World Commodity Prices and Economic Activity in Advanced and Emerging Economies

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Abstract

We investigate the volatility dynamics of commodity price and the dependence structure between commodity prices and output growth in the G7 and EM7 economies using a semiparametric GARCH-in-Mean copula approach. We show that for the G7 economies, a symmetric weak tail dependence exists between commodity prices and outputs in France, Germany, and Japan. For the EM7 economies, a lower tail dependence is observed between commodity prices and output growth in Brazil, and a symmetric weak tail dependence is observed in Indonesia. No statistically significant tail dependence between commodity prices and output growth is found for the rest of the G7 and EM7 economies.

Keywords Copula · Dependence · GARCH-in-Mean model

JEL Classification C32 · E37 · Q02 · O57

1 Introduction

World commodity prices are known to display long cycles and are often with macro-economic fluctuations. Since the 1960s, commodity prices have displayed two major peaks: one in the early 1980s and the other in the early 2000s. Both sharp fluctuations and shocks in commodity prices present serious challenges for policymakers due to their impacts on the level of economic activity. However, not all countries are influenced equally by commodity price fluctuations. Thus, understanding the various relationships between commodity prices and output growth in the G7 and EM7 economies has important implications for policy design and investment management.

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Although there is a voluminous empirical literature documenting the relationship between commodity price and output growth in developed countries, the effect of commodity price fluctuations on emerging economies has not been given enough attention, despite the tremendous ascension of emerging countries in the world economy. Moreover, the existing literature on the dependence between commodity prices and output growth has been mainly focused on the correlation framework that uses the linear correlation coefficient to measure the dependence between commodity prices and output growth. However, there is an overwhelming consensus that the global commodity market is volatile, and there are possibly nonlinear dependence and excess comovements beyond the first two conditional moments of commodity prices and output growth — see Sukcharoen et al. (2014) and Aloui et al. (2013).

This is of primary interest in the study of the contagion of risks in global commodity markets and output growth across economies around the world. Yet, only a few works have been devoted to estimating the nonlinear dependence and excess comovement between commodity prices and output growth. Furthermore, there have been significant economic structural changes, monetary policy regime shifts, and exchange rate regime reforms in the G7 and EM7 countries over the past decades accompanied by technological innovation and changes in the sources of supply and demand shocks. All these imply that the relationship between commodity prices and macroeconomic fluctuations across countries may be more complex than a single process, and the common joint normal distribution assumption might be too restrictive.

Structural models that examine the transmission mechanism between the volatility in commodity prices and output growth are under rigorous research. Fernandez et al. (2018) show that commodity prices exhibit strong comovements with other macro variables along the business cycle of the emerging economies. They embed a commodity sector into a dynamic, stochastic, multi-country business cycle model and show that commodity prices account for more than a third of the variance of real output across the emerging economies. Kohn et al. (2021a) point out that emerging economies produce and export systematically different goods than their developed counterparts, but they import similar types of goods, and such differences between emerging and developed economies can account for the higher business cycle volatility in emerging economies. Drechsel and Tenreyro (2018) show that commodity price fluctuations affect both the competitiveness of the economy and its borrowing terms, and both effects jointly result in strongly positive effects of commodity price increases on GDP, consumption, and investment, and a negative effect on the total trade balance.

In this paper, we investigate the variability and dependence structure between commodity prices and output growth in the G7 and EM7 countries. We present evidence on the dynamics of global commodity prices and output growth in these countries since the early 1960s. Particularly, we pay attention to the following questions: Does extreme value dependence exist between commodity prices and output growth? Is the dependence symmetric or asymmetric? How does the dependence structure between commodity prices and output growth vary across the G7 and EM7 countries?

To answer these questions, we use a GARCH-in-Mean copula model that goes beyond a simple single multivariate analysis. Our analysis proceeds in three steps. First, we estimate the univariate GARCH-in-Mean models for the global commodity price and output growth in each of the G7 and EM7 countries. In the second step, we construct marginal distributions of the residuals from the univariate GARCH-in-Mean models. In the third part of the analysis, we build the GARCH-in-Mean copula models to study the dependence structure between the marginal distributions of the residuals of the global commodity prices and output growth. As summarized in Patton (2006), copula-based models provide a great deal of flexibility in modeling multivariate distributions, allowing us to specify the models for the marginal distributions separately from the dependence structure that links them to form a joint distribution. In addition to flexibility, copula models can capture nonlinear, asymmetric, and tail dependencies and contain information about the joint behavior of the random variables in the tails of the distribution. Copulas are able to capture the excess comovement between commodity prices and output without the need of using discretion to define extreme outcomes. The dependence captured by a copula is invariant with respect to increasing and continuous transformations in the marginal distributions — see Castle and Shephard (2009). This model has a flexible dependence structure specification and enables us to track how risks propagate through commodity price and output growth in the G7 and EM7 countries by fitting copulas with different tail behavior.

We demonstrate that the GARCH-in-Mean model with a Student's t -distribution is the best to describe the dynamics of commodity prices and output growth evolution in the G7 and EM7 countries. We show that world commodity prices are extremely volatile and that the output growth rates in the G7 and EM7 countries experience persistent uncertainty. Volatility has a statistically significant positive effect on output growth rates in most of the G7 and EM7 countries. For the dependence between commodity prices and output growth in the G7 countries, there is weakly lower and upper tail dependence between commodity prices and output growth in France, Germany, and Japan, indicating that the contagion effect between commodity prices and output growth in these three countries is stronger at extremely low and high values. For the EM7 countries, there is lower tail dependence between commodity prices and output growth in Brazil, indicating that the contagion effect between commodity prices and output growth in Brazil is stronger when there are extremely low values. A symmetric weak tail dependence is observed for Indonesia. There is no statistically significant tail dependence between commodity prices and output growth for the rest of the G7 and EM7 countries.

Our results indicate that there is substantial heterogeneity in the linearity of the dependence between commodity price shocks and economic fluctuations across the G7 and EM7 economies. There is statistically significant excess comovement between commodity prices and output in France, Germany, Japan, and Brazil, while the excess comovement is not statistically significant in the rest of the G7 and EM7 countries. Facing the same global commodity price shocks, country-specific macroeconomic factors may have different impacts on aggregate activity, consumption, and investment in the G7 and EM7 economies. The macroeconomic response to the commodity price shocks in the G7 and EM7 economies may reflect the sensitivity of the economy to commodity price shocks.

With the advancement of economic structures, and particularly those in emerging economies, many believe that a broad range of commodities may be able to better capture the transmission mechanism of world shocks to the domestic economy, and that the effects of commodity price shocks on output may vary across sample periods and countries. For example, Collier and Goderis (2012) use VAR models and find that commodity booms have unconditional positive short-term effects on output. Fernández et al. (2017) find that world shocks mediated by commodity prices can explain one-third of output fluctuations on average, and this figure is more than double when the estimation is conducted on a more recent sample beginning in the late 1990s. Cespedes and Velasco (2012) show that commodity price shocks have a significant impact on output and investment dynamics, and the impact on investment tends to be larger for economies with less developed financial markets. More recently, Kohn et al. (2021b) find that emerging economies run trade surpluses in commodities and trade deficits in manufactures, while developed economies have balanced sectoral trade flows, and these differences amplify the response of emerging economies to commodity price fluctuations.

