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Monetary Policy and Speculative Spillovers in Financial Markets

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Abstract

This paper examines the role of monetary policy (MP) of the United States (U.S.) as a driver of connectedness patterns in speculative activities in financial markets. Examining measures of speculation in four major markets including gold, equities, Treasury bonds and crude oil, we show that speculative activities can spill over across markets with the stock market generally serving as the main transmitter of speculative shocks. While unconventional MP is associated with greater connectedness of speculative activities in financial markets, we also find that unconventional (conventional) MP drives gold (financial assets) to serve as a net transmitter of speculative shocks to the other markets. The findings establish an important link between the monetary policy signals and trading behavior in financial markets with significant policy implications.

Keywords: Monetary Policy, Speculation, TVP-VAR, Dynamic Connectedness, Quantiles

JEL codes: C32, E32, F42.

1 Introduction

Hirshleifer and Teoh (2009) note that beliefs and behaviors of investors in financial markets can be contagious although standard capital market theories largely assume away information transmission and social interaction in their models of trading and asset pricing. In reality, however, we often see investors engage in herding behaviors through rational or irrational mechanisms (e.g., Banerjee, 1992; Bikhchandani et al., 1992), while in other cases, investors go against the market consensus due to the disposition effect that affects trading tendencies towards past winner and loser assets (e.g., Odean, 1998). Regardless of the mechanism through which information transmission among investors occurs, the literature offers ample evidence suggesting that contagion in beliefs and trading behavior can contribute to market volatility, pricing inefficiencies and speculative behavior in financial markets (e.g., Bikhchandani et al., 1992; Nofsinger and Sias, 1999; Lemmon and Ni, 2008; Blasco et al., 2012, among others). Clearly, a better understanding of the nature and drivers of information transmissions, particularly speculative trading behaviors, across financial markets can help both investors and policy makers devise plans to avoid or mitigate the possible negative consequences, particularly considering the link between speculative trading behavior and asset price bubbles (e.g., Harrison and Kreps, 1978; Scheinkman and Xiong, 2003).

This paper explores information spillover effects from a novel perspective by examining the role of monetary policy as a possible driver of contagion in speculative activities in financial markets. Clearly, prolonged economic uncertainty and crisis in capital markets, particularly following the global credit crunch of 2007/2008, has presented a great challenge for policy makers in global economies, forcing them to resort to unconventional monetary policies to prevent further instability in their economies and financial markets. While such a policy stance can be argued to stabilize the economies in crisis mode by providing much needed liquidity and political support, it can also be argued that expansionary monetary policy could fuel speculative tendencies, which in turn leads to unintended instability in asset markets, possibly through contagion of speculative activities that are fueled by cheap financing of speculative positions. In this regard, Boehl (2017) establishes the preliminary evidence of a link between monetary policy and stock market fluctuations, arguing that standard monetary policy rules can contribute to greater stock price volatility driven by a feedback mechanism between financial markets and the real economy. We contribute to this debate from a different angle by examining the connectedness patterns in speculative activities in financial markets and exploring the role of monetary policy as a driver of speculative spillovers.

Utilizing measures of speculative activity in four major markets including stocks, Treasury bonds, gold and crude oil and the TVP-VAR based connectedness framework of Antonakakis and Gabauer (2017), we first show that speculative activities in these markets are indeed connected, suggesting that speculative behaviors can be contagious and spill over across markets. Observing that the connectedness of speculative activities exhibit significant time-variation and quantile specific patterns, we then document a significant relationship between monetary policy and spillovers in speculative activities by means of the quantile-on-quantile approach of Sim and Zhou (2015). While the evidence suggests that expansionary monetary policy stance by the central bank can contribute to greater spillover effects in speculative activities in financial markets, we also find that unconventional (conventional) MP drives gold (financial assets) to serve as a net transmitter of speculative shocks to the other markets. Overall, the findings establish an important link between the monetary policy signals and trading behavior in financial markets and suggest that monetary policy decisions can contribute to a domino effect in speculative activities in financial markets with the potential to amplify price fluctuations and uncertainty.

2 Methodologies

2.1 The TVP-VAR Model

We employ the TVP-VAR based connectedness framework introduced by Antonakakis and Gabauer (2017) to assess the speculative spillover effects across various asset markets. This approach combines the connectedness approach of Diebold and Yılmaz (2012, 2014) with the TVP-VAR framework of Koop and Korobilis (2014) and overcomes particular shortcomings of the rolling-window VAR methodology, such as (i) arbitrarily chosen rolling-window size, (ii) loss of observations, and (iii) outlier sensitive parameters. We employ the same TVP-VAR specification as in Antonakakis et al. (2018) and Gabauer and Gupta (2018) since both studies are also analyzng daily data. As suggested by the Bayesian information criterion, we estimate a TVP-VAR model with one lag length, outlined as follows

$$\boldsymbol{z}_t = \boldsymbol{B}_t \boldsymbol{z}_{t-1} + \boldsymbol{u}_t \qquad \boldsymbol{u}_t \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \tag{1}$$

