DLGOLD | DLEXC | DLOIL | DLSP | DLCPI | DLEPU | DTB3 |
|---|---|---|---|---|---|---|---|
| **Mean** | 0.003574 | −0.000660 | 0.002356 | 0.006695 | 0.002101 | −0.000589 | −0.000136 |
| **Median** | 0.000724 | 0.000415 | 0.011684 | 0.011765 | 0.002150 | −0.008279 | 0.000000 |
| **Maximum** | 0.163869 | 0.064736 | 0.391871 | 0.123780 | 0.013675 | 1.065333 | 0.004600 |
| **Minimum** | −0.123910 | −0.048328 | −0.394332 | −0.245428 | −0.017864 | −0.743459 | −0.008600 |
| **Std. Dev.** | 0.035060 | 0.016652 | 0.086617 | 0.043421 | 0.002536 | 0.245866 | 0.001847 |
| **Skewness** | 0.389387 | 0.005676 | −0.449746 | −1.086659 | −1.383771 | 0.477720 | −1.105768 |
| **Kurtosis** | 4.553494 | 3.430381 | 5.620810 | 6.640969 | 14.62048 | 4.175540 | 5.944455 |
| **Jarque-Bera** | 51.21130 | 3.143336 | 130.2015 | 304.9102 | 2419.868 | 38.91529 | 229.9671 |
| **Probability** | 0.000000 | 0.207698 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 |

## 4. Empirical findings

### *4.1. Spillover analysis*

Moving to the spillover analysis, Exhibit 4 presents the estimates of the total volatility spillovers. The diagonal entries in the spillover matrix are the own variance shares estimates, showing the proportion of the forecast error variance of market $i$ from its own shocks. The non-diagonal entries show the contribution to the forecast-error variance of variable $i$ originating from shocks to market $j$. The column "From Others" reports the total spillovers received by a particular market from all others, while the row "Contribution to

[12] Our choice to use log-first difference data of EPU is based on the following. Baker et al. (2016), who introduced EPU in the literature, use both log(EPU) and Δlog(EPU), while Chauvet and Potter (2000) use the log first difference of a leading economic index, and Ciminelli et al. (2022), do the same for various uncertainty indices.

[13] As far as TB is concerned, we do not use the log-first-difference but the first difference, based on the unit root results. However, the following papers use TB in log-first-difference form. For example, Cover and Keeler (1987) state clearly that "the log-first-difference form can be justified on theoretical grounds and conclude that the log-first-difference form is strongly justified empirically and theoretically"; the same is evident in Domian (1992), Chopin et al. (1997), and in Baig and Goldfajn (1999). Moving to more recent literature, Lee (2021), Ahmed and Sarkodie (2021), Naeem et al. (2021), follow the same approach. Indicatively, Naeem et al. (2021) state that SHTI is the log first-difference of three months treasury bill rate. Finally, Montes-Rojas (2019) uses the first-difference of the 3-months Treasury Bill rate, which is what we also use.

others" shows the spillovers transmitted from a particular market to all others. The row "Net Spillovers" is calculated by subtracting the row "Contribution to others" from "From Others".

The total spillover index in the lower right corner of the spillover matrix is 23.10 %, which shows that approximately 23 % of the volatility forecast error variance in the markets comes from spillovers. In other words, 77 % of the variance results from own-market spillovers. Looking at the pairwise spillovers, gold and exchange rate appear to have a strong bidirectional spillover; gold explains 11.1 % of the forecast-error variance of the effective exchange rate fluctuations and the exchange rate contributes 13.2 % to the forecast-error variance of gold returns. The stronger relation between gold and exchange rate is expected due to the store of value properties of both; when the US dollar weakens against the currencies of its trading partners, global investors seek alternative investment assets, such as gold, to store value.

Gold (crude oil) seems to explain 2.6 % (1.6 %) of variances in crude oil (gold) returns. This shows that the bidirectional spillovers between gold and oil returns are weak. However, the oil market is the biggest shock transmitter to the others in the VAR system, contributing 42 % to all the others. CPI also significantly contributes to the forecasting error variance of gold and oil markets. In fact, CPI contributes 25 % to all remaining markets, implying that inflation shocks can substantially spill over to the financial markets.

The stock market contributes 1.8 % to the forecasting-error variance of gold and 0.4 % to that of crude oil. Gold and crude oil markets transmit 1.4 % and 0.4 % to the forecasting variance of the stock market, respectively. This suggests that the oil market offers greater diversification benefits than gold market. Furthermore, EPU contributes to gold and oil market by 2.6 % and 1.4 %, respectively. The stock market is the biggest shock receiver from EPU whereas stock market explains 10.3 % of the forecast error variance of EPU. On the other hand, in net terms, the oil market seems to be the biggest shock transmitter and CPI is the main receiver. Gold market is almost neutral with a −2% net spillover value.

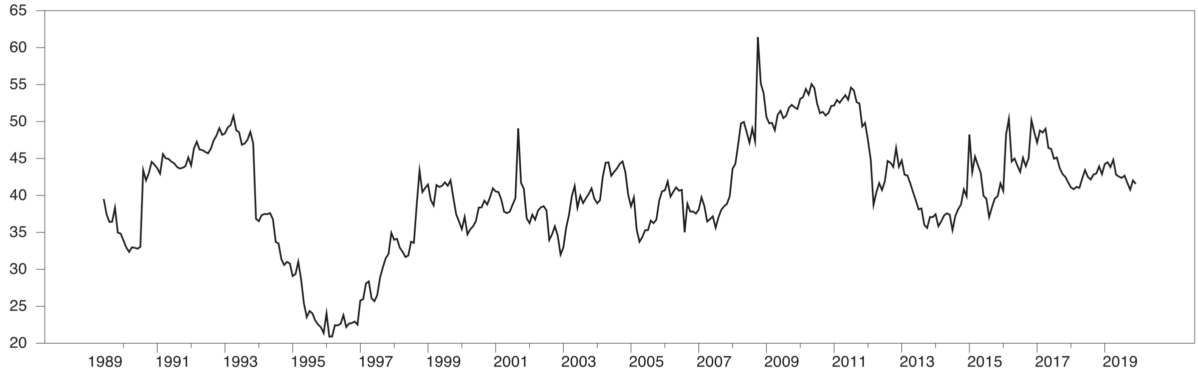
**Exhibit 4.** Spillover Matrix.

| | GOLD | OIL | SP | EXC | EPU | TB | CPI | From Others |
|---|---|---|---|---|---|---|---|---|
| **GOLD** | 76 | 1.6 | 1.8 | 13.2 | 2.6 | 0.5 | 4.3 | 24 |
| **OIL** | 2.6 | 75.1 | 0.4 | 6.2 | 1.4 | 0.6 | 13.7 | 25 |
| **SP** | 1.4 | 0.4 | 87 | 2.1 | 8.7 | 0.4 | 0 | 13 |
| **EXC** | 11.1 | 5.6 | 1.7 | 77 | 0.3 | 1.3 | 3 | 23 |
| **EPU** | 2.2 | 0.1 | 10.3 | 0.8 | 84.3 | 1.2 | 1.1 | 16 |
| **TB** | 0.3 | 6.9 | 4.7 | 0.8 | 3.9 | 80.7 | 2.7 | 19 |
| **CPI** | 4.4 | 27.8 | 1.9 | 6.3 | 1 | 0.5 | 58 | 42 |
| **Contribution to others** | 22 | 42 | 21 | 29 | 18 | 4 | 25 | 162 |
| **Contribution including own** | 98 | 118 | 108 | 106 | 102 | 85 | 83 | **23.10 %** |
| **Net Spillovers** | −2 | 17 | 8 | 6 | 2 | −15 | −17 | |

*Notes:* The variance decomposition is based upon a monthly generalized VAR model. The $(i, j)$-th value is the estimated contribution to the variance of the variable $i$ coming from innovations to the variable $j$.

The static spillovers provide a picture of pairwise and total spillovers on average while they discard the dynamic characteristics of spillovers. The analysis of the time-varying behavior of directional spillovers can give further insights and implications about the direction and magnitude of the transmission mechanism as the size of spillovers changes due to financial crises and recessions. Exhibit 5 draws the total spillovers during the sample period. The graphical evidence of the dynamic spillovers show that spillovers across markets peak during financial crises, such as the 2007–2009 Global Financial Crisis and the 2010–2012 European Sovereign Debt Crisis. Spillovers across markets reached their maximum during the Lehman Brothers collapse of September 15, 2008. This suggests potential contagion effects; global investors and traders tend to imitate each other's trading strategies under periods characterized by high uncertainty. Stronger interdependence among financial markets and contagion incidences at times of market turmoil are also found by Papavassiliou (2014) and Guidolin et al. (2019). Moreover, heightened spillovers imply decreased diversification benefits when needed most, as suggested by Al-Yahyaee et al. (2019).

