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Mississippi State University

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A Short Summary of Current Research Activity:

Currently, I am working on the interaction between monetary policy and fiscal policy. I am also conducting research on monetary policy and income inequality, and commodity price volatility. Furthermore, I am working on machine learning and deep learning, econometrics, and data analysis approaches for forecasting economic and financial time series. I have published several peer-reviewed journals and conference papers.

I also have professional experience in the field of macroeconomic modeling, planning, budgeting, growth and development, econometrics modeling, fiscal policy, data analysis, etc. I also worked in the field of energy, water and agriculture, education, health, transportation, industry and mining and environment. I also worked on the public administrative challenges at the national and local level. In addition, I worked in the field of national accounts and households' expenditures. I worked with public and private entities. Furthermore, I have experience in data science, price analysis, growth and development economics, international trade, and international development, experimental and behavioral economics and writing proposals.

Summer Institute Session:
July 19-23

I am also interested in the Summer Institute Session for the first week of July 12-17.

Curriculum Vitae

SIMA SIAMI-NAMINI, PhD

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EDUCATION

- PhD in Agricultural and Applied Economics (Minor in Statistics), *Texas Tech University*, USA, August 2020.
  Dissertation Topic: ESSAYS ON MONETARY POLICY AND INCOME INEQUALITY
- MS in Agricultural and Applied Economics, *Texas Tech University*, USA, May 2018.
  Research Topic: COMMODITY PRICE VOLATILITY AND U.S. MONETARY POLICY
- Graduate Certificate in Economics and Public Policy, *Harvard University*, USA.
  Research Topic: TAX ANALYSIS AND REVENUE FORECASTING
- MS in Planning of Economic Systems, *Shahid Beheshti University*, IRAN.
  Thesis Topic: DESIGNING OF AN ECONOMETRIC MODEL FOR DESCRIBING THE GOVERNMENT BEHAVIOR
- BS in Economics, *Alzahra University*, IRAN.

PUBLICATIONS (SELECTED)

- **Siami-Namini, S.** QUANTITATIVE EASING POLICY AND INCOME INEQUALITY IN THE U.S. ECONOMY: EVIDENCE OF A FAVAR MODEL (*forthcoming*).
- **Siami-Namini, S.** (2021). U.S. MONETARY POLICY AND COMMODITY PRICES: A SVECM APPROACH. *Economic Papers.*
- Felipe Gutie´rrez, L. **Siami-Namini, S.** Tavakoli, N. and Siami Namin A. (2020). A CONCERN ANALYSIS OF FOMC STATEMENTS COMPARING THE GREAT RECESSION AND THE COVID-19 PANDEMIC. *2020 IEEE International Conference on Big Data (Big Data)*.
- **Siami-Namini, S.** Lyford, C. and Trindade, A. (2020). THE EFFECTS OF MONETARY POLICY SHOCKS ON INCOME INEQUALITY ACROSS U.S. STATES. *Economic Papers.*
- Tavakoli, N. **Siami-Namini, S.** Adl Khanghah, M. Mirza Soltani, F. and Siami Namin, A. (2020). AN AUTOENCODER-BASED DEEP LEARNING APPROACH FOR CLUSTERING TIME SERIES DATA. *SN Applied Sciences.*
- Tavakoli, N. **Siami-Namini, S.** Adl Khanghah, M. Mirza Soltani, F. and Siami Namin, A. (2020). CLUSTERING TIME SERIES DATA THROUGH AUTOENCODER-BASED DEEP LEARNING MODELS. arXiv preprint arXiv:2004.07296.
- Abri, F. **Siami-Namini, S.** Adl Khanghah, M. Mirza Soltani, F. and Siami Namin, A. (2019). THE PERFORMANCE OF MACHINE AND DEEP LEARNING CLASSIFIERS IN DETECTING ZERO-DAY VULNERABILITIES. *IEEE Big Data 2019.*
- **Siami-Namini, S.** Tavakoli, N. and Siami Namin, A. (2019). A COMPARATIVE ANALYSIS OF FORECASTING FINANCIAL TIME SERIES USING ARIMA, LSTM, AND BILSTM. *IEEE Big Data 2019.*
- **Siami-Namini, S.** (2019). AGRICULTURE AND NON-AGRICULTURE GROWTH, INFLATION AND INCOME INEQUALITY IN DEVELOPED AND DEVELOPING COUNTRIES. *International Journal of Economics and Finance*.
- **Siami-Namini, S.** (2019). VOLATILITY TRANSMISSION AMONG OIL PRICE, EXCHANGE RATE AND AGRICULTURAL COMMODITIES PRICES. *Applied Economics and Finance*.
- **Siami-Namini, S.** and Hudson, D. (2019). THE IMPACTS OF SECTOR GROWTH AND MONETARY POLICY ON INCOME INEQUALITY IN DEVELOPING COUNTRIES. *Journal of Economic Studies*.
- **Siami-Namini, S.** and Hudson, D. (2019). INFLATION AND INCOME INEQUALITY IN DEVELOPED AND DEVELOPING COUNTRIES. *Journal of Economic Studies*.
- **Siami-Namini, S.** Hudson, D. Trindade, A. and Lyford, C. (2019). COMMODITY PRICE VOLATILITY AND U.S. MONETARY POLICY: COMMODITY PRICE OVERSHOOTING REVISITED. *Agribusiness*.
- **Siami-Namini, S.** Tavakoli, N. and Siami Namin, A. (2018). A COMPARISON OF ARIMA AND LSTM IN FORECASTING TIME SERIES. Published in *2018 17th IEEE International Conference on Machine Learning and Applications*.
- Xue, X. **Siami-Namini, S.** and Siami Namin, A. (2018). TESTING MULTI-THREADED APPLICATIONS USING ANSWER SET PROGRAMMING. *International Journal of Software Engineering and Knowledge Engineering*.
- Xue, X. **Siami-Namini, S.** and Siami Namin, A. (2018). ASSESSING THE EFFECTIVENESS OF COVERAGE-BASED FAULT LOCALIZATIONS USING MUTANTS. *International Journal of Software Engineering and Knowledge Engineering*.
- **Siami-Namini, S.** Muhammad, D. and Fahimullah, F. (2018). THE SHORT- AND LONG-RUN EFFECTS OF SELECTED VARIABLES ON TAX REVENUE: A CASE STUDY. *Applied Economics and Finance*.
- Darabseh, A. **Siami-Namini, S.** and Siami Namin, A. (2018). CONTINUOUS AUTHENTICATIONS USING FREQUENT ENGLISH TERMS. *International Journal of Applied Artificial Intelligence*.

- **Siami-Namini, S.** (2018). HEALTHCARE EXPENDITURES, ECONOMIC GROWTH, AND INFLATION IN THE G7 COUNTRIES: A PANEL COINTEGRATION APPROACH. *Research Journal of Economics*.
- **Siami-Namini, S.** (2018). THE EFFECT OF MONETARY POLICY SHOCKS ON THE REAL ECONOMY: A FAVAR APPROACH. *Research Journal of Economics.*
- **Siami-Namini, S.** (2017). CHINA'S ECONOMY AND THE GLOBAL FINANCIAL CRISIS. *International Journal of Economics and Financial Issues.*
- **Siami-Namini, S.** (2017). GRANGER CAUSALITY BETWEEN GROSS DOMESTIC PRODUCT AND ECONOMIC SECTORS IN DEVELOPING COUNTRIES: A PANEL COINTEGRATION APPROACH. *International Journal of Economics and Financial Issues.*
- **Siami-Namini, S.** (2017). GRANGER CAUSALITY BETWEEN EXCHANGE RATE AND STOCK PRICE: A TODA YAMAMOTO APPROACH. *International Journal of Economics and Financial Issues*.

CAREER / WORK EXPERIENCE

2020 - PRESENT	ADJUNCT RESEARCH FACULTY
	- Department of Computer Science & Engineering, *Mississippi State University*.
2019 - 2020	GRADUATE PART-TIME INSTRUCTOR
	- Department of Mathematics & Statistics, *Texas Tech University*.
2015 - 2019	GRADUATE RESEARCH ASSISTANT
	- Department of Agriculture & Applied Economics, *Texas Tech University*.
SUMMER 2016	DATA ANALYST INTERN
	- The Office of Revenue Analysis, *Office of The Chief Financial Officer*.
SUMMER 2015	TEACHING ASSISTANT
	- Department of Economics, *Texas Tech University*.
2002-2014	SENIOR ECONOMIST AND HEAD OF PLANNING GROUP
	- Bureau of Economic Planning, *Plan and Budget Organization*.
2001-2002	ECONOMIC RESEARCHER
	- Bureau of Economic Research and Policies, *Central Bank of Iran*.

TEACHING EXPERIENCE

- STATISTICAL METHODS, Department of Mathematics & Statistics, *Texas Tech University*, Spring 2020.
- CONTEMPORARY MATHEMATICS, Department of Mathematics & Statistics, *Texas Tech University*, Fall 2019.
- INTERNATIONAL TEACHING ASSISTANT PROGRAM, *Texas Tech University*, Summer 2019.
- FUNDAMENTALS OF AGRICULTURAL AND APPLIED ECONOMICS, Department of Agricultural and Applied Economics, *Texas Tech University*, Spring 2017.
- ECONOMICS TUTORING, Department of Economics, *Texas Tech University*, Summer 2015.
- TTU GROUNDWORK PROGRAM AT THE TEACHING, LEARNING, AND PROFESSIONAL DEVELOPMENT CENTER, *Texas Tech University*, May 2015.