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t \qquad \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{R}_t), \tag{2}$$

where $\boldsymbol{z}_t$, $\boldsymbol{z}_{t-1}$ and $\boldsymbol{u}_t$ are $k \times 1$ dimensional vectors, $\boldsymbol{A}_t$, $\boldsymbol{B}_t$ and $\boldsymbol{S}_t$ are $k \times k$ dimensional matrices, $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ represent $k^2 \times 1$ dimensional vectors while $\boldsymbol{R}_t$ is a $k^2 \times k^2$ dimensional matrix. The computation of the generalized forecast error variance decomposition (GFEVD) of Koop et al. (1996) and Pesaran and Shin (1998) requires to transform the TVP-VAR to its TVP-VMA representation via the Wold representation theorem, $\boldsymbol{z}_t = \sum_{i=1}^{p} \boldsymbol{B}_{it} \boldsymbol{z}_{t-i} + \boldsymbol{u}_t = \sum_{j=0}^{\infty} \boldsymbol{A}_{jt} \boldsymbol{u}_{t-j}$, to retrieve $\boldsymbol{A}_t$ and $\boldsymbol{S}_t$. We choose to use the GFEVD that is completely invariant of the variable ordering and as Wiesen et al. (2018) point out, this model should be preferred over the orthorgonalized forecast error variance decomposition in case no theoretical framework, which would allow to identify the error structure, is available. The GFEVD ($\tilde{\phi}^g_{ij,t}(H)$) can be interpreted as the effect a shock in variable j has on variable i in terms of its forecast error variance share and is mathematically formulated by,

$$\phi^g_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} (\boldsymbol{\iota}'_i \boldsymbol{A}_t \boldsymbol{S}_t \boldsymbol{\iota}_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\boldsymbol{\iota}_i \boldsymbol{A}_t \boldsymbol{S}_t \boldsymbol{A}'_t \boldsymbol{\iota}_i)} \qquad \tilde{\phi}^g_{ij,t}(H) = \frac{\phi^g_{ij,t}(H)}{\sum_{j=1}^{k} \phi^g_{ij,t}(H)},$$

where $\sum_{j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = k$ and $\boldsymbol{\iota}_j$ is a zero vector with unity on the jth position.

This framework allows us to derive a variety of connectedness measures for the speculative activities across the various asset markets and provide further in-depth insight into the network spillover dynamics in an aggregated and disaggregated manner. In our analysis, we are particularly interested in the link between monetary policy actions and the connectedness of speculative activities across the different market segments. Therefore, we focus on the *total connectedness index (TCI_t)* formulated as

$$TCI_t = k^{-1} \sum_{j=1}^{k} TO_{jt} \equiv k^{-1} \sum_{j=1}^{k} FROM_{jt} \tag{3}$$

where $TO_{jt} = \sum_{i=1, i \neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H)$ and $FROM_{jt} = \sum_{j=1, i \neq j}^{k} \tilde{\phi}_{ij,t}^{g}(H)$. In this formulation, since $\tilde{\phi}_{ij,t}^{g}(H)$ measures the impact a shock in market j has on market i, TO measures the aggregated impact a shock in market j has on all *other* markets which is defined as the *total directional connectedness to others*. Similarly, $FROM$ represents the aggregated influence all *other* markets have on market j which is called the *total directional connectedness from others*. The *total connectedness index (TCI_t)* in Equation (3) can thus be considered as the average impact one market has on all *others* (or all *others* has on one) such that a relatively high (low) value for TCI_t implies that the propagation of a shock in one market to all others is high (low), further implying high (low) speculative spillovers across financial markets.

In addition to the total connectedness index explained above, we also examine the net spillovers from each market in order to see whether a certain market serves as a net transmitter (or receiver) of speculative spillover effects. This is done by subtracting the impact that market j has on others from the influence *others* have on market j, resulting in *net total directional connectedness*, formulated as $NET_{jt} = TO_{jt} - FROM_{jt}$. The term NET_{jt} reveals whether a given market is a net transmitter or receiver of speculative shocks such that $NET_{jt} > 0$ ($NET_{jt} < 0$) implies that the impact market j has on others is larger (*smaller*) than the influence all others have on market j, thus categorizing market j as a net transmitter (*receiver*) of shocks. Finally, we examine the bilateral relationships between speculative activities in market j and i via *net pairwise directional connectedness ($NPDC_{ij,t}$)* formulated as $NPDC_{ij,t} = \tilde{\phi}_{ij,t}(H) - \tilde{\phi}_{ji,t}(H)$. This statistic allows us to explore whether market i drives (or is driven by) market j such that $NPDC_{ij,t} > 0$ ($NPDC_{ij,t} < 0$) implies that market j dominates (or is dominated by) market i in terms of spillover effects.

2.2 Quantile-on-Quantile (QQ) Model

Having obtained the time-varying total connectedness series from the TVP-VAR model, we next use the QQ approach of Sim and Zhou (2015) to examine the relationship between the TCI series and a uniform metric for conventional and unconventional monetary policies measured by the shadow short rate (SSR) of Krippner (2013), as will be discussed later. The QQ model is built on the following nonparametric quantile regression framework, specific to our case

$$TCI_t = \beta^{\theta}(SSR_t) + u_t^{\theta} \tag{4}$$

where TCI_t and SSR_t are the total connectedness index of the speculative ratios and the shadow short rate (SSR) in period t, respectively. In this formulation, θ represents the θ-th quantile of the conditional distribution of the TCI and u_t^{θ} is a quantile error term whose conditional θ-th quantile is equal to zero. The term $\beta^{\theta}(\cdot)$ in this framework is assumed to be an unknown functional form, which is to be determined from the data.