**Exhibit 5.** Total Spillover Index.



Exhibits 6 and 7 exhibit the directional spillovers from and to each financial market, respectively. The plots demonstrate that shock transmission varies greatly over time. The spillovers from each market seem to be negligible during tranquil times, however at periods of high volatility, the directional spillovers significantly surge. The gross volatility spillovers from the gold market to the others are generally smaller than the spillovers from the others. The most important shock transmitters are stock market, exchange rate and oil at times of market turmoil.

**Exhibit 6.** Contribution from the markets.

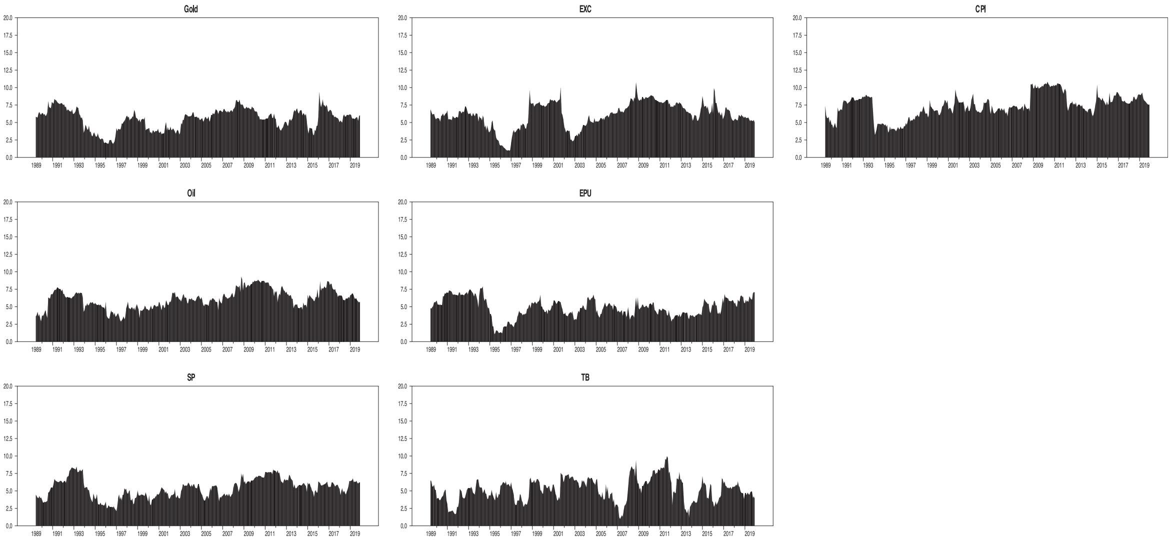



**Exhibit 7.** Contribution to the markets.

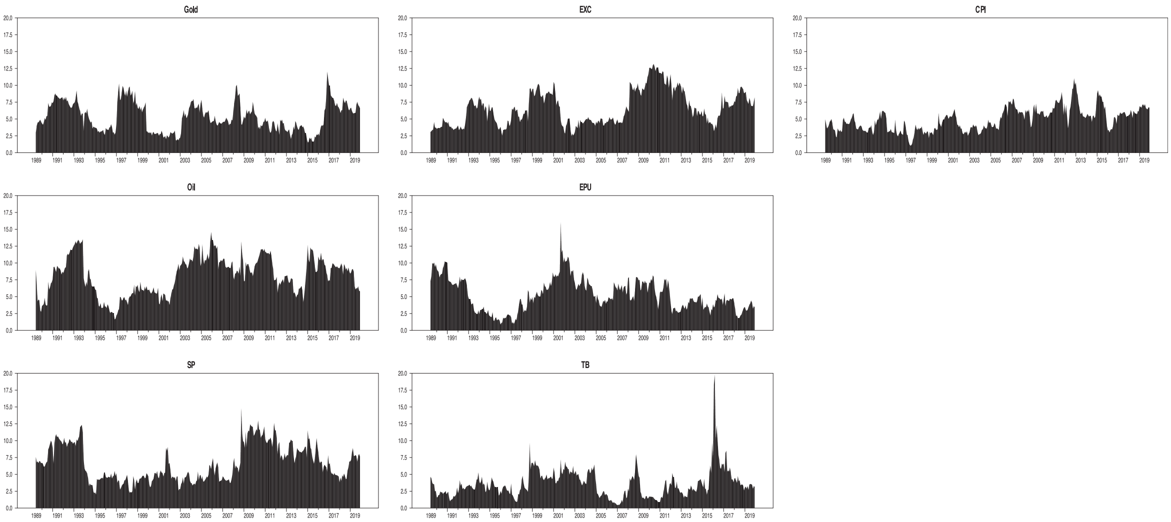
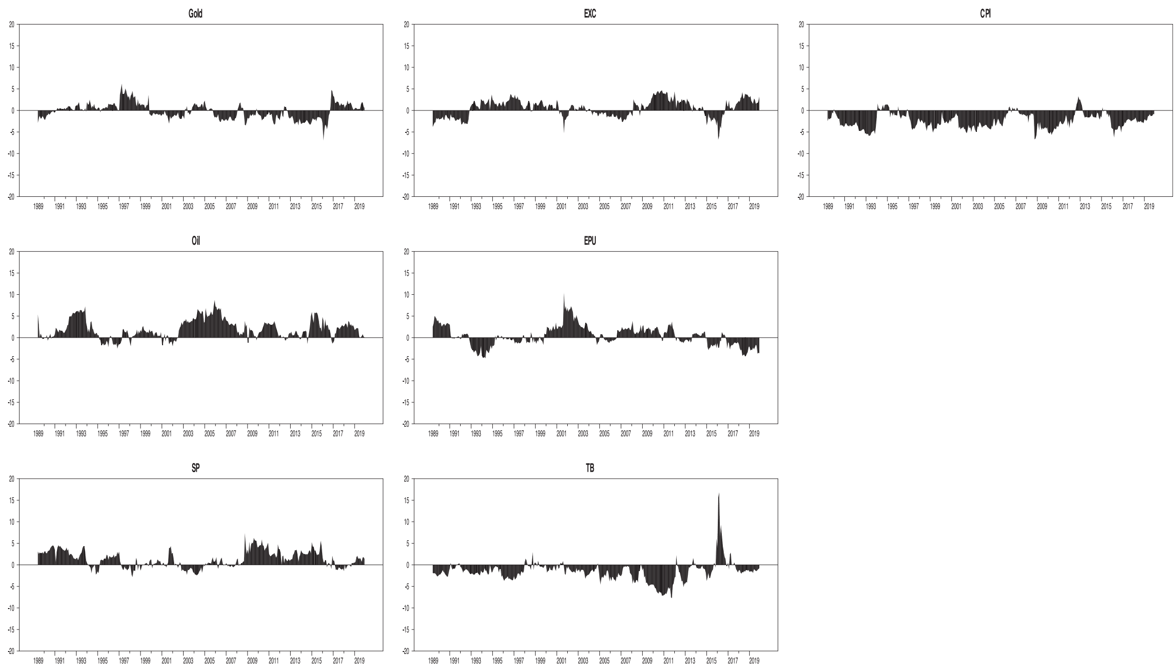



Exhibit 8 presents the net spillovers. As discussed in the methodology section, the net spillovers are calculated as the difference between the "contribution from" column sum and "contribution to" row sum. The net spillovers depict shock transmitter and receiver markets under different market conditions in a time-varying fashion. The positive (negative) values of net spillovers imply a net transmitter (recipient) position. Based on the plots in Exhibit 8, all the markets are at both the giving and receiving ends of the net shock spillovers. Crude oil seems to be net volatility spillover. Shock transmission from crude oil market reached its maximum during the Iraq and Afghanistan wars in 2003. It is also clear that EPU transmits a significant amount of shocks to the others in the system and it is a net transmitter, particularly when the market is characterized by pessimism. TB and CPI seem to be net shock recipients. Gold market is a neutral market in terms of shock transmission as positive and negative values are almost equal to each other on average, which is a finding we mentioned in static spillover analysis. The neutrality of gold suggests that gold can provide potential hedging and diversification opportunities. However, gold received volatility from others during the financial crisis of 2007–2009, which may cast doubt on the safe haven property of gold.

**Exhibit 8.** Net Spillovers.




### 4.2. Discussion

Overall, our findings add to the literature that focuses on the impact of uncertainty on macroeconomic and financial variables (Chuliá et al., 2017; Gupta et al., 2018; Gabauer and Gupta, 2020; Ma et al., 2021; Zhang et al., 2021) and on the uncertainty spillovers across countries and markets (see Castelnuovo et al., 2017, and Kang et al., 2021 for a literature review). More specifically, our empirical results indicate that there are short-run linkages among the examined assets, economic and financial variables (namely gold, crude oil, S&P 500, dollar exchange rate, inflation, economic policy uncertainty and Treasury bills). Based on a VAR methodology (available in the Appendix), various relations were identified and yielded consistent results. The prevailing interlinkages, that should be initially stressed, are the dollar depreciation that in the short-run increases the gold price, the drop of S&P 500 that increases EPU, the crude oil, and the Treasury bill decrease that decreases inflation (CPI), and vice versa.

