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Modelling the Volatility Inducement of Climate Change in Food Prices: The Role of Technological Shocks

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We used a GARCH-MIDAS framework to demonstrate that, in addition to the food system, temperature anomalies can cause food price volatility. We show that technology shock can act as an effect modifier between food prices and climate change. We infer that initiatives targeted at mitigating climate change from causing excessive volatility in food prices should involve technology in addition to modification of food demand and supply processes.

I. Introduction

Despite increased efforts to recover from the COVID-19 pandemic, the global economy has been plagued by some exogenous events, most notably the ongoing Russia-Ukraine war. With this supply bottleneck amid a wave of export restrictions resulting from Russia's invasion of Ukraine, global food prices are likely to remain high, especially given agricultural activity's rising vulnerability to climate change. This, among other issues, has reawakened debates about food security, which partially relate to food availability and food price volatility. Rapid fluctuations in food prices make it difficult for farmers to make investment decisions and consumers to choose which foods to buy. However, while unpredicted variability in global food prices may seem undesirable, a lack of change in food prices is tantamount to a nonfunctioning food system. Thus, the default inherent food price volatility reflecting producer and market responsiveness to consumer demand and underlying supply conditions is not the problem. Rather, it is excess volatility induced by exogenous factors, which impact the dynamics of food prices. Therefore, this study distinguishes between the volatility dynamic of food prices due to the demand and supply mechanisms of the food system and those triggered by factors outside the food system.

A number of exogenous factors have been listed among the underlying sources of food price variability (see Tadasse et al., 2016), including weak institutions (Bora et al., 2011), political instability (Minot, 2014), market failures (Timmer, 2017), and some emerging challenges like COVID-19 (Devereux et al., 2020). However, the interaction between temperature and precipitation has been widely acknowledged as a critical determinant of the productivity of grain crops.

Extreme rainfall, along with other aspects of climate change, is responsible for increasing grain production variability and consequently, food price volatility (see Steen et al., 2023). Thus, this study distinguishes between food price volatility induced by climate change and that induced by the demand and supply mechanism in the food system. We employed a GARCH-MIDAS framework to capture both realized and exogenously induced volatility in food price dynamics. We hypothesized that climate change is an exogenously induced factor in food price volatility, which offers insights beyond explanations for realized volatility dynamics of food prices, which, in the context of this study, is attributable to the supply and demand mechanism in the food system.

Given the foregoing, reducing food price volatility must transcend changing food demand and supply mechanisms; it must also include mitigating the volatility effect of climate change on food prices. Technological advancements are noteworthy. According to Chavas and Shi (2015), technological innovation in agriculture affects food price volatility by altering the sensitivity of aggregate farm supply to external shocks and the sensitivity of prices to supply or demand shocks. Thus, agricultural innovation has reduced the magnitude of price fluctuation. However, the extent to which technical innovation can lessen the effect of external shocks on food price volatility which underlies the volatility inducement of climate change in food prices needs to be understood. For example, Haile et al. (2017) confirm climate change as the underlying source of fluctuation in food availability and, as a result, increasing food price volatility. In this study, we extend their finding to include evidence-based insight on the potential of technological innovation to mitigate the volatility effect of climate

change on food prices. Therefore, we applied Sharma and Narayan's (2022) global technological shock (GTS) index to investigate the direct influence of technology on food prices as well as the role of technology as a "effect modifier" between climate change and food prices.

II. Data and methodology

Between January 1990 and December 2021, the monthly global food prices (GFP) utilized in this study are composite measures of international prices of a basket of food commodities, including meat, dairy, cereal, oil, and sugar prices, among others. However, whereas an indicator of climate change, for instance, temperature (TEMP) anomalies, is available monthly, the measure of the global technological shock (GTS) is only available annually, with 2021 as its end date. Thus, while monthly food price was our high-frequency variable, the *TEMP* and *GTS* were exogenous variables represented by annual frequencies and, were by implication, our low-frequency data. In line with this study's second objective, we employed the principal component analysis (PCA) procedure to form a composite index of the *TEMP* and *GTS* (TEMP-GTS) to test the validity of our hypothesis of 'effect modifier.' In sum, the food prices data were obtained from the World Bank Group online database; the climate change data from the Food and Agriculture Organization Statistics (FAOSTAT) online database; and the technological shock data from Sharma and Narayan's (2022) study.