PROFESSIONAL SERVICES

REVIEWER

For the 1) *Bulletin of Economic Research*; 2) *Entropy, MDPI* (two articles); *3) Applied Economics; 4) Development Studies Research;* 5) *Journal of Risk and Financial Management*, *MDPI* (three articles); 6) *IEEE Access* (two articles); 7) *Mathematical Problems in Engineering*; 8) *Eurasian Economic Review*; 9) *Regional Science, Policy and Practice*, and 10) *Information, MDPI*, 2021.

For the 1) *Electronics, MDPI;* 2) *Growth and Change;* 3) *IEEE Access* (seven articles); 4) *Big EACPS Workshop*; 5) *Entropy, MDPI* (three articles); 6) *Poverty and Public Policy* (four articles); 7) *Sensors, MDP;* 8) *Sustainability, MDPI* (three articles); 9) *Economic Papers*; 10) *International Journal of Electrical and Computer Engineering*; 11) *Asia-Pacific Financial Markets*; 12) *Economies, MDPI* (two articles); 13) *Bulletin of Economic Research*; 14) *South Asian Journal of Management Sciences*; 15) *World Development*; 16) *International Journal of Finance & Economics*, and 17) *PLOS ONE*, 2020.

For the 1) *IEEE Access* (three articles); 2) *Contemporary Economics*; 3) *PLOS ONE; 4) International Conference on Artificial Intelligence, Information Processing and Cloud Computing*; 5) *The Fourth International Conference on Economic and Business Management & Applied Economics*; 6) *Contemporary Economics* (two articles); 7) *Sociological Quarterly*; 8) *Journal of Educational Studies*, and 9) *Journal of Economics and Economic Education Research*, 2019.

For the 1) *Journal of Agricultural and Resource Economics;* 2) *International Workshop of Big Data Engineering and Analytics in Cyber-Physical Systems*; 3) *Academy of Strategic Management Journal*, and 4) *Journal of Economic Studies.*

PROGRAM COMMITTEE

The 3rd Workshop on Big Data Engineering and Analytics in Cyber-Physical Systems (BigEACPS'20). A Workshop Co-located with the *2020 IEEE International Conference on Big Data (IEEE BIG DATA 2020)*.

The *1st International Workshop on Deep Analysis of Data-Driven Applications (DADA)* to be held in Conjunction with COMPSAC 2019.

The *Big Data Engineering and Analytics in Cyber-Physical Systems (BigEACPS'18): A Workshop Co-located with the 2018 IEEE International Conference on Big Data (IEEE BIG DATA 2018)*.

The *Challenges of Engineering and Mining Big Data in Cyber-Physical Systems (BigEACPS'16): A Workshop Co-located with the 2016 IEEE International Conference on Big Data (IEEE BIG DATA 2016)*.

HONORS & AWARDS

- FULL TUITION ASSISTANTSHIP FOR PHD PROGRAM, *Texas Tech University*, 2015-2020.
- BAYER CROP SCIENCE FELLOWSHIP SCHOLARSHIP, *Texas Tech University*, Spring 2019.
- TRAVEL GRANT FOR SUMMER GRADUATE RESEARCH WORKSHOP, *The Institute for Humane Studies*, Bryn Mawr College, June 2019.
- TRAVEL GRANT FOR LATE STAGE GRADUATE STUDENT CAREER DEVELOPMENT SEMINAR, *THE Institute for Humane Studies*, Arlington, VA, May 2019.
- TRAVEL GRANT FOR THE 2018 AGRICULTURAL AND APPLIED ECONOMICS ASSOCIATION CONFERENCE, *Institute Humane Studies*, Washington, DC, August 2018.
- TRAVEL GRANT FOR HARWOOD GRADUATE COLLOQUIUM ON THE THEORY AND HISTORY OF MONETARY INSTITUTIONS, *American Institute for Economic Research*, Great Barrington, MA, July 2018.
- TRAVEL GRANT FOR ALTERNATIVE MONEY UNIVERSITY PROGRAM, *Cato Institute: Center for Monetary and Financial Alternatives*, Washington, DC, July 2018.
- TRAVEL GRANT FOR REFLECTIONS ON ALLAN MELTZER'S CONTRIBUTIONS TO MONETARY ECONOMICS AND PUBLIC POLICY, *Institute for Humane Studies*, Philadelphia, PA, January 2018.
- PH.D. SCHOLARSHIP, *Institute for Humane Studies*, 2018.
- J.T. AND MARGARET TALKINGTON GRADUATE FELLOWSHIP, *Texas Tech University*, 2014-2018.
- TRAVEL GRANT FOR ORIGINS OF CAPITALISM IN THE LIBERTY CONFERENCE, *Institute for Humane Studies*, Washington, DC, September 2017.
- TRAVEL GRANT FOR A BETTER WAY: PRIVACY, COMPETITION, AND THE FUTURE OF TECHNOLOGY, *Institute for Humane Studies*, The Southern Economic Association Meeting, Tampa, FL, November 2017.
- TRAVEL GRANT FOR TAX ANALYSIS AND REVENUE FORECASTING PROGRAM, *United Nations*, Harvard University, Cambridge, MA, Summer 2000.

PATENT

- AUTOMATIC DETECTION OF THREATS AND OPPORTUNITIES USING NATURAL LANGUAGE PROCESSING, Akbar Siami Namin, **Sima Siami-Namini**, and Neda Tavakoli, U.S. Provisional Patent Application Serial No. 62/781,184, 2018.

NSF GRANT PROPOSAL DEVELOPMENT & CONTRIBUTIONS

Participated in the Grant Development Activities Led by Dr. Akbar Namin:

- FORECASTING THE IMPACT OF COVID-19 ON INCOME INEQUALITY, NSF Proposal, 2020.
- FORECASTING INCOME INEQUALITY USING DEEP PANEL DATA ANALYSIS, NSF Proposal, 2019.

CERTIFICATES (SELECTED)

- STATISTICAL INFERENCE, Coursera (*Johns Hopkins University*), 2021.
- 1) WHAT IS DATA SCIENCE? and 2) TOOLS FOR DATA SCIENCE, Coursera (*IBM*), 2021.
- SQL FOR DATA SCIENCE, Coursera (*University of California*), 2021.
- FINANCING PROJECTS WITH RESOURCES FROM THE EUROPEAN UNION, TRAINING FOR EXECUTIVE AGENCIES, *Inter-American Development Bank*, 2020.
- DIGITAL FORENSICS: ATTENDED THE WORKSHOP ON "DIGITAL FORENSICS", Organized and offered by the Department of Computer Science and Psychology Department in partnership with the SANDIA National Laboratories. *Texas Tech University*, 2018.

- 1) Introduction to Marketing; 2) Decision-Making and Scenarios; 3) Modeling Risk and Realities; 4) Introduction to Spreadsheets and Models, and 5) Fundamentals of Quantitative Modeling, Coursera (*University of Pennsylvania*), 2018.
- Programming for Everybody (Getting Started with Python), Coursera (*University of Michigan*), 2018.
- Recognition of Outstanding Performance in the 2016 College Internship Program. *Office of the Chief Financial Officer*, 2016.

Conferences / Presentations (Selected)

- Commodity Prices, Monetary Policy and the Taylor Rule. *Southern Agricultural Economics Association*, Annual Meeting, Jacksonville, FL, 2018.
- The Impact of Recent Energy Prices on the U.S. Cotton Industry. *Beltwide Cotton Conferences*. Dallas, TX, 2017.
- Evaluating GDP and Inflation Forecasting Models. *IAAE Annual Conference*. Thessaloniki, GREECE, 2015.
- Mises-Hayek Monetary and Business Cycle Theory and the Current Economic Crisis. *Southern Economic Association Conference*. Atlanta, GA, 2014.

Skills

- Advanced Skills in EVIEWS, MICROFIT, XLSTAT, STATA, SAS, R, MATLAB & DYNARE Programming Language, Python, SQL, and Data Science.

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RESEARCH ARTICLE

Commodity price volatility and U.S. monetary policy: Commodity price overshooting revisited

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Abstract

Commodity price volatility has created concerns for central bank policy-makers. Recent commodity prices peaked in the consequences of the financial crisis of 2007, and they have remained relatively volatile since. As they are often seen as being connected in a cause and effect relationship with inflation and real output, the driving forces behind commodity price volatility are necessary for the conduct of monetary policy. Using an autoregressive moving average with an exponential generalized autoregressive conditional heteroscedastic (ARMA-EGARCH) process, we extract the conditional variance series to find volatility spillover between monetary policy and commodity price index. The findings show that the volatility of agricultural commodity price index and other commodities price indices overshoot the long-run equilibrium price in response to an impulse in monetary policy.

KEYWORDS

ARMA-EGARCH model, commodity prices, monetary policy, overshooting hypothesis, VECM approach

1 | INTRODUCTION

Over the last few years, commodity price volatility has created issues for virtually all economies, especially those that have used inflation targeting for monetary policy. Although the major issue within the context of an inflation targeting is price stability, commodity price fluctuations have outsized effects on inflation in economies with a high percentage of food and energy in the consumption basket and in economies with low inflation expectations (IMF, 2011). Volatility in commodity prices influence real output, which has implications for the conduct of monetary policy (Svensson, 2005). Many studies have identified the fundamental economic factors like speculation and global demand growth in line with supply shocks as major factors influencing commodity price volatility, but less attention has been devoted to the impact of monetary policy shocks on commodity price fluctuations (Glick & Leduc, 2011; Kozicki, Santor, & Suchanek, 2012).