This paper contributes to the ongoing debate on the relationship between commodity price fluctuations and business cycles in developed and emerging economies, while also helping to distinguish between competing theories. Our contribution is threefold. First, this is one of the few studies that comprehensively examines the relationship between commodity prices and output growth in major developed and developing countries, paying particular attention to the heterogeneous dependence structure between commodity prices and output growth in the G7 and EM7 countries. Second, compared to the correlation analysis framework, our copula model explores the flexible dependence structure between commodity prices and output growth, allowing for asymmetric and nonlinear dependence, as well as tail dependence at extreme values. Specifically, we estimate the volatility dynamics of global commodity prices and output growth in the G7 and EM7 countries parametrically and estimate the dependence between commodity prices and output growth using various copulas nonparametrically. Third, in contrast to assuming a single process for the joint distribution of commodity prices and output growth, we explore the general dependence structure between commodity prices and output growth without distributional assumptions on the marginals. Specifically, we fit different copulas into the GARCH-in-Mean filtered series and select the model based on the Bayesian Information Criterion (BIC). Notice that our model does not require us to impose any abrupt structural change, which is often used when there is a large amount of uncertainty. Rather, our flexible approach allows the data to speak for the potential nonlinear dependence and excess comovement between commodity prices and output growth. The key idea in our model is that risk propagation in commodity markets and output growth may be nonlinear and the dependence could vary at normal times and turmoil times in the G7 and EM7 economies.

The rest of the paper is organized as follows. Section 2 presents the data. Section 3 presents the model. Section 4 presents the empirical results regarding the dependence structure between commodity prices and output growth in the G7 and EM7 economies based on the copula GARCH-in-Mean model. The final section concludes.

2 The Data

We closely follow Fernández et al. (2020) to construct the global real commodity price index. Focusing on a broad range of commodities as in Fernández et al. (2020), the global real commodity price index is constructed based on the monthly prices of seven world commodities — beverages, food, agricultural raw materials, fertilizers, metal and minerals, precious metals, and energy. We retrieve the raw monthly commodity price data (expressed in current U.S. dollars) from the World Bank's Commodity Price database (Pink Sheet). The seven world commodities studied here are major primary commodities that are directly related to the aggregate consumption bundle and are not jointly produced. According to the definitions in the Pink Sheet, the seven commodity prices include information from all 40 commodity prices in the World Bank's Commodity Price database. Moreover, as pointed out in Fernández et al. (2020), the prices of the seven commodities are assumed to be cointegrated with a common nonstationary world shock. We deflate the monthly nominal commodity price data by the monthly CPI index of the United States to obtain real commodity prices and then take a simple average to obtain the global real commodity price index. Compared to a single commodity price, a global price index based on a broad range of commodities contains more information and enables us to capture the transmission mechanism of world shocks to the G7 and EM7 countries.

We use the total industrial production index as a proxy for real output in most of the G7 and EM7 countries, following Serletis and Liu (2020). We retrieve the output data mainly from the FRED database maintained by the Federal Reserve Bank of St. Louis. For Indonesia, due to the limitation of access to the output data, we use the Industrial/Manufacturing Production growth rate from the Asia Regional Integration Center: Economic and Financial Indicators Database of the Asian Development Bank — see Azad and Serletis (2021). For Mexico, we use the total industrial production data from the Organization for Economic Cooperation and Development (OECD) Main Economic Indicators: Production and Sales Database. For China, we use the monthly GDP series constructed by the Centre for Quantitative Economic Research of the Federal Reserve Bank of Atlanta. The constructed Chinese output data are comparable to the OECD output data — see Higgins and Zha (2015).

The commodity price growth rate is calculated as the difference of the log of the global real commodity price index, $\Delta \ln P_t = \ln P_t - \ln P_{t-1}$. Similarly, output growth is calculated as the difference of the log industrial production index, $\Delta \ln Y_t = \ln Y_t - \ln Y_{t-1}$. Table 1 shows the covered sample period for each country. For the G7 countries, the data set mostly spans the period from 1961:1 to 2020:12. It includes the commodity price supercycle in the 1970s and also the supercycle in 2003–2008. For the EM7 countries, although the data set has a shorter span, it covers the commodity price supercycle in 2003–2008 and also includes the Asian financial crisis, the Latin American financial crisis in 1997, the Great Recession of 2007 and 2009, as well as the Covid-19 recession.

Figure 1 plots the log level and the growth rate of the global real commodity price index since 1960. As can be seen, commodity prices have experienced two major price booms, one in the early 1980s and another one in the 2000s. While economists

Table 1 Data sample period

Country	Period
A. G7 countries	
Canada	1961:01-2020:12
France	1961:01-2020:12
Germany	1961:01-2020:12
Italy	1961:01-2020:12
Japan	1961:01-2020:12
United Kingdom	1961:01-2020:12
United States	1961:01-2020:12
B. EM7 countries	
Brazil	1975:01-2020:12
China	1992:01-2020:09
India	1994:01-2018:09
Indonesia	1994:01-2020:02
Mexico	1980:01-2020:12
Russia	1993:01-2020:12
Turkey	1985:01-2020:12

continue to debate the reasons behind the comovements between commodity prices and output growth, many believe that the upswing phase in supercycles is demand-driven. As Kilian and Zhou (2018) pointed out, one of the main determinants of the real price of commodities is shifts in the demand for commodities. For example, the upswing in commodity prices leading to the 1980s peak is typically attributed to the economic growth in western Europe and Japan and to the cartelization of the crude

Fig. 1 Commodity price and its growth rate

oil market — see Pindyck and Rotemberg (1990); Fernández et al. (2020). The second peak of commodity prices that occurred in the 2003–2008 cycle was driven by the demand of emerging economies, especially the explosive growth of China's raw materials demand — see Cuddington and Jerrett (2008); Kilian (2009); Roache (2012); Erten and Ocampo (2013); Buyuksahin et al. (2016); Alquist et al. (2020); Fernández et al. (2020). With the hit of the 2007–2009 financial crisis, economic growth slowed down and so did the commodity price index. Although the developing countries and particularly the EM7 countries are still seeking raw materials to fuel their infrastructure and manufacturing growth, and the EM7 countries are still expected to achieve high growth rates in the near future, other developed economies may not — see Datta and Vigfusson (2017). It seems that some recessions since the 1960s have been associated with commodity price fluctuations, although the association is less than perfect. At the beginning of the Covid-19 recession in 2020, output growth decreased significantly and so did the price of oil, while the overall commodity price index did not fluctuate as much as in previous recessions.