In addition to the monthly and annual mixed frequencies of the variables of interest, our preliminary finding prompted our preference for the GARCH-MIDAS model as the most appropriate methodological technique to address the various objectives of this study. The GARCH component of GARCH-MIDAS enabled us to capture the volatility dynamic of the data. The MIDAS feature allowed us to simultaneously retain both the monthly and annual frequencies in a single framework. Wang et al. (2020), Salisu et al. (2022), and Oloko et al. (2022) have also used GARCH-MIDAS, and the formulae are as follows:

$$r_{i,t} = \lambda + \sqrt{\eta_t \times h_{i,t} \varepsilon_{i,t} | \Phi_{i-1,t}} \sim N(0, 1), \quad (1)$$

$$\forall i = 1, \dots, N_t$$

$$h_{i,t} = (1 - \alpha - \beta) + \frac{(r_{i-1,t} - \lambda)^2}{\eta_i} + \beta h_{i-1,t} \quad (2)$$

$$\tau_i^{(r\omega)} = m^{(r\omega)} + \theta^{(r\omega)} \sum_{k=1}^K \phi_k(\omega_1, \omega_2) X_{i-k}^{(r\omega)} \quad (3)$$

Our mean Equation is represented by Equation (1), and Equations (2) and (3) represent the conditional variance of our GARCH-MIDAS model for both short- and long-run components, respectively. Regarding the individual parameters in each of the equations, the symbol λ in Equation (1) measures the unconditional mean of the global food price return, while h_{it} in Equation (2) captures the short-run conditional variance. The alpha (α) and beta (β) parameters denoting ARCH and GARCH terms are conditioned to be positive and/or at least zero ($\alpha > 0$) and $\beta \geq 0$ and sum up to less than a unit ($\alpha + \beta < 1$). The term η_t , which incorporates the exogenous series represents the long-run

component of the conditional variance. The subscript ($r\omega$) in Equation (3) expressed the implementation of a rolling-window procedure, which would enable the secular long-run component to vary monthly, while the m represents the long-run intercept. The slope coefficient is captured as θ in Equation (3) and represents the predicting power of climate change and technological shock captured separately as exogenous predictors (X_{i-k}) of global food prices, while $\phi_k(\omega_1, \omega_2) \geq 0, k = 1, \dots, K$, is the weighting scheme that must sum up to one for the parameters of the model to be identified.

III. Results and Discussion

We begin this section with the preliminary data analysis. [Table 1](#) shows that the average global food price index is 61.76, while the corresponding monthly average return is 0.25%. As expected for high-frequency data, the standard deviation statistic is relatively large for food prices. However, while the skewness is positive for food prices and climate change, it is negative for technological shock. We also found a kurtosis statistic leptokurtic for all the variables except technological shocks. The ARCH-LM results confirming the presence of heteroskedasticity, particularly in food prices, strengthened our motivation to model the volatility dynamic of global food prices. We complemented our preliminary results with a visual illustration of possible co-movements among the variables of interest (see [Figure 1](#)). A look at the combined graphs in [Figure 1](#) shows that the co-movement of food prices and climate change is in the same direction, but food prices and technological shocks move in opposite directions. The c part of [Figure 1](#), for example, depicts co-movements between climate change and technological shocks.

Moving to the focal point of this study, presented in [Table 2](#) are GARCH-MIDAS-based estimates on the volatility dynamics of global food prices, while accounting for the individual and complementary roles of climate change and technological shocks, respectively. We found the coefficient on the unconditional mean denoted as μ to be statistically significant in the Generalized Autocorrelation Conditional Heteroscedasticity (GARCH)-Mixed Data Sampling (MIDAS)-X (GARCH-MIDAS-X), where the X is exogenous variable. More so, we found that the volatility persistence usually measured in terms of the sum of the α and the GARCH (β) terms relatively was larger in the case of GARCH-MIDAS-X models compared to GARCH-MIDAS-RV, where RV means realized volatility. Thus, global food prices tend to exhibit the highest level of volatility persistence in the short term, with the evidence suggesting that the persistence is relatively more pronounced when the volatility appears to be exogenously induced.