The standard quantile regression model in Equation (4) allows the effect of the SSR to vary across the different quantiles of the TCI of the speculative ratios; however, this model is unable to capture the dependence in its entirety as the term $\beta^{\theta}(\cdot)$ is indexed on the TCI quantiles (θ) only and not the quantiles of the SSR. However, given that high (low) values for SSR imply contractionary (expansionary) monetary policy, the specification in Equation (4) fails to appropriately capture the conventional and unconventional monetary policy states as it does not differentiate between the different quantiles for SSR. Therefore, in order to get a comprehensive insight on the effect of monetary policies on the connectedness of the speculative activities, we focus on the relationship between the θ-th quantile of the TCI and the τ-th quantile of the SSR, denoted by P^{τ}. Once again, this distinction is important in our case as the lower quantiles of the SSR correspond to the unconventional monetary policy decisions. This is done by examining equation (4) in the neighborhood of P^{τ} via a local linear regression. As $\beta^{\theta}(\cdot)$ is unknown, this function is approximated through a first-order Taylor expansion around a quantile P^{τ}, such that

$$\beta^{\theta}(P_t) \approx \beta^{\theta}(P^{\tau}) + \beta^{\theta'}(P^{\tau})(P_t - P^{\tau}) \tag{5}$$

where $\beta^{\theta'}$ is the partial derivative of $\beta^{\theta}(P_t)$ with respect to P (also called the marginal effect or response) and is similar in interpretation to the coefficient (slope) in a linear regression model. Next, renaming $\beta^{\theta}(P^{\tau})$ and $\beta^{\theta'}(P^{\tau})$ as $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$ respectively, we rewrite equation (5) as

$$\beta^{\theta}(P_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(P_t - P^{\tau}) \tag{6}$$

Next, substituting Equation (6) in Equation (4), we obtain

$$S_t = \underbrace{\beta_0(\theta, \tau) + \beta_1(\theta, \tau)(P_t - P^{\tau})}_{(*)} + u_t^{\theta} \tag{7}$$

where the term $(*)$ is the θ-th conditional quantile of the TCI. Unlike the standard conditional quantile function, Equation (7) captures the overall dependence structure between the θ-th quantile of the TCI and the τ-th quantile of the SSR as the parameters β_0 and β_1 are doubly indexed in θ and τ. In the estimation of Equation (7), $\hat{P}_t$ and $\hat{P}^{\tau}$, respectively, and the local linear regression estimates of the parameters $\hat{\beta}_0$ and $\hat{\beta}_1$ are obtained by solving

$$\min_{b_0, b_1} = \sum_{i=1}^{n} \rho_{\theta} \left[S_t - \hat{\beta} - \hat{\beta}_1(\hat{P}_t - \hat{P}^{\tau}) \right] K \left(\frac{F_n(\hat{P}_t - \tau)}{h} \right) \tag{8}$$

where $\rho(u)$ is the quantile loss function, defined as $\rho(u) = u(\theta - I(u < 0))$ and I is the indicator function. $K(\cdot)$ denotes the kernel function and h is the bandwidth parameter of the kernel. Because of its computational simplicity and efficiency, the Gaussian kernel is used to weight the observations in the neighborhood of P^{τ}. Specifically, in our analysis, these weights are inversely related to the distance between the empirical distribution function of $\hat{P}_t$, denoted by $F_n(\hat{P}_t) = \frac{1}{n}\sum_{k=1}^{n} I(\hat{P}_k < \hat{P}_t)$, and the value of the distribution function that corresponds with the quantile P^{τ}, denoted by τ. The bandwidth parameter h is selected using the cross-validation regression approach with a local linear regression. Note that, though the focus is on the TCI_t, as an additional analysis, we also study how the SSR affects NET_{jt}, i.e., the net spillover across the speculative ratios.

3 Data

In this study, we use data from the Chicago Mercantile Exchange (CME) Group, which is considered to be the world's largest derivatives exchange. We focus on four key asset classes including equities (S&P 500 index futures traded on CME), Treasury bonds (U.S. Treasury Bond futures traded on CBT), gold (traded on CME) and crude oil (WTI futures traded on NYMEX) as the world's most strategic commodity.[1] Daily data for trading volume and open interest is obtained from Commodity Systems Inc. and the speculative activity in each market is measured by the speculative ratio of Chan et al. (2015), which is defined as the trading volume divided by open interest on a particular trading day. Also utilized by Lucia and Pardo (2010) as a proxy of speculative activity, this measure is regarded as an indicator of speculative tendencies relative to hedging. Noting the convention in earlier studies (e.g., Bessembinder and Seguin, 1993) that the daily open interest captures hedging activities in futures markets as it excludes all intraday positions taken by day traders with speculative tendencies, Lucia and Pardo (2010) use this ratio to capture the relative importance of speculative behavior such that high (low) values indicate greater speculative (hedging) tendency by market participants. Similarly, Chan et al. (2015) argue that a large increase in open interest relative to trading volume (hence lower speculative ratio) implies a rise in long positions as hedgers attempt to better cover their underlying positions as they see a potential for positive price movements. In an empirical application of this ratio, Balcılar et al. (2017) establish a link between the speculative activities and anti-herding behavior in the crude oil futures market, indicating a close link between speculative tendencies and risk taking by investors.

Since our main focus is the link between the spillovers in speculative activities and conventional and unconventional (such as Quantitative Easing which involves a multitude of measures like large-scale asset purchases, maturity extension programs and efforts of forward guidance in order to manage expectations of a prolonged period of low policy rates) monetary policies, we use a common metric as captured by the shadow short rate (SSR) for the United States. With policy rates in the zero lower bound (ZLB) range for a

[1]We investigate futures market due to the availability of high frequency (daily) trading data and the price discovery feature of futures markets.

prolonged period of time post the financial crisis, a great challenge to empirical researchers dealing with monetary policy has been to find alternative quantitative measures that are able to describe monetary policy at the ZLB. One such measure is the shadow short rate, developed by Krippner (2013), based on a two-factor model of the term-structure, at a daily frequency.[2] Also, employed by Wu and Xia (2016) as an indicator of the stance of monetary policy of the United States (U.S.) under conventional and unconventional environments, the two-factor yield curve-based framework developed by Krippner (2013) essentially removes the effect that the option to invest in physical currency (at an interest rate of zero) has on yield curves, resulting in a hypothetical "shadow yield curve" that would exist if physical currency were not available. The process allows one to answer the question: "What policy rate would generate the observed yield curve if the policy rate could be taken negative?" The "shadow policy rate" generated in this manner, therefore, provides a measure of the monetary policy stance after the actual policy rate reaches zero.