The size of global central bank balance sheets have expanded since the recession of 2007–2009 due to interest rate cutting and quantitative easing (QE). For instance, with the zero-lower bound (ZLB) on nominal interest rates, the

Federal Reserve (Fed) made a variety of large-scale asset purchases (LSAPs) between late 2008 and October 2014 in order to promote stronger economic recovery. These purchases increased the Fed's balance sheet from less than $900 billion before the financial crisis to about $4.5 trillion (a four-fold increase), reduced the value of the dollar, and speculation and rising commodity prices as an asset class.

The overshooting hypothesis (Dornbusch, 1976) was originally proposed as a theoretical explanation for high levels of exchange rate volatility. Later, it was generalized by Frankel (1986) for determining the influence of monetary policy on agricultural and manufacturing commodity prices, which were considered as flexible and fixed prices, respectively. Frankel demonstrated that the low-speed adjustment of the manufacturing commodity prices to the change in the stock of money adds to overshooting in the prices of agricultural commodities. This result implies that changes in the stock of money can have short-term effects on the prices of agricultural commodities. Given the assumption of neutrality of money in the long-term, the overshooting of commodity price can have effects on farm income and financial viability of farm families in the short-term (Bakucs & Ferto, 2005). This result only explains the impact of money stock changes on the price of commodities. However, there is little information about the effect of monetary policy shocks on the commodity price volatility and overshooting their long-term equilibrium level, which is the research question of this article.

The main purpose of this article is to investigate the impact of expansionary monetary policy on the volatility of commodity price indexes such as an aggregate commodity price index, agricultural commodity price index, S&P 500 commodity index, Dow Jones commodity index and NASDAQ composite index. The analysis is based on an autoregressive moving average–exponential generalized autoregressive conditional heteroscedasticity (ARMA-EGARCH) (1,1) process and a vector error correction model (VECM). The model is estimated with monthly data for a specific subset of commodity price indices during the period from February 1992 to March 2017 in the U.S. economy. We first extract conditional variance series of all series and then look at the short-term overshooting hypothesis of agricultural commodity price volatility and other commodity price volatility. The empirical evidence has implications for the neutrality of money in the long-term (Ardeni & Freebairn, 2002). Additionally, we estimate the corresponding short-term error correction model (ECM) to gain insights into the short-term adjustment toward any long-term relationship if it exists. Also, we estimate impulse response functions (IRF) to investigate the impact of monetary policy shocks on the volatility of commodity prices. The results show that there is an overshooting behavior of the conditional variance series (volatility) of commodities prices to the changes in monetary policy, suggesting that not only do price levels overshoot, but also the variance.

2 | LITERATURE REVIEW

A review of the theoretical literature describes three fundamental factors of commodity prices. First, most commodities are used as inputs in the production process so that we expect the derived demand for those commodities and their prices to increase in response to global economic expansion in the short-run (Alquist & Coibion, 2014; Kilian, 2009; Kilian & Lee, 2014; Kilian & Murphy, 2013; Lombardi & Van Robays, 2012). Second, commodity prices are typically denominated in U.S. dollars so that a depreciation of the U.S. dollar causes lower commodity prices in terms of local currency, which, in turn, increases demand for such goods and pushes up the price of the commodity in dollar terms. Therefore, the exchange rate affects the competitiveness of producers and the purchasing power of consumers (Cho, Sheldon, & McCorriston, 2002; Frankel, 1986; Saghaian, Reed, & Marchant, 2002; Schuh, 1974). Third, because monetary policy affects the price of commodities, lower interest rates cut the rate of extraction today and increase the incentives to keep up inventories. Then, the derived demand for commodities is stimulated and thus the prices of products increase (Cabrales, Granados, & Joya, 2014).

For a contemporary example, the Fed adopted QE as an unconventional monetary policy during the financial crisis and its aftermath in which the Fed purchased government and other securities to lower interest rates and increase the money supply in hopes of accelerating economic growth (Amadeo, 2017). Before the severe recession of 2007–2009, the Fed held about $800 billion in assets. The Fed started to be carrying out several rounds of LSAPs which

increased the Fed's balance sheet by four times, including about $2.5 trillion in Treasury securities and $1.8 trillion in Mortgage-Backed Securities (MBS), with the aim of cutting interest rates in long-term. This created bubbles in commodities resulting from expectations driving asset purchases (Foerster & Cao, 2013). More recently, however, signs of economic recovery have led the Fed to begin raise interest rates by shrinking the balance sheet. As a result, the market has offered a natural experiment on the impacts of monetary policy changes on commodity price volatility.

Using the Dornbusch overshooting hypothesis (DOH), Frankel (1985a) found that monetary policy and interest rates are the main factors influencing commodity prices. In Frankel's model, a decrease in the nominal money supply likely cuts the real money supply. Subsequently, interest rate increases and current commodity prices decrease. Therefore, the commodity price overshoots (i.e., downwards) their new equilibrium prices in order to generate expectations of an appreciation and neutralize the increases in interest rate in the long-term. Additionally, reducing interest rates increases the price of commodities above their equilibrium in the short-term.

Most empirical literature has focused on the effect of monetary policy and oil price fluctuations on the macroeconomic (i.e., Ardeni & Freebairn, 2002; Bernanke, Gertler, & Watson, 1997; Doh, 2010; Hamilton & Wu, 2010; Kilian, 2009; Siami-Namini, 2018). However, some other studies have investigated the impact of monetary policy as a contributory element of the commodity price volatility. Specifically, these studies address whether commodity prices respond to monetary changes in the long-term, whereas there are predictable deviations from such neutrality in the short-term (Frankel, 2006; Frankel & Hardouvelis, 1985b; Hess, Huang, & Niessen, 2008; Hua, 1998; Lunieski, 2009; Swaray, 2008). They argued that monetary changes can have real short-term effects on the commodity prices. Here, we briefly review some important points of the empirical results.

The empirical results of other studies showed that a higher money supply would increase the price of commodities (Chambers & Just, 1982; Dorfman & Lastrapes, 1996; Frankel, 1986; Orden & Fackler, 1989). For instance, Frankel (1986) postulated that the manufacturing commodity prices respond more slowly to monetary shocks than agricultural commodity prices. He argued that the lower adjustment speed of manufacturing commodity prices to monetary changes adds to overshooting in agricultural commodity prices. Using a Structural Vector Autoregressive (SVAR) models, Siami-Namini and Hudson (2016) found that a U.S. monetary contraction has a negative significant effect on the aggregate commodity price index and commodity subindices included the food price index, agricultural raw materials price index, maize (corn) price, and crude oil price, and results reinforce the overshooting hypothesis. Also, in another study, Simai-Namini and Hudson (2017) found that the volatility of the U.S. dollar exchange rate is transmitted to international agricultural commodity prices.

To the best of our knowledge, existing literature does not give evidence on the impacts of U.S. monetary policy shocks on the conditional variance series of the commodity price. Therefore, this article contributes to the current literature through estimating the conditional variance series of commodity price indices using ARMA-EGARCH (1,1) model. The measure of conditional variance series of variables is important for the design of monetary policy frameworks, as the commodity prices are volatile. Then, we analyze the impact of monetary policy shocks to the conditional variance series of commodity prices and test whether the overshooting hypothesis holds.

3 | DATA AND METHODS

We use monthly observations from February 1992 to March 2017, with the main data sources being the Federal Reserve Bank of St. Louis, the International Monetary Fund (IMF) website, and Yahoo Finance website. The variables include 10-year treasury constant maturity rate (GS10) as a measure of the interest rate for reflecting both inflation expectations and financial liquidity; M1 money stock (M1) to examine the effect of money supply on the price of commodities[1]; the trade-weighted U.S. dollar index in terms of major currencies (TWEX) of the Federal Reserve Bank of St. Louis as a measure of the exchange rate; the consumer price index (CPI) as a measure of inflation to test whether

[1] The choice of M1 is simply based on the cash or cash equivalent nature of money so that it can flow into investments most easily. Other aggregates behave similarly, but we chose the M1 as the most direct measure of free cash in the economy.

TABLE 1 Data description

Data	Description
GS10	10-year treasury constant maturities rate (Percent)
M1	M1 money stock (billions of dollars)
CPI	Consumer price index for all urban consumers (1982–1984 = 100)
TWEX	Trade weighted U.S. dollars index: major currencies (1973 = 100)
IP	Industrial production: total index (2012 = 100)
COM	Aggregate commodity price index (2005 = 100)
AGR	Agricultural commodity price index (2005 = 100), measured by food and beverage price index
SP	S&P 500 commodity index
DJ	Dow Jones commodity index (industrial average)
NASDAQ	NASDAQ composite index

commodity price impacts of monetary policy go beyond monetary neutrality to changes in relative prices; the industrial production index (IP) as an indicator of the health of the economy; the IMF aggregate commodity price index (COM) which includes both fuel and non-fuel price indices; the food and beverage price index of the IMF as a measure of agricultural commodity price index (AGR), Dow Jones industrial average index (DJ), NASDAQ composite index, and S&P 500 (SP) commodity index. The log return series are calculated based on the difference between the log series at time t and time t-1 and applied in the empirical estimation. All variables (for the log return series) were found to be stationary. A more detailed description of the data is presented in Table 1.

We extract the conditional variance series of all variables using the EGARCH model proposed by Nelson (1991) to capture the asymmetric effect of shocks on volatilities and to remove the non-negativity restrictions on the EGARCH parameters (Nelson & Cao, 1992). The first step involves the univariate time-series estimation, which allows for time variation in both the conditional mean and conditional variance. We model the conditional mean equation using an ARMA process, and the innovations are generated from an EGARCH process.