Descriptive statistics of the growth rates of the global real commodity price index and the industrial production indices are reported in Table 2. Panel A of Table 2 shows that the mean growth rates of the industrial production index for the G7 countries are ranging from a minimum of 0.001 (for France, Italy, and the United Kingdom) to a maximum of 0.003 (for Japan). As expected, the commodity price growth rate has a much larger standard deviation compared to that of the growth rate of the industrial production index, indicating that commodity prices are more volatile. There is negative skewness in output growth for all the G7 countries, as there appear

Table 2 Summary statistics

	mean	Standard deviation	Skewness	Kurtosis	Normality
A. Global commodity price and output growth in the G7 countries					
Commodity price	0.002	0.046	7.534 (0.391)	101.864 (0.000)	317659.331 (0.000)
Canada	0.002	0.013	-2.508 (0.000)	29.082 (0.000)	26091.463 (0.000)
France	0.001	0.027	-3.224 (0.000)	75.080 (0.000)	170120.916 (0.000)
Germany	0.002	0.020	-2.089 (0.000)	28.391 (0.000)	24671.488 (0.000)
Italy	0.001	0.029	-0.319 (0.000)	55.482 (0.000)	92230.717 (0.000)
Japan	0.003	0.018	-2.287 (0.000)	17.566 (0.000)	9870.457 (0.000)
United Kingdom	0.001	0.016	-3.255 (0.000)	53.805 (0.000)	87997.338 (0.000)
United States	0.002	0.009	-4.438 (0.000)	65.647 (0.000)	131467.735 (0.000)
B. Output growth in the EM7 countries					
Brazil	0.001	0.030	-1.568 (0.000)	22.430 (0.000)	11775.780 (0.000)
China	0.007	0.019	-1.601 (0.000)	90.338 (0.000)	117121.538 (0.000)
India	0.005	0.018	0.693 (0.000)	3.361 (0.000)	162.999 (0.000)
Indonesia	0.004	0.056	-0.411 (0.001)	7.959 (0.000)	1053.561 (0.000)
Mexico	0.001	0.021	-5.453 (0.000)	106.669 (0.000)	235213.523 (0.000)
Russia	0.001	0.022	0.186 (0.167)	10.810 (0.000)	1633.156 (0.000)
Turkey	0.004	0.040	-1.686 (0.000)	18.792 (0.000)	6546.934 (0.000)

to be more downward spikes in output growth than upward spikes. The skewness in the commodity price growth is not statistically significant though.

Panel B of Table 2 shows that the mean growth rates of the industrial production index for the EM7 countries are ranging between a minimum of 0.001 (for Brazil, Mexico, and Russia) and a maximum of 0.007 (for China). The industrial production index growth rate of India is the least volatile series with a standard deviation of 0.018, while the industrial production index growth rate of Indonesia (approximated by the y-to-y growth rate of total industrial production) can be considered as the most volatile in the EM7 countries, with a standard deviation of 0.056. The skewness statistics are negative for all the EM7 countries with the exception of India and Russia. The positive skewness of India and Russia indicates that the upper tail of the distribution is thicker than the lower tail.

Panels A and B of Table 2 both highlight the excess kurtosis and nonnormality of the commodity price and output growth rate series. Indeed, the normality of all the unconditional return distributions is strongly rejected by the Jarque-Bera test. These findings clearly show that the probability of observing extremely negative and positive realizations for the return series is higher than that of a normal distribution.

Before estimating the univariate GARCH model for each series, it is important to check the order of integration for the variables used in estimation by using unit root tests. We perform the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests and find that the null hypothesis of a unit root in all variables in level form cannot be rejected, while the null hypothesis of a unit root in the first differenced variables is rejected at one percent level of significance. Thus, all variables used in the study are integrated of order one, $I(1)$. Results of the unit root tests are available upon request.

3 The Model

The most common approach to understanding the dependence between commodity prices and economic activity is to choose a multivariate joint Gaussian distribution and estimate the correlation coefficient. However, the relationship between commodity prices and macroeconomic fluctuations may be beyond the first two conditional moments, indicating there is possible nonlinear and tail dependence between commodity prices and output.

We are motivated to use a flexible copula model to describe the nonlinear dependence between commodity prices and output across countries. As noted in Chen and Fan (2006), the semiparametric copula modeling approach creates additional flexibility and offers the possibility to combine various commodity prices and output return-generating models with a rich variety of available copula families.

Copulas can be used to express a multivariate distribution in terms of its marginal distributions. According to the Sklar (1973) theorem, for an unknown joint distribution $F(\epsilon_{1t}, \epsilon_{2t})$, there is a unique copula function, C , such that

$$F(\epsilon_{1t}, \epsilon_{2t}) = C(F_1(\epsilon_{1t}), F_2(\epsilon_{2t})) = C(u_1, u_2)$$

where $u_1 = F_1(\epsilon_{1t})$ and $u_2 = F_2(\epsilon_{2t})$ are the cumulative marginal distribution functions of ϵ_{1t} and ϵ_{2t} , respectively. The joint density function $f(\epsilon_{1t}, \epsilon_{2t})$ is

$$\begin{aligned} f(\epsilon_{1t}, \epsilon_{2t}) &= \frac{\partial^2 F(\epsilon_{1t}, \epsilon_{2t})}{\partial \epsilon_{1t} \partial \epsilon_{2t}} \\ &= \frac{\partial^2 C(u_1, u_2)}{\partial u_{1t} \partial u_{2t}} \frac{\partial F_1(\epsilon_{1t})}{\partial \epsilon_{1t}} \frac{\partial F_2(\epsilon_{2t})}{\partial \epsilon_{2t}} \\ &= c(u_1, u_2) f_1(\epsilon_{1t}) f_2(\epsilon_{2t}) \end{aligned} \quad (1)$$

where $c(u_1, u_2) = \partial^2 C(u_1, u_2) / \partial u_1 \partial u_2$ is the probability density function of a bivariate copula, $C(u_1, u_2)$, and $f_1(\epsilon_{1t})$ and $f_2(\epsilon_{2t})$ are the probability density functions of $F_1(\epsilon_{1t})$ and $F_2(\epsilon_{2t})$, respectively. For independent copulas, $C(u_1, u_2) = u_1 u_2$ and $c(u_1, u_2) = 1$.

As summarized in Trivedi and Zimmer (2007), the copula approach allows us to specify the marginals $F_i(\epsilon_{it})$ and the copula C separately. We can parameterize a copula to measure the dependence between marginal distributions, not only for linear dependence, but also for nonlinear dependence and tail dependence. Since a copula can capture dependence structures regardless of the form of the margins, a copula approach to modeling related variables is potentially very flexible. The estimated dependence measure of copula can be useful in understanding the comovements between commodity prices and output.

Trivedi and Zimmer (2007) argue that there are in general two approaches to estimate the parameters in a copula model. One approach is to use maximum likelihood methods to estimate the copula parameter and marginal parameters simultaneously, based on the density function as shown in (1) — see Trivedi and Zimmer (2007). In this approach, the marginal distributions need to be specified and any specification errors in the marginals will likely cause specification errors in the copula. Another approach is to use a semiparametric approach, that is, to estimate the marginals non-parametrically and then use a copula model to estimate the dependence between the marginals parametrically. The advantage of this approach is that we do not need to specify the marginals, hence the semiparametric copula estimation is robust and free of specification errors. The dependence captured by a copula is invariant with respect to increasing and continuous transformations of the marginal distributions.