Based on the availability of the futures market data, our sample covers the daily period of 4th April, 1983 to 27th September, 2019. Note that, the SSR for the US is available only from 30th November, 1985, hence we use the daily effective federal funds rate obtained from the FRED database of the Federal Reserve Bank at St. Louis to match the data for the earlier period for which the futures data is available. Table 1 presents that summary statistics for the daily speculative ratios (SRs) for each asset. We see that all series are non-normally distributed, caused by the fact that all series are positively skewed and exhibit excess kurtosis, suggesting the presence of extreme observations in all time series and tendency towards higher values implying speculative tendencies relative to hedging. Additionally, all series are stationary according to the ERS unit-root test, autocorrelated and exhibit ARCH/GARCH errors, thus providing preliminary support in favour of choosing a TVP-VAR model which accounts for both autocorrelated series and squared series. Examining the unconditional correlations in the bottom panel of the table, we observe that speculative ratios are highly correlated for commodities (SR WTI & SR Gold) followed by financial assets (SR SP500 & SR Bond), while the highest negative correlation is observed for the speculative ratios for crude oil (SR WTI) and the stock market index (SR SP500) futures. The preliminary analysis thus presents some evidence

[2]Data can be downloaded from the Reserve Bank of New Zealand.

of speculative clustering patterns in commodity vs financial assets.

4 Empirical Results

4.1 Connectedness of Speculative Ratios

Table 2 provides the summary statistics for the network transmission mechanism as described by the various connectedness measures discussed in Section 2.1. We see that, on average, 24.443% of the shock in one market spills over to all other markets, implied by the average total connectedness index (TCI) estimate. We also observe negative values for the net spillovers for crude oil, gold and Treasury bonds, implying that these markets are, on average, net receivers of speculative shocks, while the stock market is the only net transmitter. This is not unexpected as the stock market is generally considered to be a leading indicator of the macroeconomy, thus S&P 500 futures market serving as a net transmitter of speculative shocks could be due to the information captured by stock investors', later propogating to other segments of the financial market. This argument is further confirmed when we examine the aggregated and bilateral level connectedness estimates in the table as the speculative ratio for the S&P500 also dominates every other variable individually in terms of contribution to spillover effects. The weakest net receiver of speculative shocks is crude oil which dominates gold, but is dominated by financial assets (T-bonds and S&P 500). Gold, in turn, is dominated by crude oil and the S&P500, but dominates T-bonds. Finally, although the stock market is found to be the dominant net transmitter of spillover shocks, indicating that it influences other markets more than it is influenced by them, we observe that Treasury bonds are the main transmitter of shocks as 31.527% of a shock is transmitted to all other markets.

As the static TCI reported in Table 2 is simply the average value across time, hence ignoring the time-variation in the estimates, we report in Figure 1 the dynamic total connectedness estimates obtained from the time-varying parameter specification described in Section 2.1. We observe a great deal of time-variation in the connectedness estimates with multiple peaks throughout the period of analysis. A notable peak in the connectedness of speculative ratios is observed towards late 1990s during the notorious dot-com bubble period when the hysteria on the new economy stocks eventually led to a bubble and a subsequent crash in early 2000, wiping out large sums of capital in the stock market. Another notable spike, although not as large as the one observed during the dot-com period, is noted during the period into the global financial crash when financial markets experienced a bubble in the commodity and real estate markets, in particular, once again, followed by a crash. Finally, an all-time high in the total connectedness index is observed towards the end of the sample period, perhaps driven by the uncertainty revolving around the trade negotiations and changing geopolitical landscape following the election of the new U.S. administration. Nevertheless, the time-variation in the connectedness of the speculative ratios across the four market segments indeed captures several notable turning points in financial markets, with the speculative activites becoming more connected as we progress into the peak of a bubble pattern.

Further examining the influence a particular market has on other markets, we present in Figure 2 the net directional connectedness estimates for each market. As explained earlier, positive (negative) values for NET_{jt} imply that the impact market j has on others is larger (*smaller*) than the influence all others have on market j, thus classifying market j as a net transmitter (*receiver*) of shocks. Consistent with our earlier inferences from Table 2, we observe that the stock market generally serves as the main transmitter of speculative shocks, implied by consistently positive values throughout the sample period. The role of the stock market as a net transmitter of speculative shocks strengthens particularly during the global financial crisis period and later towards the end of the sample period. Interestingly, we see that the only notable prolonged net transmission originated from the crude oil market in early 1990s, implied by positive net directional connectedness values for crude oil, while other markets were net receivers. Considering that this was a period of turmoil in the oil market ignited by Iraq's invasion of Kuwait which consequently led to the Gulf War in 1991, our findings suggest that the crude oil market served as a net transmitter of speculative shocks to the other markets during this period.

Finally, we report in Figure 3, the bilateral relationships between speculative activities in various market pairs measured by the *net pairwise directional connectedness* $(NPDC_{ij,t})$. As mentioned earlier, a positive (negative) value for this statistic implies that market j dominates (or is dominated by) market i in terms of spillover effects. The plots that involve S&P 500 in Figure 3 confirm our earlier inferences in that the stock market serves as the net pairwise transmitter of speculative shocks, implied by the sign of the $NPDC$ estimates. Overall, the dynamic analysis of connectedness measures clearly point to the stock market serving as a net transmitter of speculative shocks to the other markets, possibly driven by the leading role of stock valuations regarding future economic fundamentals.