We have also proceeded to a VAR based spillover index method which allows us to capture dynamic transmission mechanisms over time. Opposed to Adewuyi et al. (2019), that employ a multivariate GARCH model to examine the gold-stock nexus without capturing the time varying nature of spillovers, we have managed to detect those. By analyzing the dynamic dependencies, not only between gold and stock returns (see Boako et al., 2019; Triki and Maatoug, 2021),[14] but between more variables, we have detected various pairwise and dynamic spillovers. At the pairwise spillovers we show that gold and the exchange rate appear to have a strong bidirectional spillover effect; more specifically, gold explains 11.1 % of the forecast-error variance of the effective exchange rate fluctuations and the exchange rate contributes 13.2 % to the forecast-error variance of gold returns. While bidirectional spillovers between gold and oil returns are weak, the oil market is the biggest shock transmitter to the others, contributing 42 % to all the others. On the other hand, CPI contributes 25 % to all the remaining markets, implying that inflation shocks can substantially spill over to the financial markets. The stock market is the biggest shock receiver from EPU whereas the stock market explains 10.3 % of the forecast error variance of EPU. At times of market turmoil the most important shock transmitters are the stock market, the exchange rate, and oil. Dynamic spillovers across markets peak during financial crises, such as the 2007–2009 Global Financial Crisis and the 2010–2012 European Sovereign Debt Crisis. Subsequently, a contagion risk sharing between the markets is identified in the case of the USA.[15] Thus, it can be concluded that investors and traders tend to imitate each other's trading strategies under turbulent periods, and the safe haven attribute of gold could be questioned as well.

Returning to the non-time varying VAR model results (see Appendix), we find strong and persistent evidence that gold price is primarily influenced by CPI, while it is also led by economic policy uncertainty index, and is related to the dollar exchange rate. More

[14] Boako et al. (2019) by employing full-range tail dependence and the stochastic copula model, detect that there is contagion risk between stock and gold returns, rejecting the safe haven attribute of gold.

[15] The risk of contagion among the Brent crude oil market, London gold market, and stock markets (Chinese and European) are studied by Lin et al. (2019) detecting that there is a bidirectional risk of contagion among these markets in extreme events.

specifically, the appreciation of the dollar decreases the price of gold, and vice versa, promoting gold's hedge function, which is in line with the findings of Capie et al., (2005), Baur (2011), Gangopadhyay et al. (2016), Dong et al. (2019), Giannelis and Koukouritakis (2019), Sui et al. (2021), and partly Sari et al. (2010); while Sari et al. (2010) find weak long-run equilibrium among spot prices of gold, oil price, and the dollar/euro exchange rate, we find stronger ones holding in a short-run context. Subsequently, gold could be perceived as the so called "anti-dollar", a view which is present in Tully and Lucey (2007), Beckmann et al. (2015), and Lin et al. (2016).

To continue with the Economic policy uncertainty index, an EPU increase increases gold price, which is practically in line with the findings of Yin and Han (2014), Wei et al. (2017), Gozgor et al. (2019), Piffer and Podstawski (2019), Ma et al. (2021), and Zhang et al. (2021) contradicting Reboredo and Uddin (2016). Market participants seem to change their gold preference in a time-varying mode. Ma et al. (2019) also capture a positive and significant EPU impact on the crude oil return volatility, which is a short-lived one and decays within one year; a result which is supported by our DY rolling window estimates showing a time-varying impact as well, as it is evident in Beckmann et al. (2019), and Feng et al. (2020).

What needs to be stressed here is that in our time-varying approach, we have found EPU being a main transmitter, while gold, along with the dollar exchange rate, act both as receivers and transmitters over the sample period. It is interesting to add the GIRFs that capture a positive response of gold to increased EPU, for a period of three to four months, which is a shock that wears out.

The negative CPI and gold relation are captured too, meaning that gold acts as a hedge of inflation; a finding which is consistent with the work of Gangopadhyay et al. (2016), partly of Beckmann et al (2019a), and of Xu et al. (2021). The short-run responses of gold to shocks from S&P 500 though were not detected,[16] thus the portfolio hedge role of gold was not confirmed, something which is partly in line with the work of Shrydeh et al. (2019). These results are not in line with Basher and Sadorsky (2016), Gangopadhyay et al. (2016), Bouri et al. (2017), Chen and Wang (2017), Dar and Maitra (2017), and Kumar (2017).

Apart from gold, crude oil prices have shown an inverse relation to the US dollar exchange rates as well. These findings, and especially the short-term behavior and the causality direction between gold and crude oil are consistent with Sari et al. (2010), Ciner et al. (2013), Reboredo (2013a), Wang and Chueh (2013), Gokmenoglu and Fazlollahi (2015), Tiwari and Sahadudheen (2015), Van Hoang et al. (2016), Śmiech and Papież (2017), and partly of Wen et al. (2020).

Overall, gold, which is known as a permanent component of wealth and seemingly an irreplaceable asset in the global economy – especially now that its price is at a historical peak –acts as an important investment asset. We have shown that it keeps on playing a central role both as a receiver and as a transmitter over the studied period, but it still needs to be monitored on a time varying way. Given that the dynamic spillovers across markets peaked during the two recent financial crises (the Global Financial Crisis of 2007–2009 and the European Sovereign Debt Crisis of 2010–2012) there is evidence that shows the existence of potential contagion effects, and the tendency of global investors and traders to imitate one another on their trading strategies, especially during periods of increased uncertainty. Additionally, based on net spillovers, the neutrality of gold suggests that it can provide potential hedging and diversification opportunities. However, gold received volatility from others during the financial crisis of 2007–2009, which may cast doubt on its safe haven property.

Additionally, crude oil – based on GIRFs – responds negatively to the exchange rate and to EPU shocks, verifying the findings of Yao et al. (2020), while also partly those of Lin and Bai (2021), and positively to the rest of the variables, with varying results in terms of statistical significance and time profiles. A positive impact running from gold to crude oil in the short-run was captured by the VAR as well, along with the negative EPU short-run uni-directional Granger-causality, which also calls for our attention. At the same time the GIRFs of CPI show that it responds negatively only to the exchange rate, for a sustained period of five to six months, meaning that when dollar depreciates inflation increases, which is also the case in Usupbeyli and Ucak (2020). In terms of the CPI response to EPU in the case of USA, it wears out comparatively quickly and it is not statistically significant throughout, in contrast to Jeon (2018) who detects a negative response on four Asian economies.

Last but not least, the GIRFs of EPU show that the variable responds negatively only to S&P 500, for a period of approximately-two months, meaning that when S&P 500 decreases, EPU increases (and vice versa), supporting the findings of Antonakakis et al. (2013), Brogaard and Detzel (2014), Kang and Ratti (2013, 2014), Liu and Zhang (2015), and Arouri and Roubaud (2016), and positively in the cases of gold and CPI, for one month. The GIRFs of the three month Treasury bill display that it responds negatively only to EPU, for a period of four to five months, and positively in the cases of dollar exchange rate, crude oil and S&P 500, for varying time periods, lasting from one to five to six months, respectively.

## 5. Conclusion

Our study employs a joint model which involves several factors, such as commodities (gold and crude oil), investment instruments (Treasury bills), macroeconomic variables (inflation, exchange rate), and an unpredictability factor (economic policy uncertainty). We have applied a Vector Autoregressive model (VAR), and the spillover index of Diebold and Yilmaz (DY), and our specifications have managed to capture accurately gold's behavior as a hedge tool that can provide diversification opportunities. However, based on net dynamic spillovers, gold received volatility from other markets during the financial crisis of 2007–2009, which may cast doubt on its safe haven property.

By utilizing the forecast-error variance decomposition framework of a generalized VAR model proposed by Diebold and Yilmaz

[16] Singhal et al. (2019), employing an ARDL Bound testing Cointegration approach, show that international gold prices positively affect the stock price of Mexico, while oil price affects them negatively.

(2012), first, we have identified the spillover effects as opposed to common shocks affecting the entire financial system, and second, we have used the identification of directional shocks to document differences in their magnitude moving from tranquil to crisis times. Our results suggest that gold and the US dollar, still play a prominent role as amplifiers of systemic risk but in a time-varying way. Moreover, this econometric approach, with the use of a rolling window, has allowed us to quantify the intra-month spillover effects between different sets of financial and macroeconomic variables in a time-dependent fashion. Thus, by doing so, we have investigated the inter-connectedness of financial markets, which is of crucial importance for the understanding of financial crises and their propagation mechanisms. This finding is critical both for the systemic risk identification and the financial stability preservation (Hartman et al., 2004).

Our findings indicate that the selected variables are closely interlinked; proving integration among the examined markets, and the existence of a transmission mechanism which is studied as well. Based on VAR methodology, the relations identified yielded consistent results throughout. The analysis of the period from 1st of January 1986 to 31st of December 2019 provides strong evidence that gold is primarily influenced by its past values and the value of the US dollar, identifying gold as a strong dollar hedge, while crude oil, and Treasury bills, drive inflation. Along with that, we have detected through the DY spillover index, results and implications that pertain to US environment and investors.