In this paper, we take the second approach to estimate the dependence structure between commodity prices and output, and the semiparametric copula model is similar to Chen and Fan (2006). Chen and Fan (2006) use a GARCH model to capture the volatility dynamics of each variable and use the residuals of the GARCH model to construct the empirical cumulative distribution functions of the marginals. Then, copulas are used to measure the dependence between the marginals. The GARCH model is widely used to model the persistent volatility in time series data. However, for commodity prices and output growth data, besides the persistence in the volatility, it is also very likely that the uncertainty in commodity prices and output can directly impact the mean of commodity prices and output growth. Thus, in this paper, we use a GARCH-in-Mean model to capture the evolution dynamics of the commodity prices and output series, and

use a semiparametric copula model to capture the dependence structure between commodity prices and output growth. The GARCH-in-Mean model, based on Engle (1982) and Bollerslev (1987), estimates the first and second moments of the return series simultaneously. It is commonly used to examine the evolution path and volatility in financial time series data. Here, it allows us to measure the uncertainty effect in commodity prices and output growth by allowing the volatility to directly affect the conditional means of commodity prices and output growth, respectively.

The estimation steps are as follows:

- **Step 1:** Estimate the evolution path of commodity prices and output growth using the univariate GARCH-in-Mean model. The model is given by

$$y_t = \phi_0 + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=1}^q \eta_j \epsilon_{t-j} + \psi \sqrt{h_t} + \epsilon_t \quad (2)$$

$$h_t = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} \quad (3)$$

$$\begin{aligned} \epsilon_t &= \sqrt{h_t} v_t \\ v_t &\sim P_v(0, 1) \end{aligned} \quad (4)$$

where y_t denotes the return (logarithmic first difference). Equation (2) shows that current returns, y_t , depend on past returns, y_{t-i} , current and past innovations, ϵ_t and ϵ_{t-j} , and the current conditional standard deviation, $\sqrt{h_t}$. Equation (3) shows that the conditional variance of returns at time t , h_t , depends on both past innovations, ϵ_{t-1} , and the past conditional variance, h_{t-1} . The conditional variance process is positive and stationary if $\omega > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$, and $\alpha_1 + \beta_1 < 1$. Equation (4) shows that the standardized innovations, v_t , are i.i.d. distributed with $E(v_t) = 0$ and $E(v_t^2) = 1$. P_v is the probability distribution function for v_t . To better capture the fat-tailed characteristic of v_t , we examine three distributions: the normal distribution, $P_v = N(0, 1)$, the Student's t -distribution, $P_v = t_v(0, 1)$, and the generalized error distribution, $P_v = GED_v(0, 1)$.

- **Step 2:** We estimate F_j , $j = 1, 2$, using the empirical cumulative distribution functions of the residuals, $\epsilon_{jt}(\Theta)_{t=1}^n$, where Θ denotes all the parameters in the marginal densities, namely, all the parameters in the GARCH-in-Mean models. We have

$$\hat{F}_j(x) = \frac{1}{n+1} \sum_{t=1}^n 1(\epsilon_{jt}(\Theta) \leq x), j = 1, 2 \quad (5)$$

where n is the number of observations.

- **Step 3:** The bivariate copula dependence parameter α is estimated by

$$\hat{\alpha} = \arg \max_{\alpha} \frac{1}{n} \sum_{t=1}^n \ln c(\hat{F}_1(\epsilon_{1t}), \hat{F}_2(\epsilon_{2t}); \alpha). \quad (6)$$

To summarize, we assume a GARCH(1,1) specification for the variance Eq. (3) and use the BIC to determine the optimal values of p and q in the mean Eq. (2) and the error distribution. After estimating the GARCH-in-Mean model, we obtain the standardized residuals and construct the empirical cumulative distribution functions of the residuals. We then use copulas to measure the nonlinear dependence between commodity prices and output growth. Chen and Fan (2006) have shown that the distribution of the copula parameter α is not affected by the estimation of the parameters Θ in the GARCH model, and its asymptotic variance does not depend on the functional forms of the marginal distributions. Chen and Fan (2006) also develop the model selection procedures and establish the asymptotic distribution of the pseudo likelihood ratio (PLR) criterion, and show that the estimator is close to and asymptotically efficient to the maximum likelihood estimator under some regularity conditions.

Since Chen and Fan (2006), there are also some works that apply the semiparametric copula model to analyze the volatility and dependence structure between macroeconomic and financial variables across countries. For example, Rodriguez (2007) uses a semiparametric mixed copula to study the dependence across international stock markets and Liu and Serletis (2021a, b) use the GARCH-in-Mean copula model to study the volatility and nonlinear dependence in the energy markets and financial markets, respectively.

4 Empirical Results

4.1 Volatility Analysis

Tables 3 and 4 show the results of univariate GARCH-in-Mean models for the commodity price and output growth series in the G7 and EM7 economies. For the G7 countries, as can be seen in panel A of Table 3, the GARCH-in-Mean term is not statistically significant for the commodity price series, but is positive and statistically significant for the output series of all the G7 countries. The GARCH-in-Mean term is largest for Japan and France, with values of 0.382 and 0.381, respectively, and smallest for Italy, with a value of 0.106. Also, uncertainty in output growth increases the output growth in Canada by 0.237, in Germany by 0.274, in the United Kingdom by 0.174, and in the United States by 0.120. Moreover, all these parameter estimates are statistically significant at the one percent level, except for Canada where the GARCH-in-Mean term is statistically significant at the five percent level. Panel B of Table 3 shows that the GARCH term is positive and statistically significant for all the G7 countries, indicating the persistence of volatility. The Student's t -distribution shape parameter is also statistically significant for all the G7 countries, indicating fat tailed distributions.

For the EM7 countries, as shown in Table 4, the GARCH-in-Mean term is positive and statistically significant for China, India, and Turkey, with the values of 0.177, 0.143, and 0.305, respectively. The GARCH-in-Mean term is negative and statistically significant for Brazil, Indonesia, and Russia with values of -0.155,

Table 3 Univariate GARCH-in-Mean models for global commodity price and output growth of the G7 countries