4.2 The Effect of Monetary Policy on the Connectedness of Speculative Ratios

Having established evidence of significant spillover effects in speculative activities across the four asset markets examined, we next analyze the effect of monetary policy on the connectedness of speculative ratios. As noted earlier, we use the shadow short rate (SSR) as a proxy for the monetary policy stance such that high (low and even negative) values for SSR imply conventional (unconventional) monetary policy. As a preliminary check, estimating a standard ordinary least squares (OLS) regression to examine the response of TCI to SSR yields the conditional mean-based estimate of 0.7705, significant at the highest level. This yields the initial evidence of a statistically significant positive effect of monetary policy on the connectedness of the speculative ratios. While the OLS result is informative, it fails to capture the complete picture for the relationship between the two variables, conditional on the normal and extreme states of TCI and the SSR. As displayed in Figure 1, the spillover effects across these markets are rather time-varying with notable jumps during periods preceding market crashes, suggesting the presence of regime-specific patterns in the connectedness of speculative activities. Similarly, conventional and unconventional monetary policy stance by the Federal Reserve reflect distinct market states during which macroeconomic trends as well as investors' risk preferences are drastically different. Accordingly, it can be argued that the relationship between the TCI and SSR series is nonlinear with regime specific patterns and the QQ approach discussed earlier allows us to formally assess those relationships at the level of quantiles that reflect various market states due to both variables.

Figure 4 presents the QQ model results that relate the TCI of the speculative ratios with the SSR. Specifically, we plot the estimates of the impact of the various quantiles of the SSR on the quantiles of the TCI, i.e., $\beta_1(\theta, tau)$, as described in Equation 7. As noted earlier, these estimates are similar to the slope term in a linear regression model, reflecting the sensitivity of the TCI to the SSR. However, given that $\beta_1(\theta, tau)$ is doubly indexed in θ and τ, the estimates presented in Figure 4 measure the relationship between the θ-th quantile of TCI (placed on the y-axis) and the τ-th quantile of the SSR (placed on the x-axis). The plots are color-coded in such a way that the color represents the degree of sensitivity (red indicating higher sensitivity). We observe that, while the result is generally consistent with the finding of a positive relationship obtained from the OLS regression, the relationship between monetary policy and the total connectedness index displays quantile specific patterns in terms of the strength of the monetary policy effect. Indicated by the dark red region in the upper left corner of the figure, we see that the effect of monetary policy on the connectedness of speculative ratios is particularly strong during periods of unconventional monetary policy, captured by the extreme low quantiles of SSR. This suggests that monetary stimulus or loose monetary policy stance by the central bank is associated with greater spillover effects in speculative activities in financial markets. One argument that can be made in this regard is that loose monetary policy allows speculators to enjoy cheap financing for their speculative bets, thus contributing to greater interaction of speculative activities across financial markets. This could indeed be a concern for policy makers as speculative spillovers could potentially trigger simultaneous bubbles and subsequent crashes in multiple market segments. Further examining Figure 4, we also note that the relationship between SSR and TCI turns highly negative when both variables are at quantiles around the median. This suggests that conventional monetary policy can help lower spillover shocks during normal market states. Nevertheless, the findings point to a clear monetary policy effect on the transmission of speculative shocks across financial markets, although the effect is rather regime-specific depending on the state of monetary policy stance.

The inferences from Figure 4 are further enhanced when we examine the effect of monetary policy on the net spillovers for each market. Figure 5 presents the quantile-on-quantile slope estimates for the net spillovers for each market (NET_{jt}) described in Section 2.1 due to SSR. As explained earlier, positive (negative) values for NET_{jt} imply that market j is a net transmitter (receiver) of speculative shocks. We observe in Figure 5 two distinct patterns for commodities and financial assets. For gold in particular (Panel C), we see that net spillovers are strongly and positively related to SSR at the extreme low quantiles for SSR. This suggests that unconventional monetary policy generally drives gold to be a net transmitter of speculative shocks. Considering that unconventional monetary policy is generally associated with periods of turmoil or economic instability, it is not unexpected to see that gold, as the traditional safe haven asset, plays a more dominant role as a net transmitter of speculative spillover effects to the other markets. Accordingly, one can argue that the speculative trends in the gold market play a leading role in the transmission of information during such periods.

In the case of crude oil (Panel D), however, we see that the relationship between net spillovers and SSR is the strongest (and positive) when both variables are at their low quantiles below the median. This means that unconventional monetary policy contributes to the transmission of speculative spillovers into the market for crude oil, driving crude oil to be a net receiver of shocks. Given that fluctuations in oil prices are highly sensitive to economic fundamentals, it is not surprising that speculative tendencies by oil traders follow macroeconomic trends during periods of instability accompanied with unconventional monetary policy stance of the Fed, thus driving crude oil to be a net receiver of speculative shocks. In the case of financial assets (Panels A and B), on the other hand, we observe that the strong positive monetary policy effect (indicated by dark red regions in the plots) occurs around the median quantiles for SSR in both figures, suggesting that conventional monetary policy has a significant effect on the net speculative spillovers from financial assets to the others, driving these assets to serve as a net transmitter of shocks. Considering that conventional monetary policy is generally associated with normal market states, the role of financial assets as a net transmitter of speculative shocks can be due to the leading role of financial markets regarding future economic expectations, thus contributing to net positive spillovers from financial assets to commodities.