Our rolling window DY estimates indicates strong spillover effects between exchange rate and gold returns. In general, co-movement dynamics display state-dependent characteristics. Both total and directional spillovers increase significantly during market turbulence caused by severe financial crises such as the GFC of 2007–2009. Net spillovers switch between positive and negative values for all the markets, implying that recipient/transmitter position changes drastically with market events. Economic policy uncertainty, stock market returns, and crude oil price returns are the main transmitters while Treasury bills and CPI are the main return shock recipients. Gold and exchange rate act both as receivers and transmitters over the sample period.

Overall, we have added to the understanding of the existing interlinkages of the studied variables and stressed the importance of a time-varying approach. Subsequently, one should bear in mind that each of the analyzed factors in this paper contains information for forecasting the price of gold, crude oil and the dollar exchange rate, and should be taken into account, both in the short-run and dynamically. Financialization of commodity markets, tightened regulations, depletion of resources, and geopolitical pressures extend some explanation for the observed intensity. Lastly, it is in some manner dispiriting that most linkages explain US (and wider) macroeconomic stance and state-policies, as the underlying factors that influences gold horizons. It remains to be seen whether and how much irregular market events and complex linkages are going to affect the price of gold. The suggestions on the standard hedge aspects of it or leading predictors of its price can be deceptive if one does not consider the wider context and stance.

Our findings have certain implications for investors, policymakers, and scholars. The detected interdependencies across the investigated assets, economic and financial variables, have a significant impact in the decision-making process of various stakeholders. For a policy maker, it is important to know that the US financial markets are not only highly integrated, but shocks to one market cause certain, measurable, crisis-related, and time-dependent comparable spillovers to other market segments. Within this context, it is of paramount importance for the preservation of the stability of the financial system by policy makers to know which are the factors, including commodities, investment instruments, macroeconomic variables, and unpredictability indices, that act as receivers or as transmitters of shocks. Additionally, the financial friction which may exacerbate the negative impact of cash flow uncertainty on innovation activities (Beladi et al., 2021) could be addressed more effectively as well.

Furthermore, for the policy maker to know, indicatively, that inflation (CPI) and Treasury bills are net receivers, adds value to the economic policy design and conduct. It is important to know that shocks to stock markets and crude oil are more likely to be transmitted to the rest of the markets. Thus, stock markets and crude oil, along with Economic Policy Uncertainty index (EPU), should be closely monitored and possibly used in an early warning indicator system.

Moreover, the fact that the Treasury Bills, along with Inflation, play a crucial role in receiving and eventually mitigating uncertainty to the rest of the financial markets, strengthens the idea of central policy actions. Examples of these policy actions include the US Federal Reserve's 2 USD trillion stimulus package on March 2020,[17] and the ECB's rescue plan launched on March 2020, the temporary asset purchase program of private and public sector securities of €750 billion, named as a Pandemic Emergency Purchase Programme (PEPP), with an explicit target to "*counter the serious risks to the monetary policy transmission mechanism and the outlook for the euro area posed by the outbreak and escalating diffusion of the coronavirus, COVID-19*".[18] These policies limit widespread contagion effects. Finally, as far as investors are concerned, they can enhance their hedging and portfolio diversification practices, by determining and fine-tuning their strategies to take advantage of the increased know-how regarding the way markets influence one another in a time-dependent way.

To conclude, the current study has multiple implications. Firstly, the strengthened level of total and directional spillovers during market turbulence caused by severe financial crises suggests the deteriorated diversification benefits when needed most. Secondly, gold, probably along with crude oil futures, may provide hedging as their dynamics seem to be independent of S&P 500 and Treasury bills, and partly in line with other macro-financial variables, including the dollar exchange rate and CPI. They could subsequently help investors build more effective hedging strategies in managing market risk. Finally, comprehending what drives gold, crude oil, dollar exchange rate markets, and S&P 500 index, is relevant for policy makers and authorities, in determining, for example, their monetary policy making, and probably whether cryptocurrencies should serve as a medium of exchange and/or a store of value as well. This could be further considered and explored as another import driver in expanding the present research in the future.

[17] Your Guide To The Federal Stimulus Package (forbes.com) Announcement of 27.03.2020.

[18] ECB announces €750 billion Pandemic Emergency Purchase Programme (PEPP) (europa.eu).Announcement of 18.03.2020.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

## Appendix

*Supplement part on Methodology and model specification*

*A Vector Autoregressive model (VAR), Granger Causality tests, and Generalized Impulse Response Functions (GIRFs)*

On the first part of our empirical analysis, we employ Vector Autoregressive (VAR) methodology, Granger causality tests, and Generalized Impulse Response Functions (GIRFs) to focus both on the statistical causality of the investigated variables within a VAR framework, and their responsiveness to certain shocks. Since VAR and GIRFs are well established in the literature, it has to be noted that VAR, promoted by Lucas (1976) and Sims (1980), is a statistical model that captures the relationships between multiple variables (Hamilton, 1994; Lütkepohl, 2009). Being a type of a stochastic process model, it generalizes the univariate autoregressive model by allowing for multivariate time series (Granger, 1981; Engle and Granger, 1987).[19] Each one of our seven variables has an equation explaining its evolution over time, which includes the variable's lagged values, the lagged values of the other variables in the model, and an error term.

Once the choice of the VAR's order (the lag-length) is determined, which is made on the basis of minimizing the Akaike information criterion (AIC), a third order VAR model is accepted.[20] Without presenting the VAR(3) specifications,[21] we proceed with the investigation of the statistical causality between the variables by performing Granger-causality tests. As known, if a variable is found to have a statistically significant impact on another variable, or group of variables, then it is said to Granger-cause it/them.[22] Finally, within the VAR framework we proceed with impulse response analysis. Specifically, we inspect and evaluate the impact of shocks across variables, tracing the evolutionary path of an impacted variable over time. Impulse response functions (IRFs) are usually portrayed graphically -a shock to each of the *n* variables results in *n* responses functions and graphs (Wang, 2008). The IRFs largely depend on the specific ordering of variables, founded in economic reasoning or financial theory, as per Lütkepohl et al. (2006). Still, the GIRFs solve the problem of orthogonalization (Pesaran, 2015) and accordingly we use those.

## Supplement part on empirical findings

*Unit root tests*

The construction of the multivariate VAR model is founded on the assumption that the incorporated variables are stationary. Thus, in testing if each variable is stationary, the ADF equation is estimated and the respective ADF *t*-statistic is compared at 1%, 5% and 10% levels of significance and the respective pseudo-*t* critical values. The ADF regression functions, for each variable are also being tested in having (or not) statistically significant intercepts, intercepts and deterministic trends, or none of the above, and accordingly we use those functions to provide the respective statistics on Exhibit 1. The null hypothesis (i.e., $H_{0:}$ unit root is present) can be rejected if the ADF statistic is lower than the pseudo *t*-critical value for any given level of significance or if the probability is lower than the respective level of significance. We have cross-checked the results by applying the adjusted *t*-statistic of Phillips-Perron as well.

The unit root ADF, and the Phillips-Perron tests applied, strongly indicate that for both tests and at the 0.01 level of significance the variables are integrated of order zero or one. Specifically, and as it can be seen on Exhibit 1, gold, dollar exchange rate, crude oil, Standard & Poor's 500 and the three month Treasury bill are integrated of order one, i.e. LGOLD~I(1), LEXC~I(1), LOIL~I(1), LSP~I(1) and TB3~I(1), while economic policy uncertainty and the consumer price index are integrated of order zero, i.e. LEPU~I(0) and,

[19] For further details refer to Koop et al. (1996) and Pesaran and Shin (1998).

[20] Two tests must be conducted prior to the construction of the VAR model. Primarily, the lag length criteria test which captures the number of lags that should be used and then the inverse root of AR characteristic polynomial to check for model stability. To do so, apart from the Akaike information criterion (AIC), the Final Prediction Error (FPE) is used, and both criteria suggest 3 lags. Furthermore, the inverse root of AR characteristic polynomial is used to establish whether the Vector Autoregressive model satisfies the stability condition as well. Additionally, the AR graph for the model suggests all roots within the unit circle, providing evidence the model also satisfies the stability conditions. On top of the above, the multivariate LM tests with the null hypothesis of no serial correlation were not rejected. The results are available upon request.

[21] The results are available upon request.

[22] As per Lütkepohl et al. (2006) and Verbeek (2008), Granger causality tests are to be used within a VAR. Two tests are performed for Granger causality - under the null hypothesis *x* does not Granger cause *y*, and vice versa for the second test. The causality can yield three types of patterns - unidirectional (*x* Granger causing *y*, but not the other way around or *y* Granger causing *x*, but not the other way around), bidirectional (*x* Granger causing *y* and *y* Granger causing *x*), and no causality or independent pattern for the variables if both $H_0$ are rejected (Hurn et al., 2021).

LCPI~I(0). The unit root results are provided on Exhibit 1, below.