The time series $\{R_{j,t}\}$ is an ARMA (p, q) process if $\{R_{j,t}\}$ is a stationary solution of Equation (1) for every t,

$$R_{j,t} = \mu + \sum_{i=1}^{p} \varphi_i R_{j,t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{j,t-i} + \varepsilon_{j,t}, \tag{1}$$

where $R_{j,t}$ denotes the log return of price index $j = 1, \ldots, n$ at time t, μ is constant, φ_i are parameters of the autoregressive part, θ_i are parameters of the moving average part, and the innovations process $\{\varepsilon_{j,t}\}$ is a serially uncorrelated sequence with zero mean and constant variance. To model the dependence structure in the innovations, Equation (2) is added:

$$\varepsilon_{j,t} = \sigma_{j,t} v_{j,t}, \tag{2}$$

where the $\sigma^2_{j,t}$ component is the conditional variance of the innovations, and $v_{j,t}$ is an independent and identically distributed sequence with mean zero and unit variance. The natural logarithm of the conditional variance is then assumed to follow the recursions given in Equation (3), which characterize an EGARCH (1,1) process, a variation on GARCH allowing for asymmetry in the lagged innovations $\varepsilon_{j,t-i}$:

$$ln\,\sigma^2_{(j,t)} = \omega_j + \sum_{i=1}^{p=1} (\alpha_i |z_{j,t-i}| + \gamma_i z_{j,t-i}) + \sum_{i=1}^{q=1} \beta_i \ln \sigma^2_{j,t-i}, \text{ and} \tag{3}$$

$$z_{j,t-i} = \frac{\varepsilon_{j,t-i}}{\sqrt{\sigma^2_{j,t-i}}}. \tag{4}$$

where the ω_j are constants, and $z_{j,t-i}$ are the standardized innovations from the conditional mean equations. The parameter γ_i allows for an asymmetric ARCH-like effect on the volatility. Statistically significant values of $\gamma_i < 0$ signal when the effect of negative returns on future volatility are greater than the positive returns. Likewise, values of $\gamma_i > 0$ indicates that positive returns have a higher impact on volatility than do negative returns.

For the second step, we construct the GARCH variance series (or conditional variance series) from an ARMA-EGARCH (1,1) process for all variables. The results of the Johansen cointegration test applied to the GARCH variance series, suggests the existence of long-term relationships between series, indicating the need for construction of the VECM in order to estimate the parameters pertaining to long-term equilibrium relationships between the variables, as well as the appropriate short-term adjustment coefficients.

To identify and evaluate the impact of the U.S. monetary policy on the volatility of commodity price, we consider the following VECM:

$$\Delta y_t = \alpha + \pi y_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta y_{t-i} + \epsilon_t, \tag{5}$$

where α is constant, y_t is a $n \times 1$ vector holding the series of conditional variances to be studied ($n = 6$), Δ is the first difference operator, π and ϕ_i are matrices of parameters to be estimated, and ϵ_t is assumed to be independent and identically distributed with mean zero. In this article, the vector of endogenous variables is as follows:

$$y_t = \begin{bmatrix} \mathrm{COM}_t \\ \mathrm{GS10}_t \\ \mathrm{M1}_t \\ \mathrm{TWEX}_t \\ \mathrm{IP}_t \\ \mathrm{CPI}_t \end{bmatrix}. \tag{6}$$

For evaluating the impact of monetary policy shocks on the other commodity price indices, we employ the commodity price indices individually in place of the aggregate commodity price index in the first element of the vector in Equation (6). We assume all variables to have contemporaneous effects on the commodity prices. The final step in our investigation involves analyzing the IRF characteristics of the model to determine the existence of overshooting behavior in the commodity prices conditional variance series in response to monetary policy shocks.

4 | EMPIRICAL RESULTS

4.1 | The results of ARMA-EGARCH (1,1) model

Figure 1 plots the squared log returns of the time series over the whole study period from February 1992 to March 2017. The plots indicate the presence of volatility clustering, implying that low/high values of volatility tend to be followed by low/high values. The results of a Lagrange Multiplier (LM) heteroscedasticity test reject the null hypothesis of no ARCH effect. Therefore, we estimate the conditional mean and conditional variance equations using the ARMA-EGARCH (1,1) model described above.

Based on the Akaike's Information Criterion (AIC), we identify appropriate univariate ARMA (p, q) model orders for the conditional mean equation, allowing for maximum values of $p = 13$ and $q = 13$. The resulting ARMA models, presented in panel A of Table2, indicate which coefficients are statistically significant (Siami-Namini & Siami Namin, 2018). The results of subsequent EGARCH (1,1) volatility modeling based on the residuals of the fitted ARMA models displayed in panel B of Table 2, indicate that the ARCH parameters, α_i, are statistically significant for all series, and then confirming the rejection of the null hypothesis of no ARCH effect alluded to earlier. The volatility persistence, the degree of which is measured by the GARCH parameter β_i are significant for all series. This fact suggests the presence

TABLE 2 Parameter estimates of the ARMA-EGARCH (1,1) model

Panel A: Conditional Mean equation	IP ARMA (10,12)	CPI ARMA (10,12)	COM ARMA (13,13)	AGR ARMA (12,13)	SP ARMA (13,13)	DJ ARMA (13,13)	NASDAQ ARMA (13,13)	TWEX ARMA (11,11)	M1 ARMA (13,13)	GS10 ARMA (13,12)
Intercept	–	0.00095	–	–	0.01196	0.00672	0.01048	–	–	−0.00378
	(–)	(0.0000)	(–)	(–)	(0.0000)	(0.0021)	(0.0000)	(–)	(–)	(0.0000)
AR (1)	0.550060	0.37866	0.264687	0.315875	–	–	−0.19311	0.754204	–	–
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(–)	(–)	(0.0001)	(0.0000)	(–)	(–)
AR (2)	0.201340	−0.16024	−0.033409	−0.195080	–	–	0.13646	−0.261838	0.168846	–
	(0.0000)	(0.0000)	(0.0000)	(0.0004)	(–)	(–)	(0.0298)	(0.0000)	(0.0078)	(–)
AR (3)	0.055334	–	–	–	0.47541	–	−0.19624	–	–	0.43477
	(0.0000)	(–)	(–)	(–)	(0.0000)	(–)	(0.0000)	(–)	(–)	(0.0000)
AR (4)	–	0.14654	−0.503578	–	–	–	−0.26716	0.173447	–	−0.34397
	(–)	(0.0000)	(0.0000)	(–)	(–)	(–)	(0.0000)	(0.0000)	(–)	(0.0000)
AR (5)	–	0.06822	0.157153	–	–	–	−0.26692	−0.240263	0.131790	–
	(–)	(0.0000)	(0.0000)	(–)	(–)	(–)	(0.0000)	(0.0000)	(0.0109)	(–)
AR (6)	–	–	–	–	−0.10051	–	−0.30354	−0.380241	0.115374	–
	(–)	(–)	(–)	(–)	(0.0000)	(–)	(0.0000)	(0.0000)	(0.0117)	(–)
AR (7)	–	–	0.220047	−0.410676	–	–	0.09594	0.198830	–	–
	(–)	(–)	(0.0000)	(0.0000)	(–)	(–)	(0.0563)	(0.0000)	(–)	(–)
AR (8)	0.101644	–	−0.057895	–	–	–	–	–	0.244992	–
	(0.0000)	(–)	(0.0000)	(–)	(–)	(–)	(–)	(–)	(0.0007)	(–)
AR (9)	0.378482	–	–	–	–	0.22953	–	–	0.148747	−0.44693
	(0.0000)	(–)	(–)	(–)	(–)	(0.0000)	(–)	(–)	(0.0000)	(0.0000)
AR (10)	−0.298190	0.49807	0.348774	–	−0.06647	–	–	–	−0.251258	0.08779
	(0.0000)	(0.0000)	(0.0000)	(–)	(0.0000)	(–)	(–)	(–)	(0.0002)	(0.0355)
AR (11)	–	–	–	−0.182605	0.26615	0.47471	−0.52537	−0.478901	–	–

(continued)