5 Conclusion

This paper examines the role of U.S. monetary policy as a driver of connectedness patterns in speculative activities in financial markets. Utilizing measures of speculative activity in four major markets including stocks, Treasury bonds, gold and crude oil and the TVP-VAR based connectedness framework of Antonakakis and Gabauer (2017), we first show that speculative activities are indeed connected across these markets, suggesting that speculative activities can be contagious and spill over across markets. While the speculative ratios become more connected as we progress into the peak of a bubble pattern, we also observe that the stock market generally serves as the main transmitter of speculative shocks to the other markets. Next, utilizing a common metric for the monetary policy stance of the Fed and utilizing the quantile-on-quantile approach of Sim and Zhou (2015) to capture the conventional and unconventional monetary policy regimes, we show that monetary policy indeed serves as a driver of connectedness patterns in speculative activities in financial markets. Our findings suggest that the effect of monetary policy on the connectedness of speculative ratios is particularly strong during periods of unconventional monetary policy, captured by the extreme low quantiles of SSR, suggesting that loose monetary policy stance by the central bank can contribute to greater spillover effects in speculative activities in financial markets. Interestingly, however, while unconventional monetary policy generally drives gold to be a net transmitter of speculative shocks, we also find that conventional monetary policy drives financial assets (stocks and bonds) to serve as a net transmitter of speculative shocks. Overall, our findings suggest that the monetary policy stance of the Fed can have distinctly different effects on commodities and financial assets, with these markets serving as net receivers or transmitters of speculative shocks during conventional and unconventional monetary policy states. Given the evidence of strong speculative spillover effects across these markets, our results suggest that monetary policy decisions can contribute to a domino effect in speculative activities in financial markets with the potential to cause simultaneous bubbles and subsequent crashes.

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Table 1: Summary Statistics

	SR WTI	SR Gold	SR SP500	SR Bond
Mean	0.356	0.304	0.293	0.613
Variance	0.02	0.031	0.111	0.092
Skewness	0.965***	1.426***	2.307***	1.067***
	(0.000)	(0.000)	(0.000)	(0.000)
Kurtosis	2.175***	3.216***	5.984***	1.199***
	(0.000)	(0.000)	(0.000)	(0.000)
JB	3249.775***	7104.603***	21945.716***	2304.331***
	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-18.312***	-16.018***	-5.012***	-10.491***
	(0.000)	(0.000)	(0.000)	(0.000)
$Q(20)$	54770.874***	57684.855***	146303.195***	39991.600***
	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(20)$	28504.039***	24099.016***	68121.046***	18093.442***
	(0.000)	(0.000)	(0.000)	(0.000)
		Unconditional Correlations		
SR WTI	1.000	0.441	-0.310	-0.144
SR Gold	0.441	1.000	-0.181	-0.020
SR SP500	-0.310	-0.181	1.000	0.297
SR T-Bond	-0.144	-0.020	0.297	1.000

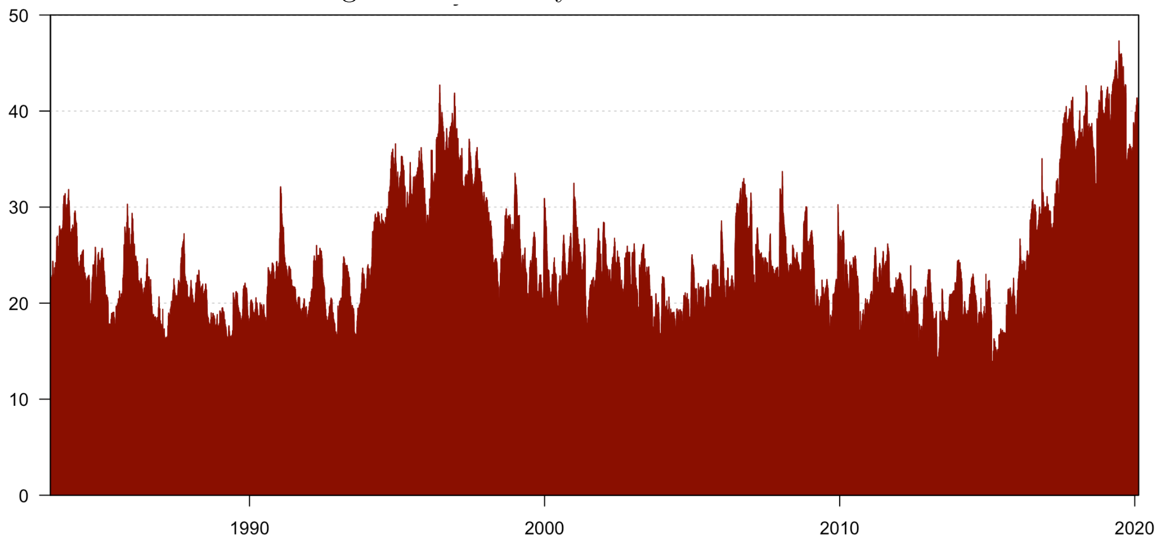
Note: This table reports the summary statistics for the daily speculative ratios (SR) over the period 4th April, 1983 to 27th September, 2019. SR WTI, SR Gold, SR SP500 and SR Bond refer to the daily speculative ratios for WTI crude oil, gold, S&P 500 index and U.S. Treasury bond futures, respectively. The numbers in parentheses are the p-values. ***, **, and * represent significance at 1, 5, and 10 percent, respectively.