**Exhibit 1.** Unit root test for LGOLD, LEXC, LOIL, LSP, LCPI, LEPU, TB3, DLGOLD, DLEXC, DLOIL, DLSP, DLCPI, DLEPU, DTB3

| Variable | ADF *t*-statistic | Prob. * | Variable | ADF *t*-statistic | PP Adj. *t*-statistic | Prob. * |
|---|---|---|---|---|---|---|
| LGOLD | 1.757311 | 0.9812 | DLGOLD | -17.02792 | -17.16476 | 0.0000 |
| LEXC | -2.737139 | 0.0687 | DLEXC | -14.05914 | -13.59756 | 0.0000 |
| LOIL | -2.978082 | 0.1397 | DLOIL | -15.72416 | -15.40805 | 0.0000 |
| LSP | 2.975675 | 0.9994 | DLSP | -19.36700 | -19.35964 | 0.0000 |
| LCPI | -3.859352 | 0.0026 | DLCPI | -13.32698 | -12.36769 | 0.0000 |
| LEPU | -6.888625 | 0.0000 | DLEPU | -13.87673 | -32.87292 | 0.0000 |
| TB3 | -2.879359 | 0.1704 | DTB3 | -7.041321 | -12.39996 | 0.0000 |

*Probability values are calculated from a pseudo *t*-distribution in the case of the ADF statistics.

The *t*-statistics are the ADF statistics. The adj. *t*-statistic is the Phillips-Perron.

All prob. values of *t*-statistic and PP on first differenced variables are equal to zero, thus the unit root hypotheses are being rejected throughout.

### Vector Autoregression results (VAR, Granger Causality tests, and GIRFs)

This section uses the multivariate VAR(3)[23] results to present the Pairwise Granger Causality tests, and the GIRFs. The Pairwise Granger causality tests results are reported in Exhibit 2. Note that only the statistically significant results are included.

**Exhibit 2.** Pairwise Granger Causality Tests

| Null Hypothesis | F-stat | Prob. |
|---|---|---|
| DLGOLD does not Granger Cause DLOIL | 3.58139 | 0.0140** |
| DLCPI does not Granger Cause DLGOLD | 3.07378 | 0.0276** |
| DLEXC does not Granger Cause DLCPI | 4.53060 | 0.0039* |
| DLEXC does not Granger Cause DLEPU | 2.65603 | 0.0481** |
| DLSP does not Granger Cause DLOIL | 2.71959 | 0.0443** |
| DLOIL does not Granger Cause DLCPI | 18.6587 | 2.E-11* |
| DLEPU does not Granger Cause DLOIL | 3.20002 | 0.0234** |
| DLOIL does not Granger Cause DLEPU | 3.82319 | 0.0101** |
| DLSP does not Granger Cause DLCPI | 5.64575 | 0.0009* |
| DLSP does not Granger Cause DLEPU | 7.63214 | 6.E-05* |
| DLSP does not Granger Cause DTB3 | 5.58017 | 0.0009* |
| DLEPU does not Granger Cause DLCPI | 2.41836 | 0.0658*** |
| DTB3 does not Granger Cause DLCPI | 5.58722 | 0.0009* |
| DLCPI does not Granger Cause DTB3 | 5.21268 | 0.0015* |
| DLEPU does not Granger Cause DTB3 | 3.93605 | 0.0087* |

* denotes significance at the 0.01 significance level,

** denotes significance at the 0.05 significance level,

*** denotes significance at the 0.10 significance level

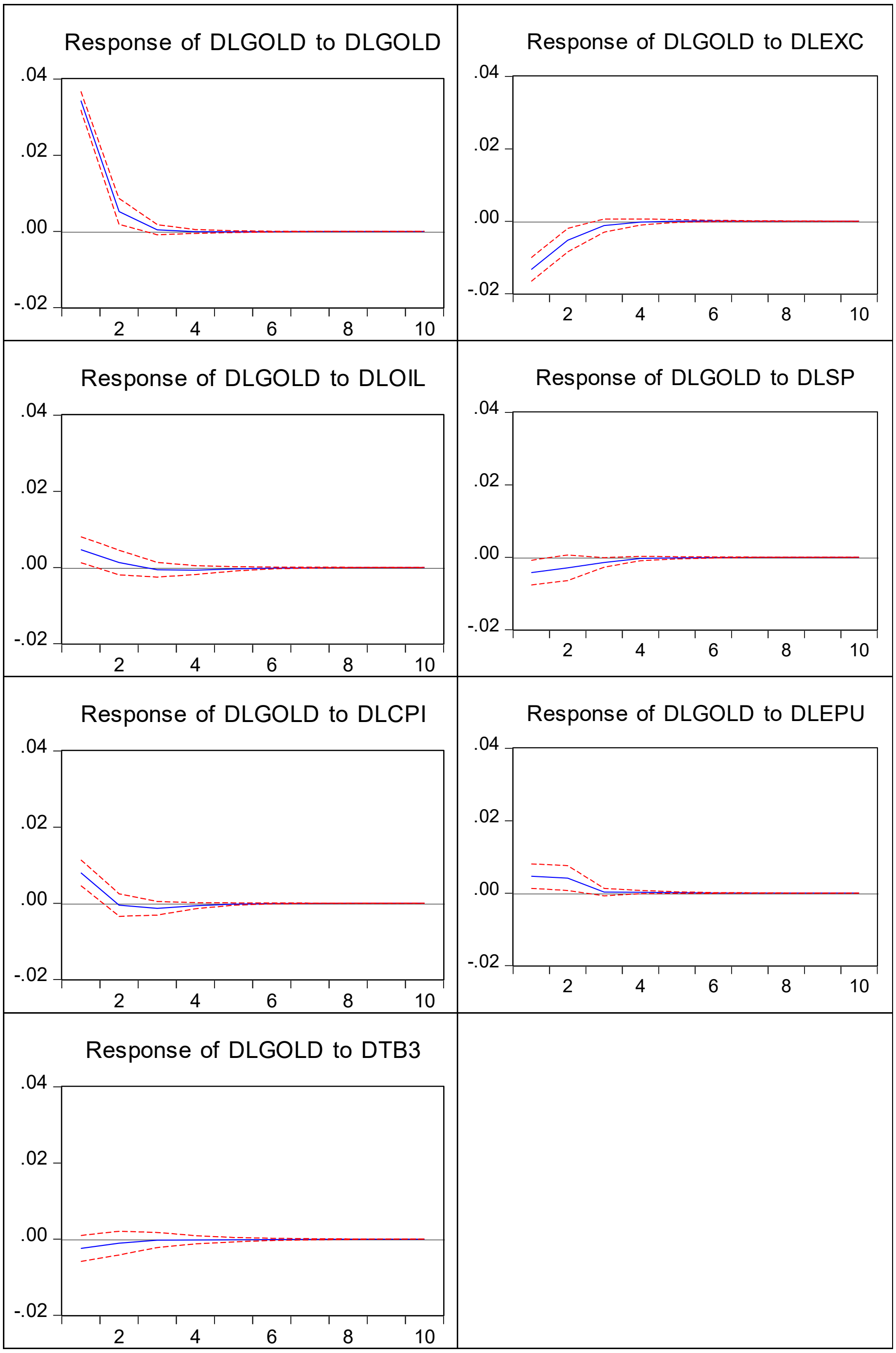
The strongest results, holding at 0.01 level of significance, are the uni-directional Granger-causalities running from exchange rate to CPI, from crude oil to CPI, from S&P 500 to CPI, from S&P 500 to EPU, from S&P 500 to 3-month Treasury bill, from 3-month Treasury bill to CPI (and vice versa, from CPI to TB3), and from EPU to three month Treasury bill. Also, at 0.05 level of significance gold Granger-causes crude oil, CPI Granger-causes gold, exchange rate Granger-causes EPU, and S&P 500 Granger-causes crude oil. There is also a bi-directional Granger-causality between EPU and crude oil, holding at 0.05 significance level, and a bi-directional Granger-causality between CPI and the 3-month Treasury bill (as stated above), which holds at 0.01 level of significance. Finally, EPU Granger-causes CPI at a 0.10 level of significance.

Moving to GIRFs the exhibits below present the response functions of each variable separately to -one standard deviation Innovations (+/- 2 S.E)- shocks coming from the rest of the economic and financial variables. Starting from the GIRFs of gold (see Exhibit 3), our impulse response analysis results reveal, for the sample period under study, that gold is strongly influenced by the dollar exchange rate, negatively and in a statistically significant way, for a time period of three to four months. Note that the results are statistically significant if both the upper and the lower bound are on the same positive or negative part of the vertical axis at the same time. Also note that the vertical axis shows the percentage change of every response, and the horizontal axis shows the number of months.

[23] Note that the VAR(3) is a robust model. The VAR residual serial correlation LM tests, using the Edgeworth expansion corrected likelihood ratio statistic (LRE), and the RAO F-statistic, does not reject the null hypothesis of no serial correlation at lag *h*, where *h* is 12 (months). The results are available upon request.