TABLE 2 Continued

Panel A: Conditional Mean equation	IP ARMA (10,12)	CPI ARMA (10,12)	COM ARMA (13,13)	AGR ARMA (12,13)	SP ARMA (13,13)	DJ ARMA (13,13)	NASDAQ ARMA (13,13)	TWEX ARMA (11,11)	M1 ARMA (13,13)	GS10 ARMA (13,12)
	(–)	(–)	(–)	(0.0027)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(–)	(–)
AR (12)	–	–	–	0.423187	−0.05066	−0.46756	–	–	0.445339	0.47716
	(–)	(–)	(–)	(0.0000)	(0.0000)	(0.0000)	(–)	(–)	(0.0000)	(0.0000)
AR (13)	–	–	0.374827	–	0.40167	−0.33690	0.51880	–	−0.264432	−0.34670
	(–)	(–)	(0.0000)	(–)	(0.0000)	(0.0000)	(0.0000)	(–)	(0.0000)	(0.0000)
MA (1)	−0.654146	–	–	–	–	–	0.17427	−0.396000	–	0.26521
	(0.0000)	(–)	(–)	(–)	(–)	(–)	(0.0000)	(0.0000)	(–)	(0.0000)
MA (2)	–	–	0.062240	0.184894	–	–	−0.21557	–	–	−0.11518
	(–)	(–)	(0.0000)	(0.0000)	(–)	(–)	(0.0000)	(–)	(–)	(0.0081)
MA (3)	–	−0.06865	–	–	−0.47014	–	0.14570	–	0.183413	−0.46185
	(–)	(0.0000)	(–)	(–)	(0.0000)	–	(0.0000)	(–)	(0.0017)	(0.0000)
MA (4)	–	−0.15820	0.621467	–	–	0.05011	0.22201	–	–	0.21800
	(–)	(0.0000)	(0.0000)	(–)	(–)	(0.0025)	(0.0000)	(–)	(–)	(0.0002)
MA (5)	–	−0.16034	−0.030057	–	–	–	0.26189	–	–	–
	(–)	(0.0000)	(0.0000)	(–)	(–)	(–)	(0.0000)	(–)	(–)	(–)
MA (6)	–	–	–	–	–	–	0.39468	0.574888	–	–
	(–)	(–)	(–)	(–)	(–)	(–)	(0.0000)	(0.0000)	(–)	(–)
MA (7)	–	–	−0.246592	0.522335	–	–	−0.11347	−0.234224	–	–
	(–)	(–)	(0.0000)	(0.0000)	(–)	(–)	(0.0011)	(0.0000)	(–)	(–)
MA (8)	−0.189304	–	−0.109788	0.042299	–	–	–	–	−0.244127	–
	(0.0007)	(-)	(0.0000)	(0.0050)	(-)	(-)	(-)	(-)	(0.0018)	(-)
MA (9)	−0.271248	–	–	–	–	−0.24352	–	–	–	0.20632
	(0.0000)	(-)	(-)	(-)	(-)	(0.0000)	(-)	(-)	(-)	(0.0002)
MA (10)	0.195999	−0.59722	−0.345049	–	–	–	–	–	0.213558	–

(continued)

TABLE 2 Continued

Panel A: Conditional	IP	CPI	COM	AGR	SP	DJ	NASDAQ	TWEX	M1	GS10
Mean equation	ARMA (10,12)	ARMA (10,12)	ARMA (13,13)	ARMA (12,13)	ARMA (13,13)	ARMA (13,13)	ARMA (13,13)	ARMA (11,11)	ARMA (13,13)	ARMA (13,12)
	(0.0000)	(0.0000)	(0.0000)	(-)	(-)	(-)	(-)	(-)	(0.0032)	(-)
MA (11)	−0.139850	−0.15287	–	0.210346	−0.35362	−0.52415	0.55982	0.611868	–	−0.22479
	(0.0000)	(0.0000)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(-)	(0.0000)
MA (12)	−0.081974	−0.14143	–	−0.523568	–	0.55518	–	–	−0.420607	−0.66041
	(0.0324)	(0.0000)	(-)	(0.0000)	(-)	(0.0000)	(-)	(-)	(0.0000)	(0.0000)
MA (13)	–	–	−0.519750	−0.100312	−0.50719	0.32551	−0.73071	–	0.269606	–
	(-)	(-)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(-)	(0.0000)	(-)

Panel B: Conditional variance equation	IP	CPI	COM	AGR	SP	DJ	NASDAQ	TWEX	M1	GS10
ω	−2.379568	−2.40503	−0.635627	−0.442759	−1.24946	−1.91302	−1.04602	−12.85460	−2.637805	−2.68816
	(0.0002)	(0.0000)	(0.0156)	(0.0211)	(0.0009)	(0.0047)	(0.0026)	(0.0000)	(0.0017)	(0.0000)
α	0.156604	0.35213	0.323982	0.140718	0.23024	0.26631	0.57922	−0.245001	0.663444	0.81126
	(0.0557)	(0.0000)	(0.0001)	(0.0056)	(0.0003)	(0.0184)	(0.0000)	(0.0575)	(0.0000)	(0.0000)
γ	−0.362360	0.17502	−0.049288	0.039251	−0.26767	−0.27396	−0.07717	−0.093583	0.155944	−0.33437
	(0.0000)	(0.0000)	(0.2828)	(0.2649)	(0.0000)	(0.0009)	(0.2093)	(0.2454)	(0.0435)	(0.0000)
β	0.786628	0.82946	0.942313	0.955143	0.83635	0.74462	0.90092	−0.516368	0.789692	0.66099
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0316)	(0.0000)	(0.0000)

Panel C:	IP	CPI	COM	AGR	SP	DJ	NASDAQ	TWEX	M1	GS10
AIC	−7.739411	−9.49209	−3.736963	−4.650431	−3.69528	−3.74347	−2.95469	−5.656322	−7.10200	−3.10833
LL	1145.954	1401.85	555.9912	689.3125	547.97	554.93	449.9533	837.9948	1043.239	467.15

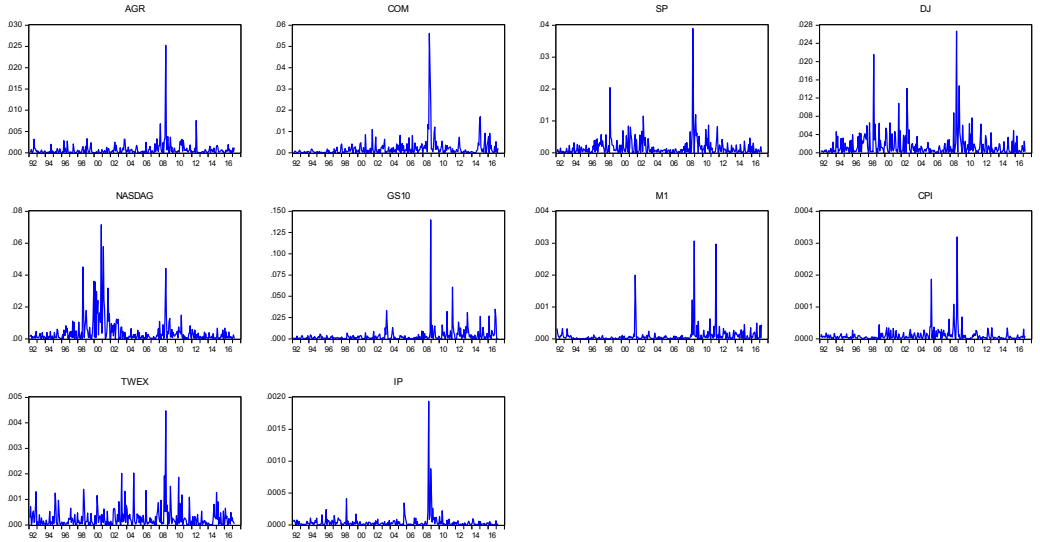


FIGURE 1 Squared log returns of time series over study period [Color figure can be viewed at wileyonlinelibrary.com]

of volatility clustering in the log returns of all variables, whence we can conclude that the volatility in previous periods partially explains the current volatility. A larger ARCH parameter implies short-term volatility, whereas a larger GARCH parameter indicates long-term volatility. As shown in Table 2, the absolute value of GARCH parameters are larger than the absolute value of ARCH parameters for all series. Therefore, they have long-term volatility. As a result, the estimates of the EGARCH (1,1) model show that the volatility processes of the commodities return in question (3) are dominated by ARCH and GARCH effects.

The asymmetric effect parameter, γ_i are not significant for aggregate commodity price index (COM), agricultural commodity price index (AGR), NASDAQ composite index (NASDAQ), and trade-weighted U.S. dollar index (TWEX). A negative/positive sign for the asymmetric effect parameter, γ_i show that a negative/positive shock does have a higher impact on future. Usually, the effect of a positive shock on future volatility is more than a negative shock. The results of the asymmetric effect parameter of all series are negative except for inflation, agriculture commodity price index and money supply, which have a positive asymmetric effect.

4.2 | The results of VECM

Using the conditional variance series of all variables obtained from last part, we built five individual vectors autoregressive (VAR) models based on the structure of the Equation (6). We selected the optimal lag length for Model 1 to Model 5, respectively. This is performed based on minimizing the Bayesian Information Criterion (BIC) and eliminating serial correlation in the residuals. The results of the Johansen cointegration test suggested the existence of a long-term relationship between the conditional variance series in all five models. Therefore, we constructed our models based on the VECM approach for identifying the short- and the long-term relationships between the conditional variance series.