Table 2: Connectedness Table

	SR WTI	SR Gold	SR SP500	SR Bond	FROM
SR WTI	78.482	6.410	10.596	4.512	21.518
SR Gold	7.681	73.612	10.982	7.725	26.388
SR SP500	5.221	4.808	81.663	8.308	18.337
SR Bond	4.503	8.323	18.701	68.473	31.527
Contribution TO others	17.406	19.540	40.279	20.546	TCI
Net spillovers	-4.112	-6.848	21.941	-10.981	24.443

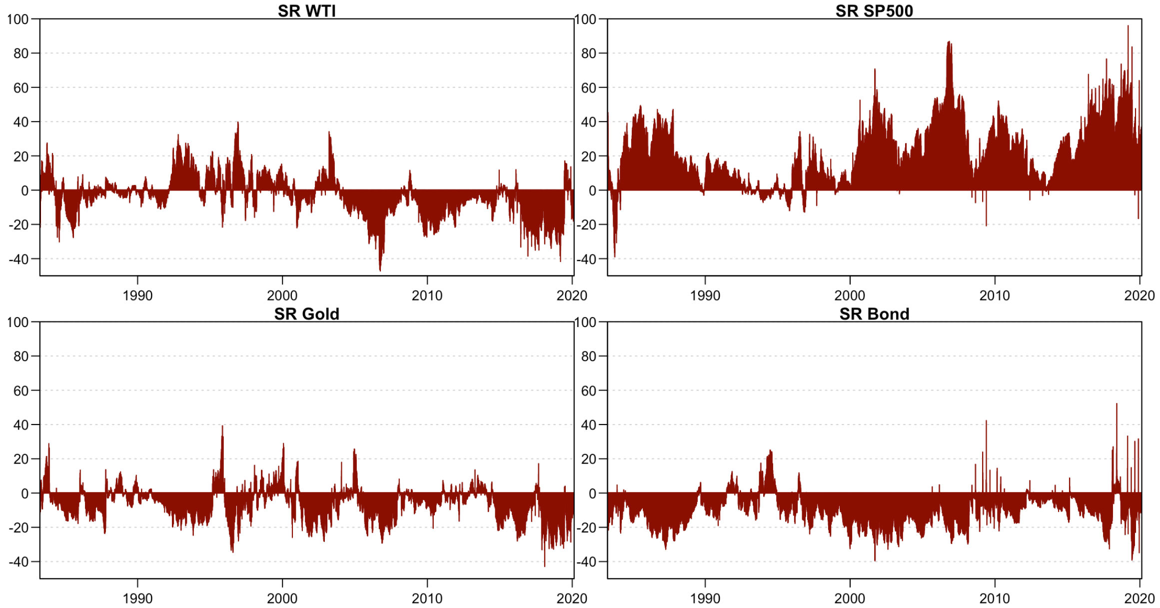
Note: This table reports the summary statistics for the connectedness measures discussed in Section 2.1. SR WTI, SR Gold, SR SP500 and SR Bond refer to the daily speculative ratios for WTI crude oil, gold, S&P 500 index and U.S. Treasury bond futures, respectively.

Figure 1: Total Dynamic Connectedness



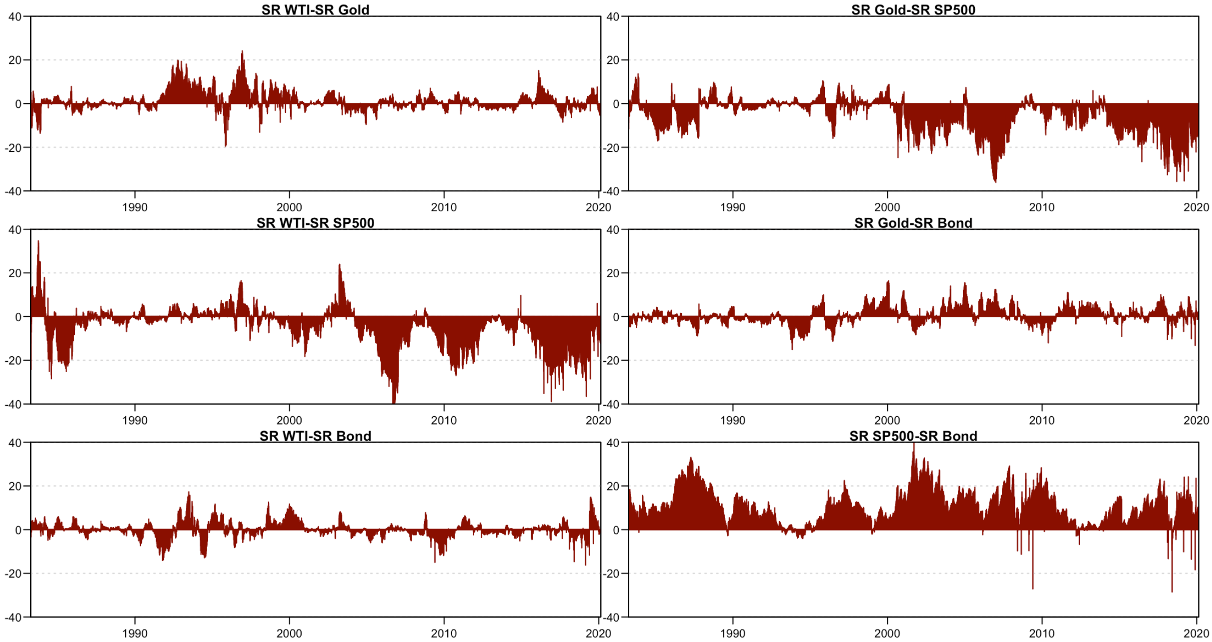
Note: This figure depicts the time-varying total connectedness index estimates obtained from the TVP-VAR model using Equation 3.