It is interesting to add another statistically significant finding, which is the positive response of gold to increased economic policy uncertainty (EPU), for a period of three to four months; a shock that wears out, which is the case throughout the GIRFs. Gold also responds positively to crude oil and CPI as well, but for a shorter time period.

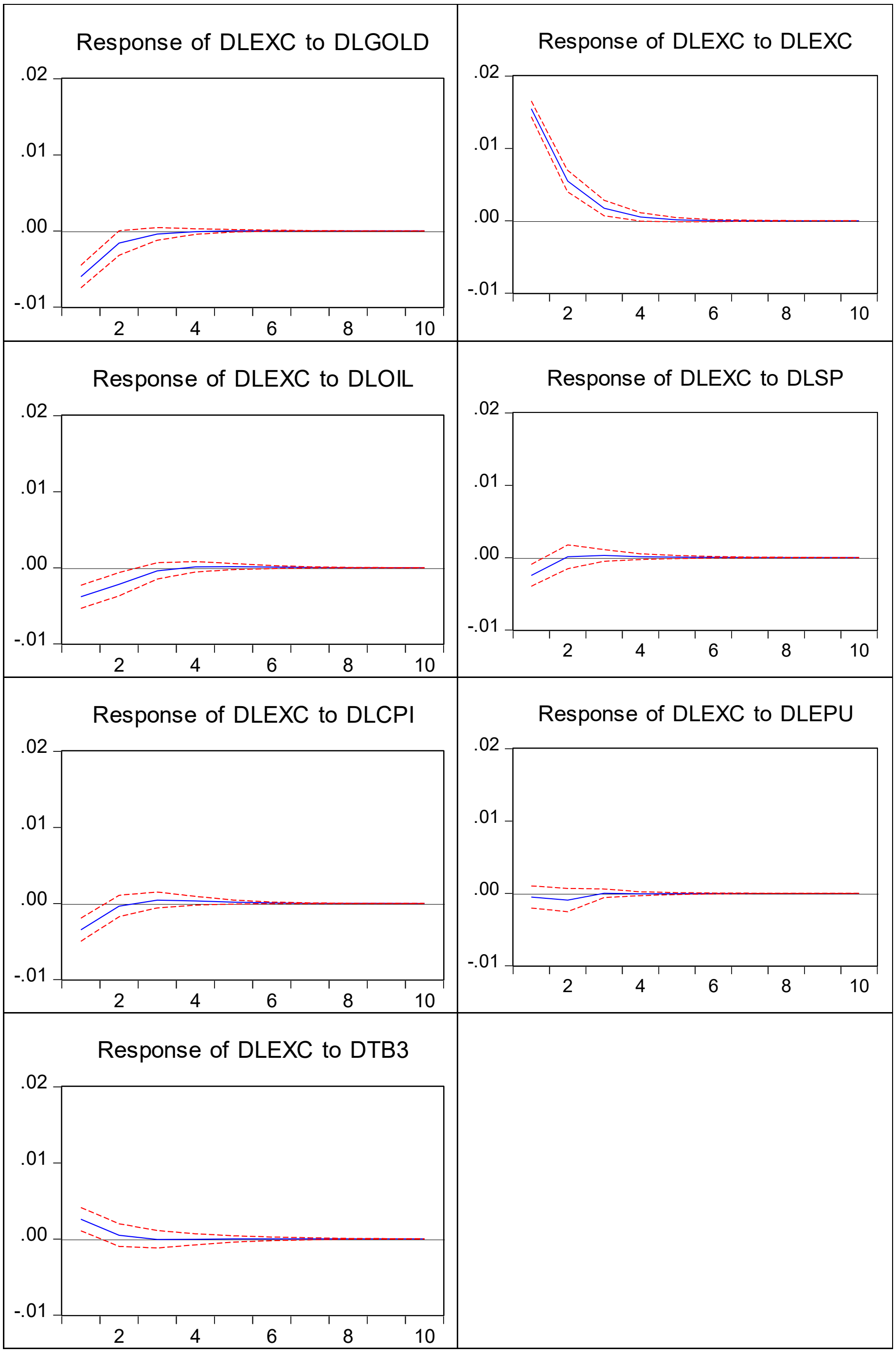
**Exhibit 3.** Generalized impulse response functions (GIRFs) of gold to -one standard deviation Innovations (+/- 2 S.E)- shocks to the rest of the economic and financial variables




*Note*: The percentage change of every response is captured on the vertical axis and the number of months is captured on the horizontal axis.

To continue with the GIRFs of the exchange rate (see Exhibit 4), dollar responds negatively to gold and crude oil shocks, for a period of two months, and negatively as well to CPI and S&P 500, for one month after the shock (note that only the statistically significant results are commented). Dollar responds positively to the 3-month Treasury bill, for a period of one month, confirming the expectations of economic theory.

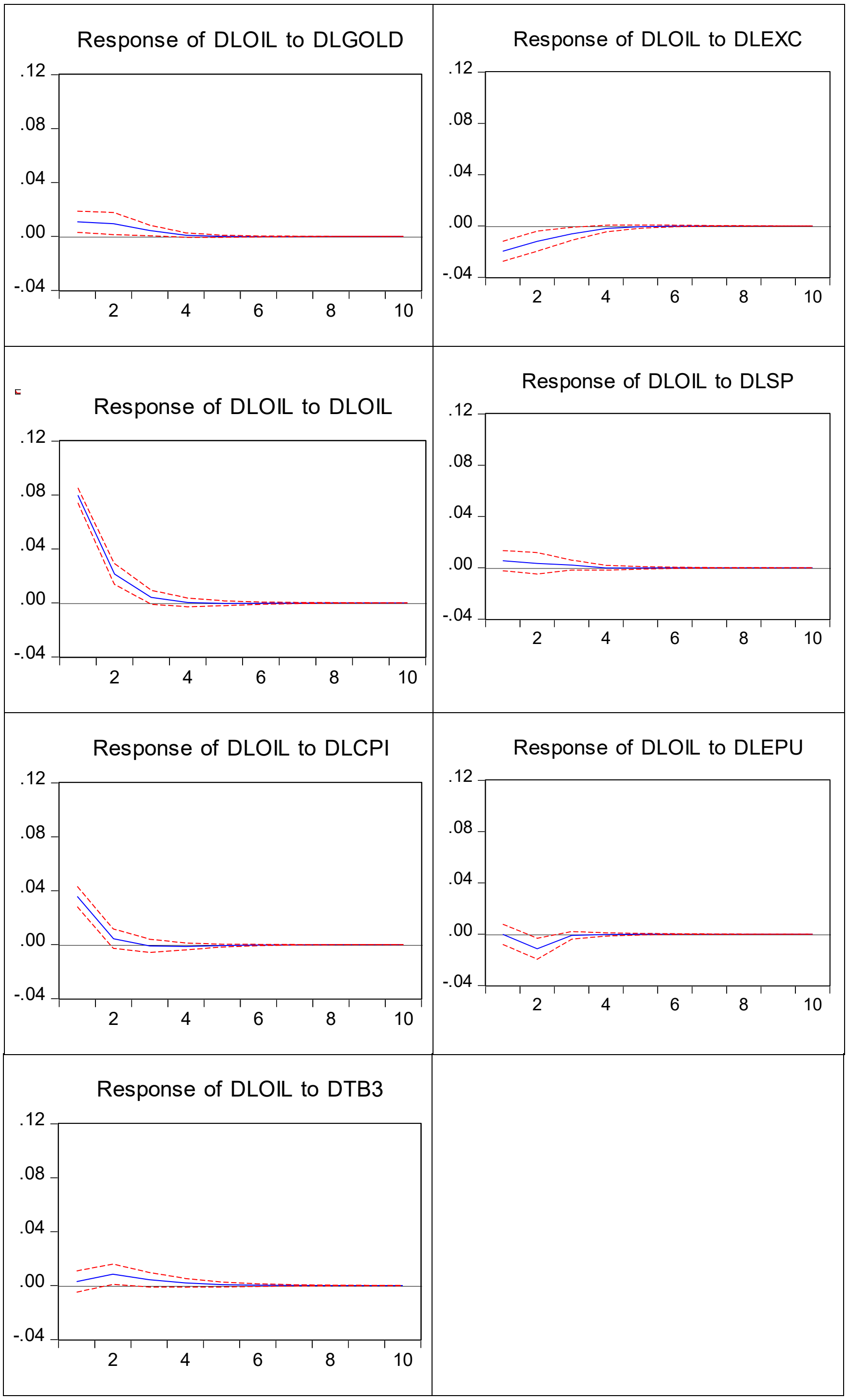
**Exhibit 4.** Generalized impulse response functions (GIRFs) of Exchange Rate to -one standard deviation Innovations (+/- 2 S.E)-shocks to the rest of the economic and financial variables




*Note*: The percentage change of every response is captured on the vertical axis and the number of months is captured on the horizontal axis.

To continue with the GIRFs of crude oil (see Exhibit 5), oil responds negatively to the exchange rate and the EPU shocks, for a period of three to four months, and positively to the rest of the variables, with varying results in terms of statistical significance and time profiles.