The results from the VECM estimation in terms of normalized cointegrating equations and error correction coefficients are presented in Table 3. The coefficients corresponding to the conditional series of GS10 in all models are negative and statistically significant, with exception of Model 1, where the conditional series of aggregate commodity price index is used. The negative signs confirm the inverse relationship between the conditional series of interest rates and the conditional series of the commodity price, which is consisted with theory. The coefficients of the conditional variance series of M1 in all models are positive and significant. In fact, the conditional variance series of the commodity price increases are caused by an expansion in the conditional variance series of the money supply due to a reduction in

TABLE 3 The results of vector error correction models (VECM)

Variables	Model 1: COM	Model 2: AGR	Model 3: SP	Model 4: DJ	Model 5: NASDAQ
Normalized cointegrating equations					
GS10 (−1)	−0.06014 [−0.9947]	−0.486098 [−2.6993]	−0.585979 [−3.2232]	−0.545551 [−5.4396]	−3.505369 [−4.6299]
M1 (−1)	11.10005 [2.5459]	48.63376 [3.7970]	55.6647 [4.3479]	24.59053 [3.4099]	329.7911 [5.9105]
TWEX (−1)	−238.3851 [−8.3372]	438.9918 [4.6685]	510.9413 [5.5053]	182.1848 [3.7115]	1896.768 [4.9172]
IP (−1)	19.77689 [1.7389]	−112.1454 [−3.3927]	−71.0002 [−2.1465]	−18.73303 [−1.0101]	−282.3715 [−2.0649]
CPI (−1)	118.0315 [1.2379]	344.5884 [1.3485]	252.8734 [0.9667]	361.5105 [2.3366]	157.2567 [0.1418]
Intercept term	0.04462	−0.08106	−0.09439	−0.03301	−0.35129
Error correction (EC) coefficients					
EC Term	−0.012679 [−1.1472]	−0.001557 [−1.3605]	−0.013996 [−1.3637]	−0.028883 [−1.8896]	−0.00539 [−0.6286]
Intercept term	7.36E-06 [0.3493]	2.21E-06 [0.6046]	4.29E-06 [0.1077]	3.77E-06 [0.0881]	1.20E-05 [0.0820]

the conditional variance series of interest rates. The coefficients of the conditional variance series of the exchange rate (TWEX) in all models are significant but appear with a negative sign in Model 1. The conditional variance series of the exchange rate is not the cause of the change in the conditional variance series of the commodity price. The main reason is that the conditional variance series of exchange rates and the conditional variance series of the commodity price are commonly determined as the outcome of other factors which might see the strong or weak similar movement between the volatile commodity prices and exchange rates. The coefficient of the conditional variance series of industrial production is negative and significant in Model 2, 3, and 5. The coefficient of the conditional variance series of inflation is positive and significant in model 4. Error correction terms (ECTs) are also negative, which have the correct signs, but they are not significant in all five models.

4.3 | The results of short- and long-term granger causality/wald test results

The results of the *F*-test values for both short- and long-term Granger causality are reported in Table 4. Here we focus on the short- and long-term relationship between the conditional variance series of individual commodity prices and the conditional variance series of the interest rate as a channel of transmission of monetary policy. As shown in panel A of Table 4, there is short-term Granger causality running from the conditional variance series of interest rate (GGS10) to the conditional variance series of agricultural commodity price index (GAGR) and to the conditional variance series of Dow Jones commodity index (GDJ) in Model 2 and Model 4, respectively. Also, there is a short-term Granger causality running from the conditional variance series of aggregate commodity price index (GCOM) to the conditional variance series of interest rate (GGS10) in Model 1. It means that the aggregate commodity price volatility could influence the interest rate volatility, which should be considered in monetary policy decisions.

In addition, as the VECM established a long-term relationship between the conditional variance series of variables in all five models, the estimated coefficients can be used to identify the adjustment period to reach a new equilibrium price. The ECT coefficient presents, the speed of adjustment to the new long-term equilibrium. As shown in panel B of Table 4, there is a unidirectional long-term relationship running from the conditional variance series of agricultural commodity price index (GAGR); running from the conditional variance series of S&P 500 commodity price index (GSP); and running from the conditional variance series of NASDAQ composite index (GNASDAQ) to the conditional variance series of interest rate (GGS10) in Model 2, 3, and 5, respectively. Similarly, there is a bidirectional long-term relationship between the conditional variance series of interest rate (GGS10) and the conditional variance series of Dow Jones commodity index (GDJ) in Model 4.

Furthermore, the joint test represents the short-term response of all variables to any shocks in the system of equations in order to restore new equilibrium in the long-term. As shown in panel C of Table 4, the joint test indicates that there is (1) a unidirectional relationship running from the conditional variance series of aggregate commodity price index (GCOM) to the conditional variance series of interest rate (GGS10) in Model 1, (2) a unidirectional strong causality from the conditional variance series of interest rate (GGS10) to the conditional variance series of agricultural commodity price index (GAGR) in Model 2, (3) a unidirectional causality running from the conditional variance series of Dow Jones industrial average index (GDJ) to the conditional variance series of interest rate (GGS10) in Model 4.

4.4 | The results of IRF

As explained in Section 3, the U.S. monetary policy shock is identified in a six-variable VAR system. Here, we only analyze the response of the conditional variance series of individual commodity price to the monetary policy shock, defined as an increase in the conditional variance series of interest rate (GGS10).

Focusing on the response of the conditional variance series of aggregate commodity price index (GCOM) to the monetary policy shock, as shown in Figure 2, the effect slowly diminishes until second month, and then the effect quickly diminishes until 8 months, and starts to increase, and hence bringing back GCOM to equilibrium. The response appears to be significant, as the effects remain significant up to third years after the shock has occurred. The other responses have the expected significant sign for the conditional variance series of money supply (GM1), the

TABLE 4 The granger-causality/wald test results

	Panel A: Short-term						Panel B: Long-term	Panel C: Joint (Short- and Long-term)					
Model 1	**ΔGCOM**	**ΔGGS10**	**ΔGM1**	**ΔGTWEX**	**ΔGIP**	**ΔGCPI**	**ECT**	**ΔGCOM, ECT**	**ΔGGS10, ECT**	**ΔGM1, ECT**	**ΔGTWEX, ECT**	**ΔGIP, ECT**	**ΔGCPI, ECT**
ΔGCOM	7.76061	0.33049	2.31526	1.43899	33.41310	4.27832	1.31600	6.64462	0.65036	2.59360	1.64510	31.84722	3.60435
	(0.0000)	(0.8573)	(0.0578)	(0.2215)	(0.0000)	(0.0023)	(0.2524)	(0.0000)	(0.6615)	(0.0261)	(0.1485)	(0.0000)	(0.0036)
ΔGGS10	4.93269	20.74206	0.53989	0.28653	19.46099	1.29374	0.59601	4.30400	16.97142	0.53369	0.25053	16.19209	1.15657
	(0.0008)	(0.0000)	(0.7066)	(0.8866)	(0.0000)	(0.2729)	(0.4408)	(0.0009)	(0.0000)	(0.7507)	(0.9393)	(0.0000)	(0.3311)
ΔGM1	2.91671	1.08700	4.74082	2.45789	2.77289	3.14942	4.40141	3.54951	1.48450	6.75936	2.38627	3.78106	3.18398
	(0.0219)	(0.3634)	(0.0010)	(0.0461)	(0.0277)	(0.0149)	(0.0369)	(0.0040)	(0.1952)	(0.0000)	(0.0387)	(0.0025)	(0.0083)
ΔGTWEX	2.67134	0.52004	4.77300	2.42345	3.70461	1.79316	54.08414	12.3464	11.65205	11.96881	183.4673	11.82312	12.04811
	(0.0327)	(0.7211)	(0.0010)	(0.0487)	(0.0060)	(0.1306)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ΔGIP	5.78547	0.95232	0.69405	1.18105	15.90886	5.36821	0.16372	4.72718	0.78429	0.60936	2.09787	14.51009	4.29591
	(0.0002)	(0.4343)	(0.5967)	(0.3195)	(0.0000)	(0.0004)	(0.6861)	(0.0004)	(0.5618)	(0.6928)	(0.0661)	(0.0000)	(0.0009)
ΔGCPI	1.23814	0.30468	0.26527	0.85350	0.41011	7.83544	1.46880	1.29067	0.56540	0.44122	0.68723	0.65356	6.28564
	(0.2951)	(0.8747)	(0.9001)	(0.4925)	(0.8013)	(0.0000)	(0.2266)	(0.2683)	(0.7265)	(0.8195)	(0.6335)	(0.6590)	(0.0000)
Model 2	**ΔGAGR**	**ΔGGS10**	**ΔGM1**	**ΔGTWEX**	**ΔGIP**	**ΔGCPI**	**ECT**	**ΔGAGR, ECT**	**ΔGGS10, ECT**	**ΔGM1, ECT**	**ΔGTWEX, ECT**	**ΔGIP, ECT**	**ΔGCPI, ECT**
ΔGAGR	0.89193	2.18520	1.73527	1.75329	6.66944	0.99780	1.85090	1.00695	1.94464	1.55338	1.77135	6.20034	1.08604
	(0.5239)	(0.0294)	(0.0913)	(0.0874)	(0.0000)	(0.4385)	(0.1750)	(0.4352)	(0.0468)	(0.1305)	(0.0746)	(0.0000)	(0.3739)
ΔGGS10	1.12269	6.65288	1.00732	0.80689	18.6772	1.77809	3.19033	1.36201	11.94874	1.11144	0.72939	16.93521	2.08450
	(0.3487)	(0.0000)	(0.4312)	(0.5971)	(0.0000)	(0.0823)	(0.0754)	(0.2065)	(0.0000)	(0.3554)	(0.6817)	(0.0000)	(0.0318)
ΔGM1	1.02358	0.46215	1.62715	0.89059	3.30357	1.05872	0.84198	0.98618	0.41173	3.66431	1.20909	3.008969	1.12141
	(0.4189)	(0.8818)	(0.1180)	(0.5251)	(0.0014)	(0.3931)	(0.3598)	(0.4521)	(0.9282)	(0.0003)	(0.2902)	(0.0021)	(0.3483)
ΔGTWEX	1.05758	2.54956	1.53178	3.03761	2.27602	2.43309	12.6109	2.31100	2.45629	1.95264	98.6909	2.63861	3.82099
	(0.3939)	(0.0111)	(0.1471)	(0.0029)	(0.0232)	(0.0153)	(0.0005)	(0.0167)	(0.0109)	(0.0458)	(0.0000)	(0.0063)	(0.0002)
ΔGIP	5.16134	0.52149	0.54356	1.47141	2.55578	2.75511	3.30736	5.07086	0.63324	0.63568	1.99226	4.84977	2.60100
	(0.0000)	(0.8398)	(0.8229)	(0.1686)	(0.0110)	(0.0063)	(0.0703)	(0.0000)	(0.7681)	(0.7660)	(0.0411)	(0.0000)	(0.0071)
ΔGCPI	2.24946	1.43972	0.64607	1.60245	0.89416	5.52842	0.52832	2.09542	1.30043	0.57457	1.44059	0.93221	5.19971
	(0.0249)	(0.1809)	(0.7384)	(0.1250)	(0.5221)	(0.0000)	(0.4681)	(0.0308)	(0.2375)	(0.8173)	(0.1717)	(0.4978)	(0.0000)