Regarding the MIDAS slope coefficient (θ), which is of particular interest to validating the various hypotheses of this study, we found it to be statistically significant in the GARCH-MIDAS with realized volatility (RV) and in each of the variants of the GARCH-MIDAS-X models. The positive slope coefficient in the RV indicates that the bigger the fluctuation in the RV, which measures volatility inherently realized in the food supply and demand mechanism,

Table 1. Preliminary Results

	Global Food Price Index		Climate Change & Technological Shocks	
	Level	Return	TEMP	GTS
Descriptive/Summary Statistics				
Mean	61.76	0.25	0.37	0.10
Standard Deviation	29.62	3.33	0.33	0.76
Skewness	0.74	0.13	0.27	-0.47
Kurtosis	3.11	6.71	2.00	4.27
No. of Observation	756	755	63	
Frequency	Monthly =High frequency		Annual = Low frequency	
Start Date	January 1960		1960	
End Date	December 2022		2022	
Conditional Variance & Autocorrelation tests				
ARCH-LM(2)	26.14***	16.02***	0.83	0.22
ARCH-LM-(4)	13.92***	8.47***	0.51	0.63
ARCH-LM-(6)	9.67***	8.95***	0.52	0.45
Q-stat-(2)	174.85***	1.97	13.91***	3.17
Q-stat-(4)	186.75***	7.51	24.62***	11.84
Q-stat-(6)	189.87***	11.61	36.75***	15.90
Q ² -stat-(2)	149.64***	16.03***	3.02	1.01
Q ² -stat-(4)	199.02***	118.29***	3.57	7.55
Q ² -stat-(6)	228.73***	185.45***	13.46	8.11

Note: The ARCH-LM test is used to test the null hypothesis of homoscedasticity at different lag lengths, such as $k = 4$, $k = 8$, and $k = 12$. The given Q-stat. and Q²-stat. are based on the Ljung-Box serial correlation test, which was used to test the null hypothesis of no autocorrelation. The notations ***, **, and * indicate that the null hypothesis is rejected at 1%, 5%, and 10% significance levels, respectively.

Table 2. GARCH-MIDAS –based Empirical Estimates

Parameter	GARCH-MIDAS-RV	GARCH-MIDAS-X		
		TEMP	GTS	TEMP-GTS
μ	0.0011 [0.0013]	0.0386*** [0.0001]	0.0395*** [0.0001]	0.0398*** [9.34E-05]
α	0.1351** [0.0672]	0.0506*** [0.0041]	0.0501*** [0.0056]	0.0495*** [0.0051]
β	0.7293*** [0.2005]	0.9001*** [0.0168]	0.9002*** [0.0239]	0.9000*** [0.0137]
θ	0.0867*** [0.0157]	0.0012*** [0.0004]	-0.0007*** [0.0002]	-0.0008*** [0.00006]
w	36.682 [243.15]	0.5000 [0.6408]	4.9999 [8.8726]	5.0002*** [0.7034]
m	0.0002 [0.0001]	-8.05E-08*** [1.93E-08]	4.24E-06*** [1.13E-06]	2.57E-06*** [2.03E-07]

Note: The term μ denotes the unconditional mean of the food price returns, α and β are the ARCH and GARCH terms, respectively, while θ is the slope coefficient. Denoting the adjusted beta polynomial weight is the term w while m is long run constant term. The values in the square brackets are the standard errors of the parameter estimates, while ***, **, and * implies statistical significance at 1%, 5% and 10% level, respectively.

the bigger the long-term volatility in food prices. The positive slope coefficient when the X in the GARCH-MIDAS-X is captured as climate change validates our hypothesis that climate change induces global food price volatility. More importantly and interestingly, the slope coefficient representing technological shocks is negative, both regarding its individual and complimentary effects. This, among other things, validates our hypothesis of the technological shocks

being the effect modifier of climate change inducement of food price volatility. Altogether, we show that both climate change and technological shocks offer insights beyond the realized volatility of global food prices.