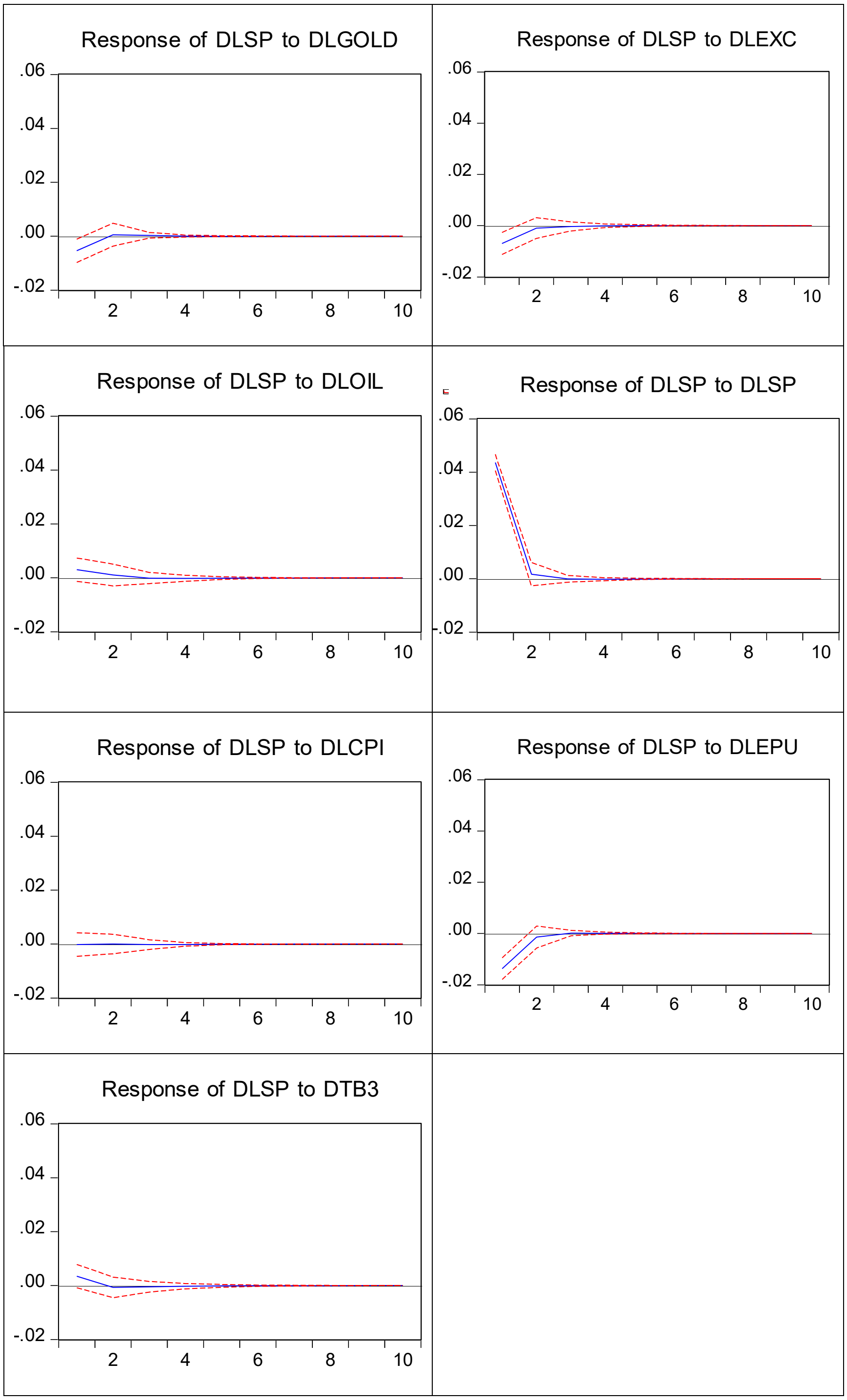
**Exhibit 5.** Generalized impulse response functions (GIRFs) of Crude oil to -one standard deviation Innovations (+/- 2 S.E)- shocks to the rest of the economic and financial variables




*Note*: The percentage change of every response is captured on the vertical axis and the number of months is captured on the horizontal axis.

Furthermore, our analysis of impulse responses of S&P 500 (see Exhibit 6) demonstrate that the globally popular and important stock market index is largely affected by EPU for a period of one to two months, and from the 3-month Treasury bill and gold as well, for one month.

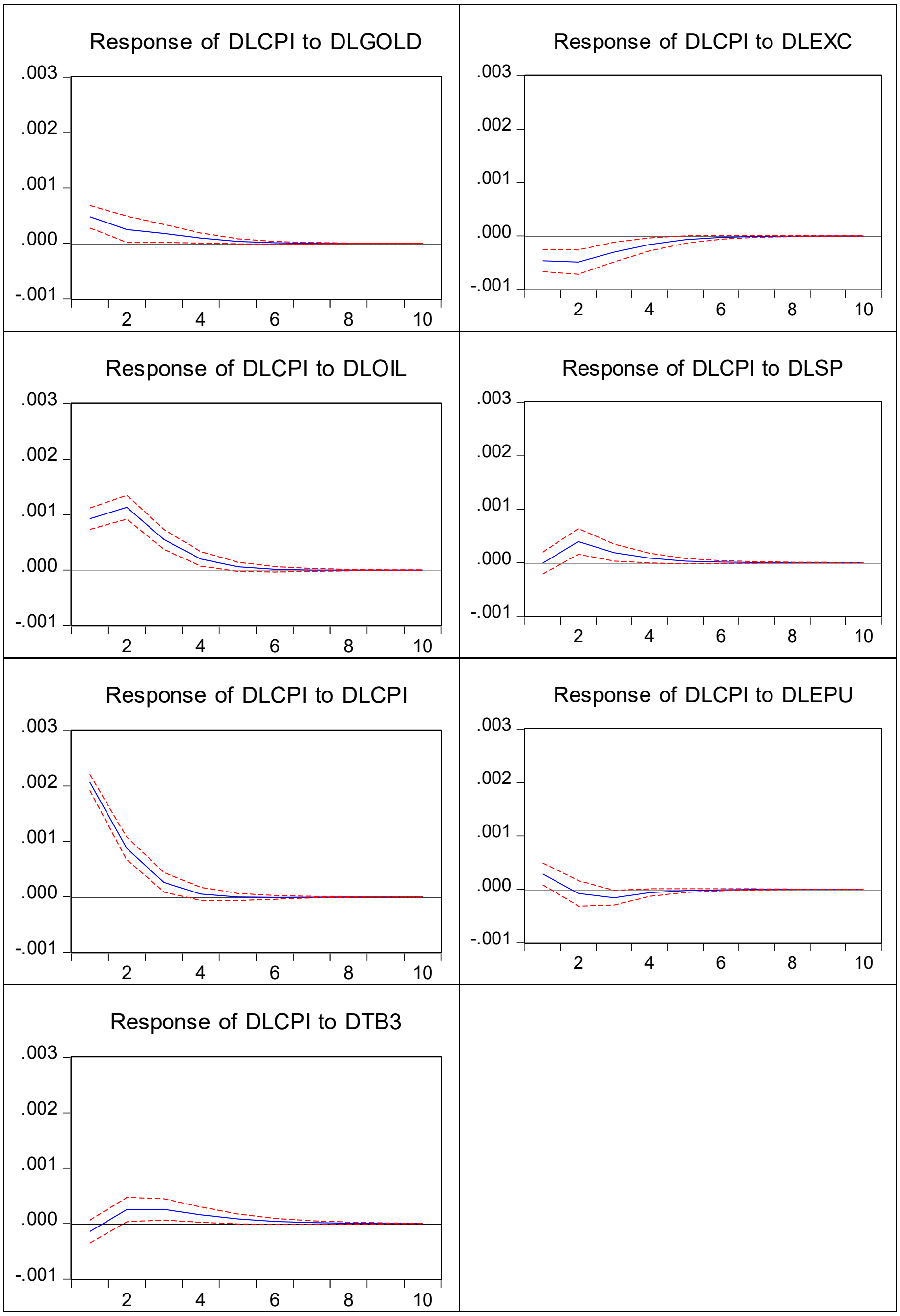
**Exhibit 6.** Generalized impulse response functions (GIRFs) of S&P's 500 to -one standard deviation Innovations (+/- 2 S.E)- shocks to the rest of the economic and financial variables




*Note*: The percentage change of every response is captured on the vertical axis and the number of months is captured on the horizontal axis.

The GIRFs of the Consumer Price Index (Exhibit 7), show that CPI responds negatively only to the dollar exchange rate, for a sustained period of five to six months, meaning that when the dollar depreciates inflation increases, and positively in the rest of the cases, i.e. on gold, crude oil, S&P 500, CPI, and EPU shocks. In the case of CPI response to EPU the response wears out comparatively quickly and it is not statistically significant throughout.