(continued)

TABLE 4 Continued

	Panel A: Short-term						Panel B: Long-term	Panel C: Joint (Short- and Long-term)					
Model 3	**ΔGSP**	**ΔGGS10**	**ΔGM1**	**ΔGTWEX**	**ΔGIP**	**ΔGCPI**	**ECT**	**ΔGSP, ECT**	**ΔGGS10, ECT**	**ΔGM1, ECT**	**ΔGTWEX, ECT**	**ΔGIP, ECT**	**ΔGCPI, ECT**
ΔGSP	4.91789	1.48087	1.03158	0.57321	21.4212	1.17929	1.85959	4.67629	1.33500	0.91890	0.63637	19.61900	1.21811
	(0.0000)	(0.1747)	(0.4096)	(0.7774)	(0.0000)	(0.3153)	(0.1740)	(0.0000)	(0.2268)	(0.5014)	(0.7468)	(0.0000)	(0.2890)
ΔGGS10	0.82395	5.83352	0.96552	0.76667	11.56377	0.90801	4.25055	1.42081	12.03733	1.08782	0.67517	10.84502	1.47425
	(0.5682)	(0.0000)	(0.4571)	(0.6158)	(0.0000)	(0.5009)	(0.0403)	(0.1884)	(0.0000)	(0.3723)	(0.7132)	(0.0000)	(0.1673)
ΔGM1	0.69489	0.45681	1.64553	1.06475	2.22899	1.53195	1.70081	0.84139	0.45152	4.19216	1.55239	2.09753	1.62021
	(0.6764)	(0.8650)	(0.1235)	(0.3869)	(0.0327)	(0.1571)	(0.1934)	(0.5670)	(0.8889)	(0.0001)	(0.1401)	(0.0368)	(0.1197)
ΔGTWEX	2.48659	3.62003	2.23549	3.51113	2.60079	1.84049	21.05828	4.45117	3.87947	3.36516	122.7190	4.82594	4.33340
	(0.0176)	(0.0010)	(0.0322)	(0.0013)	(0.0133)	(0.0804)	(0.0000)	(0.0000)	(0.0003)	(0.0011)	(0.0000)	(0.0000)	(0.0001)
ΔGIP	1.62844	0.42288	0.21397	1.11334	4.59956	3.31671	0.80699	1.51293	0.41819	0.23601	2.41250	5.09168	2.92178
	(0.1281)	(0.8875)	(0.9820)	(0.3553)	(0.0001)	(0.0022)	(0.3699)	(0.1533)	(0.9095)	(0.9838)	(0.0160)	(0.0000)	(0.0040)
ΔGCPI	0.78146	1.75871	0.90432	1.62456	0.78219	2.72315	2.64771	0.92129	1.54506	0.81081	1.58939	1.20086	5.36604
	(0.6034)	(0.0964)	(0.5037)	(0.1291)	(0.6028)	(0.0000)	(0.1050)	(0.4995)	(0.1425)	(0.5936)	(0.1286)	(0.2991)	(0.0000)
Model 4	**ΔGDJ**	**ΔGGS10**	**ΔGM1**	**ΔGTWEX**	**ΔGIP**	**ΔGCPI**	**ECT**	**ΔGDJ, ECT**	**ΔGGS10, ECT**	**ΔGM1, ECT**	**ΔGTWEX, ECT**	**ΔGIP, ECT**	**ΔGCPI, ECT**
ΔGDJ	8.64589	2.05660	0.81878	0.87603	19.89392	1.81808	3.57046	8.45131	1.76584	1.11367	1.06387	17.24416	1.74750
	(0.0000)	(0.0714)	(0.5372)	(0.4977)	(0.0000)	(0.1098)	(0.0600)	(0.0000)	(0.1066)	(0.3547)	(0.3848)	(0.0000)	(0.1105)
ΔGGS10	0.45053	1.80185	1.41135	4.06791	19.79243	1.49186	22.98068	4.05296	17.94105	4.32094	3.96189	21.27670	4.77419
	(0.8127)	(0.1130)	(0.2206)	(0.0014)	(0.0000)	(0.1929)	(0.0000)	(0.0007)	(0.0000)	(0.0004)	(0.0008)	(0.0000)	(0.0001)
ΔGM1	4.29969	0.14221	4.59206	2.07729	4.90628	2.17683	0.42673	3.68964	0.32815	4.41128	2.20504	4.29699	1.95329
	(0.0009)	(0.9822)	(0.0005)	(0.0688)	(0.0003)	(0.0573)	(0.5142)	(0.0016)	(0.9218)	(0.0003)	(0.0431)	(0.0004)	(0.0729)
ΔGTWEX	2.28725	2.77151	1.30005	20.98791	3.20434	1.78139	8.14753	2.84863	2.48209	2.31510	141.1447	3.86529	2.71212
	(0.0466)	(0.0186)	(0.2644)	(0.0000)	(0.0080)	(0.1171)	(0.0047)	(0.0106)	(0.0238)	(0.0341)	(0.0000)	(0.0010)	(0.0143)

(continued)

TABLE 4 Continued

	Panel A: Short-term						Panel B: Long-term	Panel C: Joint (Short- and Long-term)					
Model 4	ΔGDJ	ΔGGS10	ΔGM1	ΔGTWEX	ΔGIP	ΔGCPI	ECT	ΔGDJ, ECT	ΔGGS10, ECT	ΔGM1, ECT	ΔGTWEX, ECT	ΔGIP, ECT	ΔGCPI, ECT
ΔGIP	5.30836	0.84613	0.12546	1.98552	8.69006	3.86720	1.31471	4.63848	0.76895	0.29086	2.84665	7.55366	3.64494
	(0.0001)	(0.5181)	(0.9866)	(0.0813)	(0.0000)	(0.0022)	(0.2526)	(0.0002)	(0.5950)	(0.9410)	(0.0106)	(0.0000)	(0.0017)
ΔGCPI	1.00154	3.91885	1.20777	1.64459	0.48792	5.31843	7.64351	2.13179	3.28358	1.64943	1.71699	1.78206	7.48621
	(0.4174)	(0.0019)	(0.3059)	(0.1487)	(0.7852)	(0.0001)	(0.0061)	(0.0503)	(0.0040)	(0.1341)	(0.1174)	(0.1032)	(0.0000)
Model 5	ΔGNASDAQ	ΔGGS10	ΔGM1	ΔGTWEX	ΔGIP	ΔGCPI	ECT	ΔGNASDAQ, ECT	ΔGGS10, ECT	ΔGM1, ECT	ΔGTWEX, ECT	ΔGIP, ECT	ΔGCPI, ECT
ΔGNASDAQ	4.75871	0.50836	0.80574	1.23456	6.45406	0.58075	0.39509	4.25369	0.46093	0.81189	1.16216	5.78935	0.61034
	(0.0001)	(0.8279)	(0.5832)	(0.2845)	(0.0000)	(0.7713)	(0.5302)	(0.0001)	(0.8827)	(0.5927)	(0.3229)	(0.0000)	(0.7688)
ΔGGS10	0.13793	3.28532	1.20672	0.93569	15.74950	0.89496	5.23322	0.88052	11.00744	1.20784	0.82689	14.8995	1.65622
	(0.9952)	(0.0024)	(0.2997)	(0.4795)	(0.0000)	(0.5111)	(0.0230)	(0.5335)	(0.0000)	(0.2950)	(0.5796)	(0.0000)	(0.1100)
ΔGM1	5.07344	0.74487	1.14204	0.71169	4.02638	1.52830	4.85397	5.09092	0.81824	4.84464	1.61963	4.01628	2.03786
	(0.0000)	(0.6342)	(0.3375)	(0.6622)	(0.0003)	(0.1583)	(0.0285)	(0.0000)	(0.5871)	(0.0000)	(0.1199)	(0.0002)	(0.0429)
ΔGTWEX	5.27717	4.48688	2.36010	5.49901	3.56182	2.14776	23.96488	5.91494	4.36496	3.53539	130.7151	5.75539	4.90025
	(0.0000)	(0.0001)	(0.0239)	(0.0000)	(0.0012)	(0.0396)	(0.0000)	(0.0000)	(0.0001)	(0.0007)	(0.0000)	(0.0000)	(0.0000)
ΔGIP	1.16527	0.53613	0.16017	0.89672	5.54261	2.92699	0.45475	1.02043	0.54230	0.20261	2.53843	4.98479	2.78256
	(0.3235)	(0.8067)	(0.9924)	(0.5097)	(0.0000)	(0.0059)	(0.5007)	(0.4212)	(0.8239)	(0.9902)	(0.0114)	(0.0000)	(0.0058)
ΔGCPI	0.62245	1.65195	0.61027	1.81771	0.67596	5.60696	1.80780	0.69902	1.46477	0.54353	1.73024	0.93144	4.93684
	(0.7372)	(0.1218)	(0.7472)	(0.0846)	(0.6924)	(0.0000)	(0.1801)	(0.6923)	(0.1709)	(0.8230)	(0.0922)	(0.4911)	(0.0000)