Coefficient	Commodity price	Canada	France	Germany	Italy	Japan	United Kingdom	United States
A. Conditional mean equation								
constant	-0.001 (0.229)	-0.002 (0.000)	-0.004 (0.000)	-0.002 (0.044)	-0.000 (0.949)	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)
y_{t-1}	0.436 (0.006)	0.673 (0.000)	-0.071 (0.065)	-0.097 (0.020)	-0.148 (0.000)	0.493 (0.000)	0.164 (0.000)	0.882 (0.000)
y_{t-2}		0.158 (0.000)				0.346 (0.000)		
e_{t-1}	-0.219 (0.124)	-0.719 (0.000)	-0.280 (0.000)	-0.191 (0.000)	-0.142 (0.000)	0.305 (0.000)	-0.330 (0.000)	-0.690 (0.000)
$\sqrt{h_t}$	-0.020 (0.287)	0.237 (0.016)	0.381 (0.000)	0.274 (0.000)	0.106 (0.000)	0.382 (0.000)	0.174 (0.000)	0.120 (0.000)
B. Conditional variance equation								
constant	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
e_{t-1}	0.321 (0.000)	0.165 (0.001)	0.236 (0.000)	0.389 (0.000)	0.197 (0.000)	0.261 (0.000)	0.437 (0.000)	0.323 (0.000)
h_{t-1}	0.791 (0.000)	0.365 (0.000)	0.311 (0.000)	0.089 (0.037)	0.788 (0.000)	0.374 (0.000)	0.300 (0.000)	0.237 (0.000)
<i>shape</i>	2.757 (0.000)	7.250 (0.000)	4.179 (0.000)	5.660 (0.000)	4.960 (0.000)	5.192 (0.000)	4.621 (0.000)	4.222 (0.000)
C. Standardized residual diagnostics								
$\hat{\varepsilon}$ mean	0.086	-0.030	-0.095	-0.038	-0.042	-0.059	-0.053	-0.022
$\hat{\varepsilon}$ standard error	1.032	1.015	1.471	1.037	1.197	1.106	1.018	1.012
<i>Jarque – Bera</i>	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q(8)$	(0.666)	(0.023)	(0.842)	(0.000)	(0.026)	(0.107)	(0.076)	(0.272)
$Q^2(10)$	(1.000)	(0.000)	(1.000)	(0.669)	(1.000)	(1.000)	(1.000)	(0.000)
Log likelihood	1592.966	2227.474	2048.728	2488.402	1873.042	2065.171	2214.305	2622.271
BIC	-4.364	-6.131	-5.633	-5.424	-5.144	-5.678	-6.095	-7.228

Numbers in parentheses are p-values

Table 4 Univariate GARCH-in-Mean models for output growth of the EM7 countries

Coefficient	Brazil	China	India	Indonesia	Mexico	Russia	Turkey
A. Conditional mean equation							
constant	0.008 (0.000)	0.005 (0.000)	0.003 (0.000)	0.701 (0.000)	0.001 (0.026)	-0.007 (0.000)	-0.003 (0.003)
y_{t-1}	-0.515 (0.000)	0.066 (0.000)	-0.153 (0.004)	0.921 (0.000)	-0.639 (0.000)	-0.062 (0.240)	-0.207 (0.000)
ϵ_{t-1}	0.381 (0.000)	-0.466 (0.000)	-0.286 (0.000)	-0.440 (0.000)	0.522 (0.000)	-0.122 (0.037)	-0.043 (0.396)
$\sqrt{h_t}$	-0.155 (0.000)	0.177 (0.000)	0.143 (0.000)	-0.072 (0.000)	0.085 (0.102)	-0.244 (0.000)	0.305 (0.000)
B. Conditional variance equation							
constant	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	15.901 (0.015)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
ϵ_{t-1}	0.592 (0.000)	0.755 (0.000)	0.177 (0.000)	0.531 (0.051)	0.518 (0.000)	0.873 (0.000)	0.418 (0.000)
h_{t-1}	0.152 (0.003)	-0.034 (0.000)	0.771 (0.000)	0.200 (0.002)	0.146 (0.007)	0.290 (0.000)	0.372 (0.000)
<i>shape</i>	3.581 (0.000)	3.259 (0.000)	5.118 (0.000)	2.834 (0.000)	3.585 (0.000)	2.828 (0.000)	3.122 (0.000)
C. Standardized residual diagnostics							
$\hat{\epsilon}$ mean	-0.024	0.033	0.016	-0.019	0.014	0.032	-0.011
$\hat{\epsilon}$ standard error	1.002	1.022	1.079	0.867	1.067	0.958	0.964
<i>Jarque – Bera</i>	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q(8)$	(0.586)	(0.220)	(0.535)	(0.051)	(0.021)	(0.003)	(0.042)
$Q^2(8)$	(0.622)	(0.070)	(0.136)	(0.041)	(0.917)	(0.131)	(0.978)
Log likelihood	1336.950	1178.792	816.015	-908.260	1499.325	931.643	904.756
BIC	-4.770	-6.737	-5.378	5.950	-6.019	-5.440	-4.095

Numbers in parentheses are p-values

-0.072 and -0.244, respectively. All these parameter estimates are statistically significant at the one percent level. The GARCH-in-Mean term is not statistically significant for Mexico. Same as for the G7 countries, panel B of Table 4 shows that the Student's t -distribution shape parameter and the GARCH terms are statistically significant for all the EM7 countries, suggesting fat tailed distributions and the persistence of the volatility in the growth rates of the EM7 countries.

Notice that the sum of the GARCH coefficients for commodity prices and output growth for Russia is slightly greater than one. It implies that the long-run variance for the evolution path of commodity prices and output growth in Russia could be unstable. We tried to increase the GARCH orders and the AR orders in the univariate model of the commodity prices and output growth in Russia to check whether we could achieve a stable univariate GARCH process, yet such an attempt still yields a sum of the GARCH coefficients that is greater than one. The fact that the sum of the GARCH coefficients of the univariate model of the commodity prices and output growth in Russia is greater than one limits our ability for long-run inference, but also opens research opportunities for the future.

We also perform diagnostic tests for the univariate models of world commodity prices and output growth rates of the G7 and EM7 countries. Panel C of Tables 3 and 4 reports diagnostic test statistics based on the standardized residuals, $\hat{\epsilon}_t = \epsilon_t / \sqrt{h_t}$. For commodity prices, the Ljung-Box Q test cannot reject the null hypothesis that the residuals are independently distributed with p -values of 0.666 for the commodity price index. Also, the McLeod-Li Q^2 test cannot reject the null hypothesis that the squared residuals are independently distributed with p -values of 1.000. For the output series in the G7 and EM7 countries, the diagnostic tests also show that the GARCH-in-Mean model can capture most of the serial correlations in the growth rate series.

Theories that argue for a positive and negative relationship between uncertainty and output growth both exist. For example, Bernanke (1983); Brennan and Schwartz (1985); Gibson and Schwartz (1990); Pindyck (1991) argue the “investment under uncertainty theory,” that firms are likely to delay making irreversible investment decisions in the face of uncertainty in future returns, thus an increase in uncertainty delays investment and lowers growth. However, Sandmo (1970) argues that uncertainties could cause precautionary agents to increase savings and result in a higher growth path in equilibrium. Black (1987) argues that uncertainties due to technology innovations could lead a positive relationship between uncertainties and output growth. Changes in output uncertainty could also affect the rate of inflation and thus impact the macroeconomic performance and output growth — see Grier and Perry (2000); Grier et al. (2004); Bredin and Fountas (2005). Fountas and Karanasos (2007) find empirical evidence that output growth uncertainty is a positive determinant of the output growth in the G7 countries. Recently, Serletis and Liu (2020) empirically examine the real and nominal effects of uncertainty and show that the uncertainty effects on macroeconomic performance, such as output growth and inflation, are different across the G7 and EM7 countries.