IV. Conclusion

Employing a GARCH-MIDAS framework, we distinguished between the inherent global food price volatility

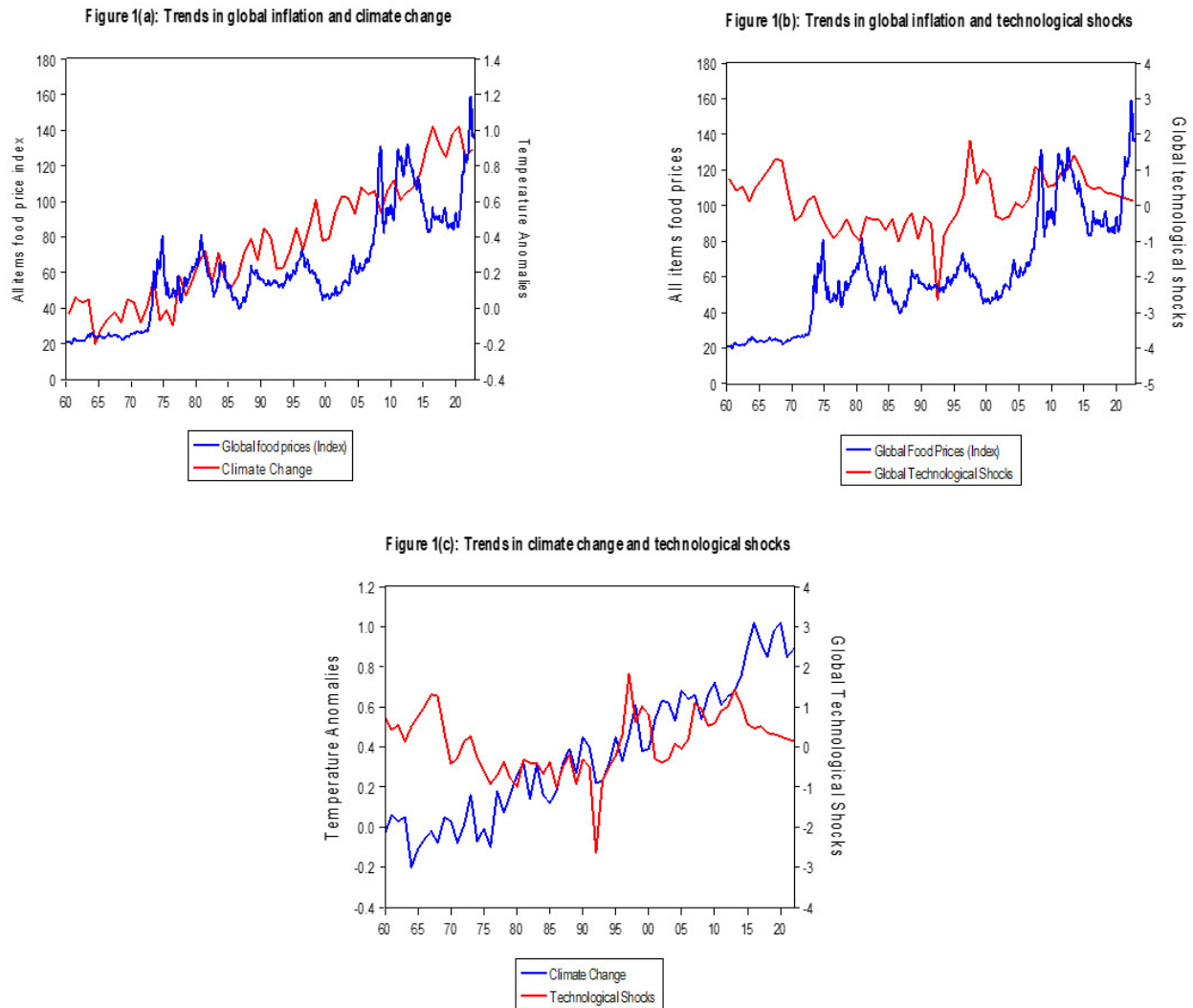


Figure 1. Historical Co-movement Among the Variables

Note: The combine Figure depicts trends in food inflation and climate change, food inflation and technology, climate change and technologies

attributable to the food system's demand and supply mechanisms and food price volatility that is exogenously induced. Essentially, we showed that, in addition to the food system, climate change measured in terms of temperature anomalies has the potential to induce the volatility dynamic of global food prices. More importantly, we demonstrated the potential of technological shock as an effect modifier of climate change's inducement of food price

volatility. Thus, any initiative aimed at mitigating climate change from excessive volatility in global food prices should consider technology in addition to modification of food demand and supply processes.

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