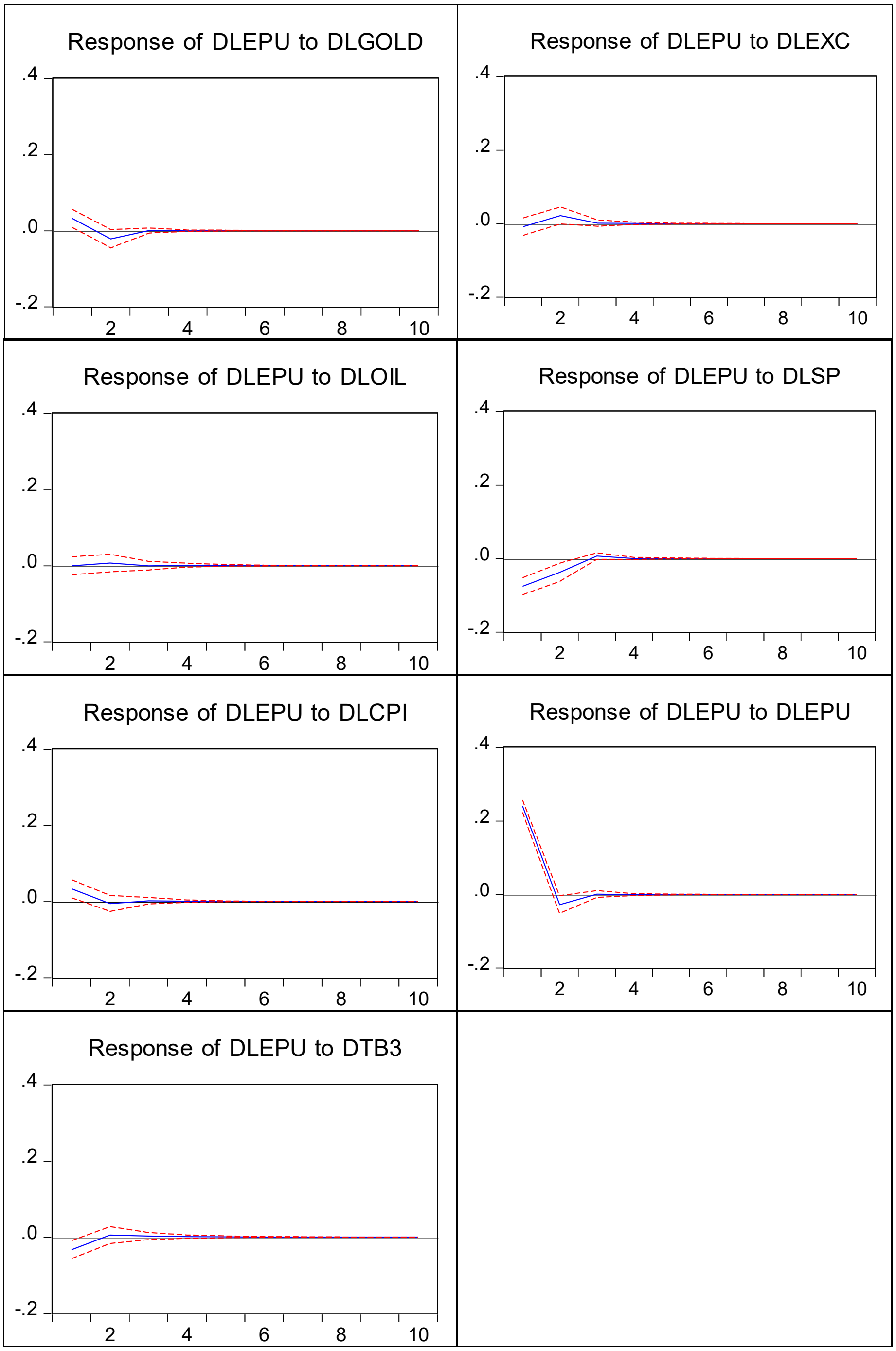
**Exhibit 7.** Generalized impulse response functions (GIRFs) of Consumer Price Index (CPI) to -one standard deviation Innovations (+/- 2 S.E)- shocks to the rest of the economic and financial variables




*Note*: The percentage change of every response is captured on the vertical axis and the number of months is captured on the horizontal axis.

The GIRFs of the economic policy uncertainty (Exhibit 8) show that EPU responds negatively only to S&P 500, for a period close to two months, meaning that when S&P 500 decreases EPU increases (and vice versa, as we have seen above), and positively in the cases of gold and CPI, for one month.

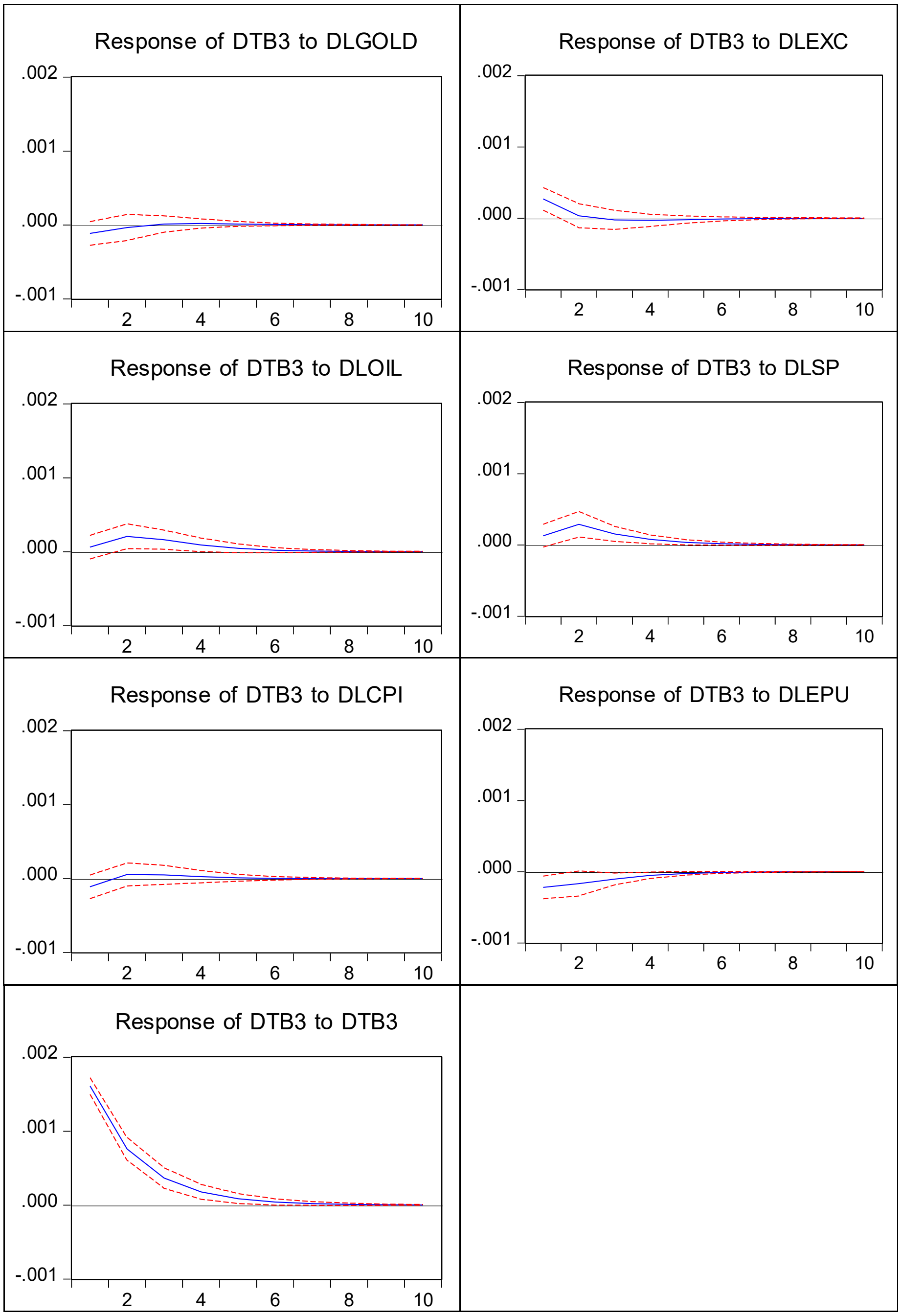
**Exhibit 8.** Generalized impulse response functions (GIRFs) of Economic Policy Uncertainty (EPU) to -one standard deviation Innovations (+/- 2 S.E)- shocks to the rest of the economic and financial variables




*Note*: The percentage change of every response is captured on the vertical axis and the number of months is captured on the horizontal axis.

Last but not least, the GIRFs of the 3-month Treasury bill (Exhibit 9) display that TB3 responds negatively only to EPU, for a period of four to five months, and positively in the cases of dollar exchange Rate, crude oil and S&P 500, for varying time periods, lasting from one to five to six months, respectively.

**Exhibit 9.** Generalized impulse response functions (GIRFs) of Treasury bill to -one standard deviation Innovations (+/- 2 S.E)-shocks to the rest of the economic and financial variables




*Note*: The percentage change of every response is captured on the vertical axis and the number of months is captured on the horizontal axis.

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