4.2 Measuring Dependence

To explore the dependence structure between global commodity prices and output growth, and the choice of the appropriate copula to use, we measure the dependence statistics between global commodity prices and output growth. The most commonly known measure of dependence is correlation. It measures the linear dependence between random variables and provides information of the average of the deviations from the mean. It is defined as:

$$\rho = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}}.$$

As noted by Poon et al. (2004), correlation assumes a linear relationship between variables which follow a joint Gaussian distribution. This can be a very restrictive assumption for time series data. Moreover, correlation is a symmetric measure of dependence and it cannot distinguish the dependence between positive and negative growth rates, neither the large nor small values. A third limitation of the correlation measure is that although it is invariant with respect to linear transformations of the variables, it is not invariant under strictly increasing nonlinear transformations. These limitations motivate an alternative measure of dependence, rank correlation.

The rank correlation is especially useful when analyzing data with a number of extreme observations, since it is independent of the levels of the variables, and therefore robust to outliers. In contrast to linear correlation, where the dependence is measured based on the actual values of the data, rank correlations use the rankings of the data to measure the relationship between two variables. Consider X and Y to be two random variables, with distribution functions F_1 and F_2 , respectively, and joint distribution function F . Spearman's ρ is defined as

$$\rho_S(X, Y) = \rho(F_1(X), F_2(Y)) = \frac{\text{Cov}(F_1(X), F_2(Y))}{\sqrt{\text{Var}(F_1(X))\text{Var}(F_2(Y))}}.$$

Also, Kendall's τ can describe the nonlinear tail dependence structure. Kendall's τ is defined as

$$\rho_\tau(X, Y) = \Pr[(X_1 - X_2)(Y_1 - Y_2) > 0] - \Pr[(X_1 - X_2)(Y_1 - Y_2) < 0]$$

where $\Pr[(X_1 - X_2)(Y_1 - Y_2) > 0]$ is referred to as $\Pr[\text{concordance}]$, that is large values of one random variable are associated with large values of another, and $\Pr[(X_1 - X_2)(Y_1 - Y_2) < 0]$ is referred to as $\Pr[\text{discordance}]$ that large values of one being associated with small values of the other — see Trivedi and Zimmer (2007). $\rho_S(X, Y)$ is the linear correlation between $F_1(X)$ and $F_2(Y)$, which are integral transforms of X and Y . As demonstrated by Embrechts et al. (2002), rank correlations are more robust measures of dependence.

Table 5 shows the dependence between output growth and commodity prices in the G7 and EM7 countries. Overall, the relationship is stronger during recessions, indicating stronger comovements and increased dependence between

output growth and commodity prices during economic contractions. We also show that the two measures of rank correlation between commodity prices and output growth in the G7 and EM7 countries are generally consistent with each other. The rank correlations for commodity prices and output growth in the EM7 countries are generally higher than those of the G7 countries, although there are a few exceptions.

For the G7 countries, as shown in panel A of Table 5, the three measures of dependence, correlation coefficient, Kendall's τ , and Spearman's ρ , are positive for all the countries during the whole sample period, except for the United Kingdom, where the linear correlation coefficient is negative in the whole sample period. The positive relationship between commodity prices and output growth suggests that commodity prices and output growth move together in the same direction overall. During the whole sample period, the correlation between commodity prices and output growth is largest in the United States with the value of the Pearson correlation coefficient being 0.072. During recessions, the dependence between commodity prices and output growth is stronger for all the G7 countries. The correlation coefficient is 0.121 for the United States during recessions. The highest Kendall's τ and Spearman's ρ values during the recessions are for the United States and Japan, indicating that the probability of concordance in commodity prices and output growth movements is higher than the probability of discordance, and the joint probability of observing extreme values of commodity prices and output growth rates is higher in those two countries.

For the EM7 countries, the dependence measures are shown in panel B of Table 5. During the whole sample period, the dependence measures are positive for commodity prices and output growth in Brazil, India, and Turkey, while they are negative for China, Indonesia, and Russia. Over the whole sample period, the correlation between commodity prices and output growth is largest for India, as shown by the Pearson correlation coefficient of 0.121. During recessions, the correlation is also highest for India with a value of 0.364. The correlation is lowest for Mexico, which is zero for the overall sample period. During recessions, the highest Kendall's τ and Spearman's ρ values are for India and Brazil, indicating that for these two countries, the probability of concordance in commodity prices and output growth movements is higher than the probability of discordance.

We scatter plot the residuals of ϵ_{it} and ϵ_{jt} ($i \neq j$) in Figs. 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14 and 15. We do not observe the clustering of the dots in one tail to be significantly more sizeable than the clustering of the dots in the other tail in most of the countries. In other words, the scatter plots are not clear about the tail dependence structure between commodity prices and output growth in the G7 and EM7 countries. To assess whether the dependence structure is stronger at extreme values, we use the copula approach in the next section.

Table 5 Bivariate dependence between global commodity price and output growth rates

	Overall			Non-recession			Recession		
	Correlation	Kendall	Spearman	Correlation	Kendall	Spearman	Correlation	Kendall	Spearman
A. G7 countries									
Canada	0.026	0.013	0.020	-0.037	-0.018	-0.027	0.134	0.104	0.159
France	0.066	0.052	0.076	0.031	0.042	0.062	0.174	0.081	0.112
Germany	0.047	0.050	0.075	0.037	0.036	0.056	0.056	0.116	0.155
Italy	0.048	0.022	0.031	-0.008	-0.006	-0.010	0.157	0.145	0.194
Japan	0.069	0.081	0.120	0.044	0.060	0.090	0.113	0.153	0.215
United Kingdom	-0.021	0.026	0.038	-0.002	0.012	0.018	-0.094	0.067	0.093
United States	0.072	0.067	0.099	0.027	0.026	0.038	0.121	0.189	0.274
B. EM7 countries									
Brazil	0.076	0.083	0.125	0.047	0.049	0.074	0.203	0.274	0.390
China	-0.017	0.030	0.044	0.044	0.038	0.057	-0.136	-0.067	-0.075
India	0.121	0.102	0.148	0.094	0.084	0.119	0.364	0.296	0.415
Indonesia	-0.005	0.028	0.041	-0.017	0.023	0.034	0.103	-0.048	-0.066
Mexico	0.000	0.013	0.022	-0.008	-0.001	0.000	-0.007	0.046	0.075
Russia	-0.031	-0.016	-0.025	-0.068	-0.045	-0.067	0.194	0.188	0.240
Turkey	0.019	0.015	0.021	-0.013	-0.020	-0.032	0.127	0.243	0.338

Fig. 2 Residual scatter plots of global commodity prices and output growth for Canada

Fig. 3 Residual scatter plots of global commodity prices and output growth for France

Fig. 4 Residual scatter plots of global commodity prices and output growth for Germany

Fig. 5 Residual scatter plots of global commodity prices and output growth for Italy

Fig. 6 Residual scatter plots of global commodity prices and output growth for Japan

Fig. 7 Residual scatter plots of global commodity prices and output growth for the United Kingdom

Fig. 8 Residual scatter plots of global commodity prices and output growth for the United States

Fig. 9 Residual scatter plots of global commodity prices and output growth for Brazil

Fig. 10 Residual scatter plots of global commodity prices and output growth for China

Fig. 11 Residual scatter plots of global commodity prices and output growth for India

Fig. 12 Residual scatter plots of global commodity prices and output growth for Indonesia

Fig. 13 Residual scatter plots of global commodity prices and output growth for Mexico

Fig. 14 Residual scatter plots of global commodity prices and output growth for Russia

Fig. 15 Residual scatter plots of global commodity prices and output growth for Turkey

4.3 Copula Analysis

Conditional on the marginal specifications based on Eq. (5), we estimate copula dependence structures for each pair of the commodity prices and output growth series based on Eq. (6). Following Liu and Serletis (2021a, b), we use four copulas to capture various symmetric and asymmetric dependence structures, and select the one that has the best goodness of fit. They are the Gaussian copula, the Clayton (1978) copula, the Gumbel (1960) copula, and the Frank (1979) copula. The Gaussian specification is a natural benchmark, as it is the most common distributional assumption in finance, with zero tail dependence. The Clayton copula can capture the left tail dependence, and the Gumbel copula can capture the right tail dependence. The Frank copula can capture weak left and right tail dependence. Table 6 provides the functional forms of the copulas.