Figure 2: Net Directional Connectedness



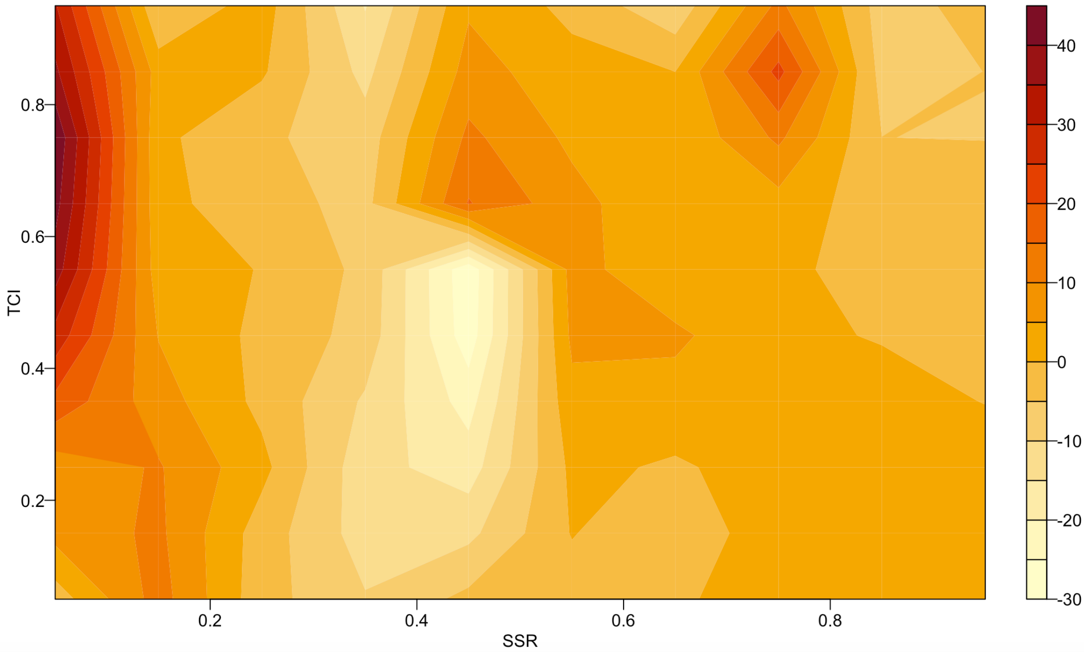
Note: This figure depicts the net speculative spillovers for each market described in Section 2.1.

Figure 3: Net Pairwise Directional Connectedness



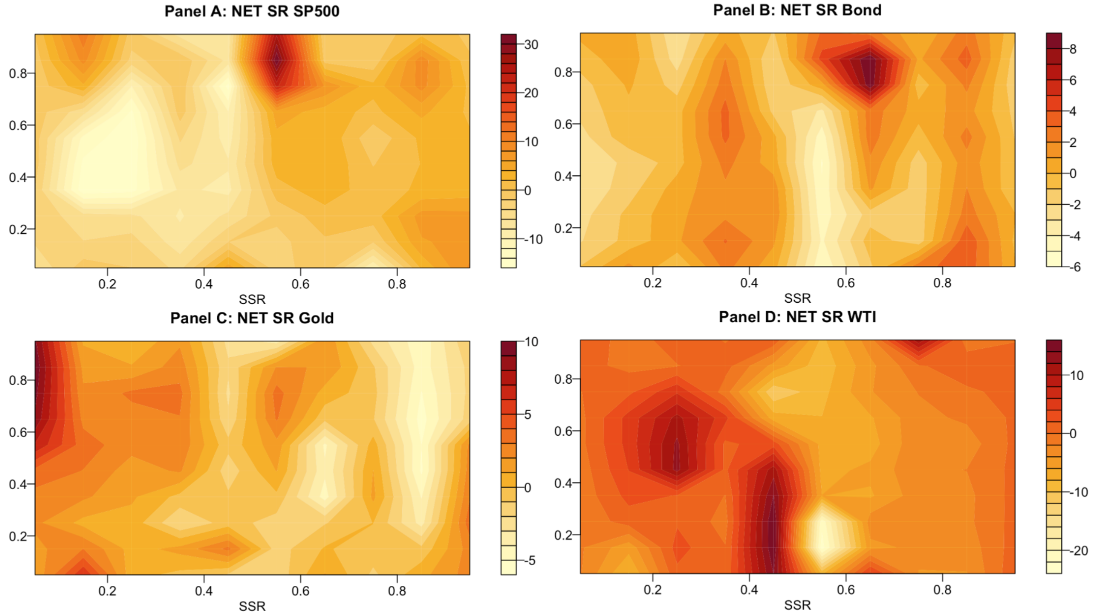
Note: This figure depicts the bilateral relationships between speculative ratios in various market pair via the *net pairwise directional connectedness* measure described in Section 2.1.

Figure 4: Quantile slope estimates for connectedness of speculative ratios due to monetary policy decisions of the U.S.



Note: This figure depicts the effect of the shadow short rate quantiles (x-axis) on the quantiles of total connectedness index (y-axis) via the quantile-on-quantile slope estimates for Equation 7 described in Section 2.2. The plot is color-coded in such a way that the color represents the degree of sensitivity (red indicating higher sensitivity).

Figure 5: Quantile slope estimates for net speculative spillovers due to monetary policy decisions of the U.S.



Note: This figure depicts the effect of the shadow short rate quantiles (x-axis) on the quantiles for the net spillovers from each market (y-axis) described in Section 2.1. The plots are color-coded in such a way that the color represents the degree of sensitivity (red indicating higher sensitivity).