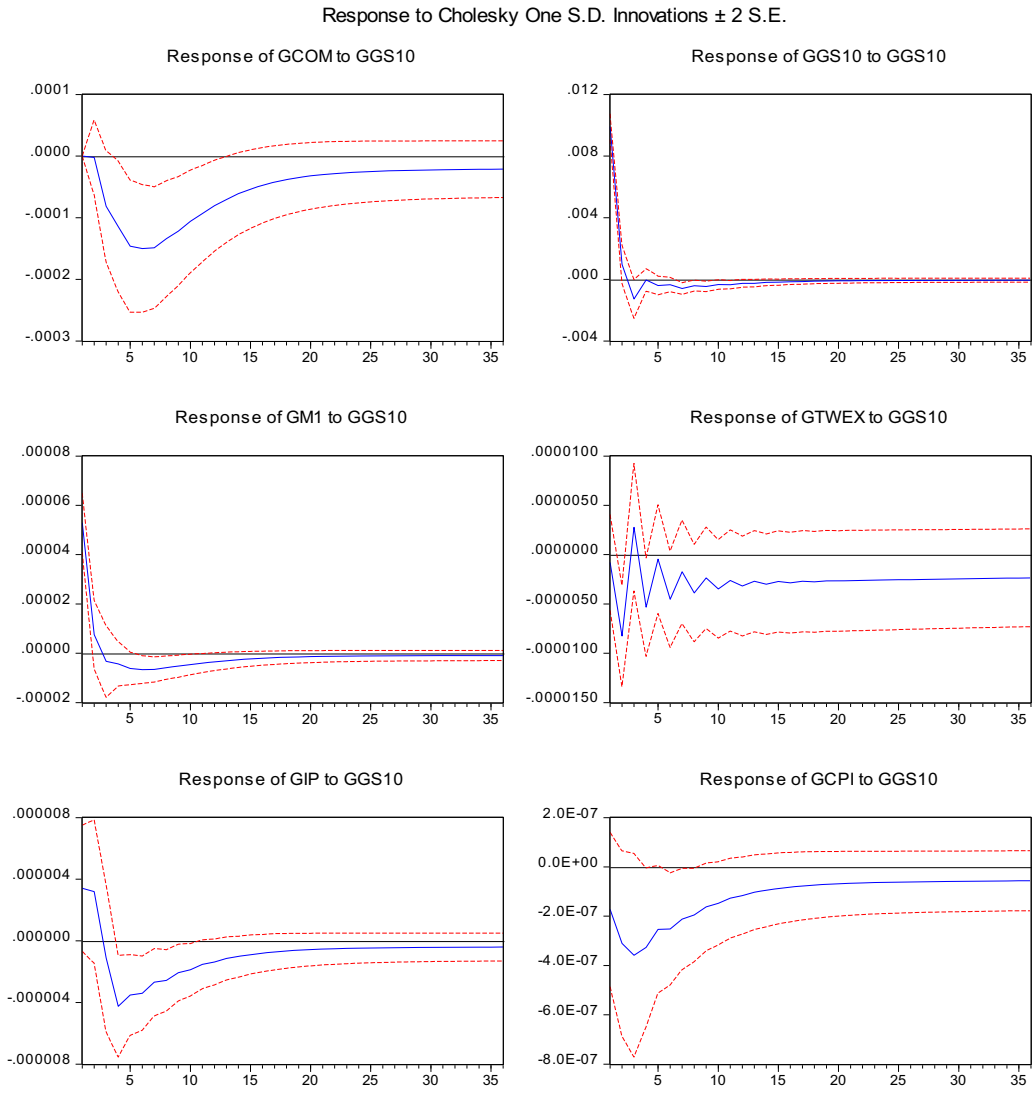


FIGURE 2 IRF of the conditional variance series of aggregate commodity price index [Color figure can be viewed at wileyonlinelibrary.com]

conditional variance series of the exchange rate (GTWEX), the conditional variance series of industrial production (GIP) and the conditional variance series of inflation (GCPI) as well. As a result, the monetary policy shock leads to a decrease of GCOM, and a temporary effect on relative prices, which is reabsorbed in the medium-term. The hump-shaped response of GCOM testifies an initial overshooting in the early periods and supports our previous work and its empirical results (Siami-Namini & Hudson, 2016).

Interestingly, as demonstrated in Figure 3, the response of the conditional variance series of agricultural commodity price index (GAGR) to an impulse in GGS10 is positive. The positive response refers to the higher cost of storage of agricultural commodities, which increase the price of this commodity. The findings show that GAGR takes a longer time to adjust to the equilibrium and support previous empirical results. Frankel (2006) found that adjustment period for a 1% increase in interest rate is about 6 months.

As shown in Figure 3, the response of the conditional variance series of S&P 500 commodity index (GSP) and the conditional variance series of Dow Jones industrial average index (GDJ) to an impulse in GGS10 are positive. The

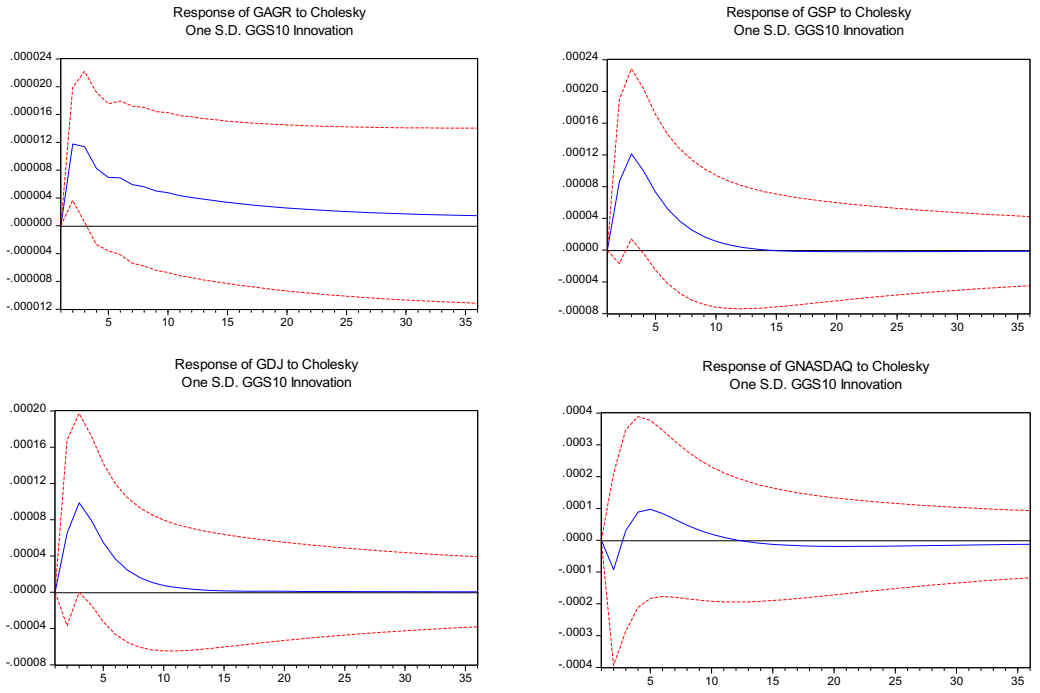


FIGURE 3 IRF of the conditional variance series of other individual commodities [Color figure can be viewed at wileyonlinelibrary.com]

positive responses continue until the second month and then decrease. This trend supports the overshooting hypothesis in the early periods. The response of the conditional variance series of NASDAQ composite index (GNASDAQ) to an impulse in GGS10 is negative in the early periods.

5 | CONCLUSION

In this article, we evaluated the impact of the U.S. monetary policy shock on the commodity price volatility. For this purpose, we used monthly data from the U.S. economy for the period of February 1992 to March 2017. Using an ARMA-EGARCH (1,1) model, we estimated conditional mean and conditional variance equation. The estimates of the EGARCH (1,1) coefficients showed that the volatility processes for the commodities return in question (3) was dominated by the ARCH and GARCH effect.

We built five individual VAR models based on six endogenous GARCH variance series of variables following structure of Equation (6). Because of existing long-term relationship between variables, we used VECM approach for identifying the short- and the long-term relationship between the conditional variance series of variables. Focusing on the short- and the long-term relationship between the conditional variance series of individual commodity prices and the conditional variance series of the interest rate as a channel of transmission of monetary policy, we found that the GGS10 could affect GAGR and GDJ in the short-term. Also, the GCOM could influence GGS10 in the short-term, which should be considered in monetary policy decisions. Furthermore, we found that GAGR, GSP, and GNASDAQ could affect GGS10 in the long-term. The findings showed that both GGS10 and GDJ could affect each other in the long-term.

The results of IRF showed that the monetary policy shock led to a decrease of GCOM, and a temporary effect on relative prices, which was reabsorbed in the medium-term. The other responses had the expected significant signs. The hump-shaped response of GCOM indicated an initial overshooting in the early periods. This observation supported

our previous empirical results (Siami-Namini & Hudson, 2016). The positive response of GAGR to GGS10 described the high cost of storage of agricultural commodities, which caused the price of the agricultural commodity to increase. The findings showed that GAGR took a longer time to adjust to the equilibrium and support previous empirical results. Additionally, the response of GSP and GDJ to an impulse in GGS10 was positive in the early periods supporting overshooting hypothesis in the early periods. The response of GNASDAQ to an impulse in GGS10 was negative in the early periods. As a result, the findings showed that U.S. monetary policy shocks had an impact on commodity price volatility, and the effect did not appear to be overwhelmingly large but took a longer time to adjust to the equilibrium.

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