Table 6 Distribution functions of various copulas

Copula	CDF	Parameter range	Complete dependence	Independence
Gaussian	$C(u_1, u_2; \alpha) = \Psi_{\Sigma, 2}(\Psi^{-1}(u_1), \Psi^{-1}(u_2); \alpha)$	$\alpha \in [-1, 1]$	$\alpha = -1$ or 1	$\alpha = 0$
Clayton	$C(u_1, u_2, \alpha) = (u_1^{-\alpha} + u_2^{-\alpha} - 1)^{-1/\alpha}$	$\alpha \in (0, \infty)$	$\alpha \rightarrow \infty$	$\alpha \rightarrow 0$
Gumbel	$C(u_1, u_2; \alpha) = \exp \left\{ -[(-\ln u_1)^\alpha + (-\ln u_2)^\alpha]^{1/\alpha} \right\}$	$\alpha \in [1, \infty)$	$\alpha \rightarrow \infty$	$\alpha = 1$
Frank	$C(u_1, u_2; \alpha) = -\alpha^{-1} \ln \left(\frac{1 - e^{-\alpha} - (1 - e^{-\alpha u_1})(1 - e^{-\alpha u_2})}{1 - e^{-\alpha}} \right)$	$\alpha \in (-\infty, \infty)$	$\alpha \rightarrow -\infty$ or $\alpha \rightarrow \infty$	$\alpha \rightarrow 0$

The symbols $u_1 = \Psi(e_{1t})$ and $u_2 = \Psi(e_{2t})$ denote the standard normal distribution

Table 7 Estimates of different copula models

Coefficient	Gaussian	Gumbel	Clayton	Frank
A. G7 countries				
Canada	0.021 (0.586)	1.000 (0.000)	0.049(0.000)	0.000 (1.000)
France	0.079 (0.035)	1.000 (0.000)	0.065(0.000)	0.420 (0.058)
Germany	0.082 (0.028)	1.000 (0.000)	0.086 (0.000)	0.446 (0.048)
Italy	0.037 (0.331)	1.000 (0.000)	0.000(0.000)	0.224 (0.315)
Japan	0.102 (0.006)	1.000 (0.000)	0.125(0.000)	0.621 (0.006)
United Kingdom	0.012 (0.743)	1.000 (0.000)	0.010(0.000)	0.174 (0.429)
United States	0.054 (0.155)	1.000 (0.000)	0.076(0.000)	0.303 (0.175)
B. EM7 countries				
Brazil	0.065 (0.086)	1.000 (0.000)	0.117(0.000)	0.304 (0.181)
China	0.042 (0.267)	1.000 (0.000)	0.068(0.000)	0.208 (0.353)
India	0.046 (0.220)	1.000 (0.000)	0.070(0.000)	0.230 (0.307)
Indonesia	0.389 (0.000)	1.120 (0.000)	0.476(0.000)	2.901 (0.000)
Mexico	0.043 (0.255)	1.000 (0.000)	0.080(0.000)	0.185 (0.410)
Russia	-0.007 (0.844)	1.000 (0.000)	0.000(0.000)	0.000 (1.000)
Turkey	-0.017 (0.649)	1.000 (0.000)	0.017(0.000)	0.000 (1.000)

Numbers in parentheses are p-values. Numbers in bold font are corresponding to the lowest BIC values

The estimates of the copula parameters are presented in Table 7. The dependence parameters are mostly positive in all cases and reveal that increases in commodity prices coincide with increases in output growth in all of the G7 and EM7 countries. The fact that commodity prices tend to be cyclically and positively related to output growth may explain such comovement. In this regard, Kilian and Park (2009) attribute the positive correlation to positive shocks to the global demand for industrial commodities that cause both higher real oil prices and higher stock prices. Moreover, all of the Clayton copula dependence parameters are highly significant yet the magnitude is quite small, thus showing evidence of slightly lower tail dependence between commodity prices and output growth in the G7 and EM7 countries. The dependence parameter for the Gumbel copula settles on the lower bound of its permissible range (1.000) for all the countries. Since the Gumbel copula mainly captures upper tail dependence, the extremely low Gumbel copula parameter indicates the lack of comovement between commodity prices and output growth at extremely high values. The Frank copula parameter is statistically significant for France, Germany, Japan, and Indonesia, but is not statistically significant for the rest of the G7 and EM7 countries. The fact that the Frank copula parameters are not statistically significant for most of the countries indicates the lack of tail dependence and weak excess comovement between commodity price and output growth for most of the countries.

Table 8 presents the BIC value of each copula model. We select the best fitted copula model based on the lowest BIC value. Panel A of Table 8 shows that the Frank copula has the lowest BIC value for most of the G7 countries, except for Italy

Table 8 BIC values of different copula functions

Coefficient	Gaussian	Gumbel	Clayton	Frank
A. G7 countries				
Canada	5.650	3.280	0.016	0.009
France	5.650	3.266	0.015	0.004
Germany	5.649	3.241	0.012	0.004
Italy	5.647	3.280	-3.971	0.008
Japan	5.644	3.212	0.006	-0.001
United Kingdom	5.656	3.307	0.018	0.008
United States	5.651	3.259	0.013	0.007
B. EM7 countries				
Brazil	5.651	3.220	0.006	0.007
China	5.653	3.267	0.014	0.008
India	5.654	3.266	0.014	0.008
Indonesia	5.478	2.971	-0.084	-0.181
Mexico	5.654	3.245	0.013	0.008
Russia	5.649	3.279	-3.959	0.009
Turkey	5.655	3.308	0.018	0.009

Numbers in bold font are corresponding to the lowest BIC values

where the Clayton copula has the lowest BIC value. Moreover, for France, Germany, and Japan, the Frank copula parameters not only have the lowest BIC values, but also are statistically significant with the parameter values of 0.420, 0.446, and 0.621 as have been discussed previously in Table 7, suggesting that there is statistically significant weak lower and upper tail dependence between commodity prices and output growth in these countries. Note that the dependence parameter is highest in Japan. The high Frank copula parameter estimate in Japan suggests that extreme outcomes (either high or low values) in the commodity market are easier to extend to output.

Panel B of Table 8 shows the BIC values of the copula parameter estimates for the EM7 countries. For China, India, Indonesia, Mexico, and Turkey, the Frank copula has the lowest BIC values. However, none of the Frank copula parameters are statistically significant in these countries except for Indonesia, where the Frank copula parameter is 2.901 with the p -value of 0.000. For Brazil and Russia, the Clayton copula has the lowest BIC values — 0.117 with the p -value of 0.000, and 0.000 with the p -value of 0.000. The statistically significant positive Clayton copula parameter between commodity prices and output growth in Brazil indicates that in times of rare negative events, such as market crashes and large changes in commodity market returns, as commodity returns tend to reach their lower limit, the output growth tends to be close to its lower limit too. We did not find statistically significant tail dependence between commodity prices and output growth in most EM7 countries, indicating the lack of excess comovement between commodity prices and output growth for most of the EM7 countries during recessions or extreme events.

Overall, the tail dependence measures for all the bivariate relationships are quite small regardless of the scenario considered. For the relationship between commodity prices and output growth, there is a notable difference between the G7 and EM7 economies. The fact that there is no statistically significant tail dependence between commodity prices and output growth in most of the G7 and EM7 countries suggests the limited ability of commodity prices to transmit risk across some major emerging economies. The observed heterogeneity implies differences in the macroeconomic impacts of commodity price shocks across the G7 and EM7 countries. The various dependence structures between commodity prices and output growth across the G7 and EM7 economies may reflect the different structural characteristics of the economy in the developed and developing countries.

The heterogeneous dependence structure between commodity prices and output growth across countries we found is generally consistent with the literature. For example, Barsky and Kilian (2004) conclude that disturbances in the oil market are likely to matter less for the United States macroeconomic performance than has commonly been thought. Recently, extending the oil price shocks literature to the global commodity prices shocks literature, Alquist et al. (2020) use a factor-based identification strategy to decompose the historical sources of changes in commodity prices and global economic activity and conclude that commodity-related shocks have contributed modestly to global economic fluctuations. Fernández et al. (2020) find that world shocks that drive commodity prices and world interest rate are major drivers of aggregate fluctuations in small open economies, and the world disturbances play an important role in commodity price movements but not dominant role in driving fluctuations in aggregate activity at the country level.

Since the empirical literature that studies on the nonlinear and asymmetric relationship between global commodity prices and output growth is scarce, we relate our results to a body of work that examines the relationship between major global commodity prices, such as crude oil price, and economic fluctuations. As summarized in Manera and Serletis (2018), there has been a view that oil price volatility tends to exacerbate the negative dynamic response of economic activity to a negative oil price shock, while dampening the response to a positive oil price shock. The asymmetric relationship between oil price volatility and output can explain larger recessions in response to positive oil price shocks as well as smaller expansions in response to negative ones — see Edelstein and Kilian (2009); Herrera et al. (2011); Kilian and Vigfusson (2011a, b). However, Kilian and Vigfusson (2011b) use structural models to show that the transmission of exogenous oil price shocks implies symmetric responses of real output to oil price increases and decreases. Also, Kilian (2008) shows that the effects of energy price shocks have weakened since the second half of the 1980s. Schubert and Turnovsky (2011) study the impact of energy prices on growth in a developing economy and find that the long-run growth rate depends on energy price shocks and the economy's internal production structure.

The globalization and financialization of the commodity markets might facilitate the transmission of world shocks to economies around the world through commodity prices. The macroeconomic effects of commodity price changes also depend on how monetary policy responds. Devereux and Smith (2021) show that, for countries that are described as having commodity currencies, such as Canada, an

improvement in a country's terms of trade through an increase in the prices of its export commodities, will lead to a real appreciation. Monetary policy is likely to react to it and such inflation targeting monetary policy could explain some of the correlation between commodity prices, nominal exchange rates, and real output. Also, as Gruber and Vigfusson (2018) summarized, in theory, lower interest rates decrease the volatility of commodity prices, since lower inventory costs promote the smoothing of transient shocks and can increase price correlation if common shocks are more persistent than idiosyncratic shocks. Barsky and Kilian (2001) argue that interest rates affect storage behavior in oil markets. Bodenstein et al. (2012) show that the United States monetary policy responses depend on the source of the observed oil price fluctuations, in the context of a global dynamic stochastic general equilibrium model with endogenous oil markets. Lombardi and Ravazzolo (2016); Datta et al. (2021) provide empirical evidence of the stronger connection between crude oil and financial markets at the zero lower bound.

Dai and Serletis (2018) find that crude oil shocks together with aggregate demand shocks account for a significant amount of the variation of the credit default swap spread, which played an important role in the 2007-2009 recession. Mallick and Sousa (2013) find commodity price shocks lead to a rise in inflation and induce central banks towards inflation stabilization and affect the output growth accordingly.

5 Conclusion

In this paper, we investigate the volatility and dependence structure between global commodity prices and economic growth in the G7 and EM7 economies using a semiparametric copula GARCH-in-Mean approach. This method is able to estimate the potential nonlinear and tail dependence between global commodity prices and economic growth which is of primary interest with the frequent shocks and increasing global uncertainties.

We fill the following gaps in the literature. First, it is commonly believed that there is a close link between commodity prices and economic growth, yet it is not clear whether the observed comovements are beyond the first two conditional moments during recessions, that is, whether there exists nonlinear and tail dependence. Moreover, the literature also falls short of adequately discussing the case of emerging economies. How the relationship is different across the developed and emerging economies is of growing interest especially with the tremendous economic growth of the EM7 economies. Also, previous literature on the relationship between commodity prices and output growth is frequently under the correlation framework with the assumption of the joint normal distribution, and therefore implicitly assumes a linear dependence structure between commodity prices and output growth.

We find that the GARCH-in-Mean model with the Student's t -distribution has the best goodness of fit and show that volatility has a statistically significant positive effect on output growth in the G7 and EM7 countries, while the uncertainty effect in commodity prices is not statistically significant. We then use copulas to model the dependence structure between commodity prices and output growth in the

G7 and EM7 economies. We find that the dependence structure between commodity prices and output growth is quite different in the G7 and EM7 economies. For the G7 economies, the Frank copula dependence parameter is statistically significant for France, Germany, and Japan, suggesting that there is weak lower and upper tail dependence between commodity prices and output growth in these countries. For the EM7 countries, the Clayton copula parameter is statistically significant for Brazil and the Frank copula parameter is statistically significant for Indonesia, suggesting that there is lower tail dependence between commodity prices and output growth in Brazil and a weak lower and upper tail dependence between commodity prices and output growth in Indonesia.

The weak or nonexistent tail dependence between commodity prices and output in the G7 and EM7 economies that we found suggests that commodity prices play a role but not a dominant role in driving fluctuations in aggregate output. The results also suggest that both dependence degree and dependence structure should be considered in structural models to understand the relationship between commodity prices and output growth. A copula approach, which is a convenient tool in modeling both aspects of the dependence is used in this paper, and we hope the results could help to assess the macroeconomic implications of commodity price shocks.

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