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Did weekly economic index and volatility index impact US food sales during the first year of the pandemic?

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Abstract

We explore the impacts of economic and financial dislocations caused by COVID-19 pandemic shocks on food sales in the United States from January 2020 to January 2021. We use the US weekly economic index (*WEI*) to measure economic dislocations and the Chicago Board Options Exchange volatility index (*VIX*) to capture the broader stock market dislocations. We validate the NARDL model by testing a battery of models using the autoregressive distributed lags (ARDL) methodology (ARDL, NARDL, and QARDL specifications). Our study postulates that an increase in *WEI* has a significant negative long-term effect on food sales, whereas a decrease in *WEI* has no statistically significant (long-run) effect. Thus, policy responses that ignore asymmetric effects and hidden cointegration may fail to promote food security during pandemics.

Keywords: COVID-19, Food sales, US weekly economic index, CBOE's volatility index, ARDL model, Bewley transformation, NARDL model, QARDL model

JEL Classification: E32, E00, Q54, C33

Introduction

The COVID-19 pandemic (hereafter pandemic) has caused an unprecedented global health crisis, causing millions of people to become ill or die. In addition, the pandemic caused unprecedented global shocks to the regional and global economic systems. The magnitude of the economic shocks stems from globally synchronized lockdowns and serious financial system dislocations (see Apergis and Apergis 2021). Although the full effect of the pandemic is still unclear, our paper explores the effect of mitigation strategies (e.g., lockdowns and social distancing) and financial system shocks on the US food sales. Food sales are critical for ensuring food security. A better understanding is required to assess whether the pandemic has had a significant impact on the world's food supply chains (see World Bank 2020; IFPRI 2020), which can have a negative long-term effect on health due to insufficient nutrient intakes even in developed nations. According to recent research, economic disruptions resulted in lost income, which is a serious implication for food sales and security (Singh et al. 2020). Economic disruptions are known to have triggered falling food sales and rising hunger and malnutrition

in low-income countries, with no known effects on food sales in advanced economies (see Mogues 2020).

This study focuses on one of the most advanced economies, the United States, which was severely impacted by the COVID-19 pandemic. We want to understand whether economic disruptions from the first wave of pandemic and shocks to financial markets, particularly the equity market, have compromised (short-run or long-run) food sales in the United States.[1] To avoid misunderstanding, we explain the rationale for conserving food sales as a variable in the United States: in the United States, the primary public food assistance program, Supplemental Nutrition Assistance Program (SNAP), seeks to protect the poor from food entitlement failures. The SNAP operates as an electronic benefit transfer that low-income people can use at retail food establishments. Hence, there is little reason to believe that the pandemic has increased food insecurity among the poor (those earning less than a certain level of income) who are covered by the public food assistance program. Similarly, there is an income threshold above in which food insecurity makes little sense since these people have the purchasing power to buy the required bundle of food items. However, the pandemic may have impacted food sales to those with intermediate incomes between these two income thresholds (lower and upper). Changes in retail food sales data can provide insight into the dynamics of food consumption of these people whose incomes are higher than the SNAP level but lower than the level that accords the full purchasing power for buying the desired bundles of food items, regardless of prices and/or economic and financial disruptions.

Several authors, including Apergis and Apergis (2021), have argued that the pandemic has impacted financial markets (primarily stock and commodity markets), sending shockwaves throughout the economy.

We developed an autoregressive distributed lags (ARDL) model to capture both the short-run and long-run effects of the weekly economic index (*WEI*) and the weekly volatility index (*VIX*) on (weekly) food sales or food consumption (Z_1).[2] To capture hidden cointegration and asymmetric effects of economic and financial shocks on food sales, we then apply the nonlinear ARDL (NARDL) methodology.[3] We further extend the analysis to determine whether the relationship between food sales and *WEI* and *VIX* varies across quantiles of the conditional distribution of food sales. For this purpose, we apply the QARDL model of Cho et al. (2015) to uncover previously unknown aspects of the quantile-specific relationships between food sales and the economic consequences of

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[1] We choose a simple indicator, or proxy, to measure the economic consequences of the pandemic mitigation strategy, or what is called lockdowns, during the initial phase of the outbreak of the pandemic in the US from January 2020 to January 2021: we use the US weekly economic index (*WEI*) as an indicator to gauge economic disruptions and supply shocks caused by the COVID-19 mitigation strategy in the United States. Further details are provided in Section "Variables and data".

[2] To avoid the trap of endogeneity between *VIX* and *WEI*, we choose the lagged value of *VIX* by a week: thus, *VIX* is not impacted by the future change in weekly activity index. We also checked the correlations between *VIX* and *WEI* and also a basic ARDL to ensure that the possibility of reverse causality from *VIX* to *WEI* is low. See Section "Baseline ARDL model" of this paper.

[3] Since the ARDL methodology assumes symmetric effects of changes in *WEI* and *VIX* on Z_1, our ARDL model is unable to detect hidden cointegration—characterised by asymmetric relationships between Z_1 vis-à-vis positive and negative shocks in *VIX* and *WEI*. To overcome this weakness of our ARDL model, we will apply the nonlinear ARDL (NARDL) methodology that can detect hidden cointegration arising from asymmetric effects of positive and negative shocks in *VIX* and *WEI* on Z_1. See Section "Nonlinear autoregressive distributed lag model: an extension" for full details.

the pandemic.[4] We use the Bewley transformation as a robustness check to test whether endogeneity issues have compromised the estimation.[5]

The remainder of this paper is as follows. Section "Background literature and empirical strategy" provides a brief review of the emerging literature and discusses the econometric methodology. Section "Results and discussion" discusses the empirical findings and their implications. Finally, Section "Conclusion" concludes the paper.

Background literature and empirical strategy

COVID-19 has caused severe supply shocks, similar to the effects of natural disasters on supply chains. However, it has been found that richer nations are more resilient to shocks than poorer nations. Our research context is one of the world's wealthiest countries, the United States, which was also severely impacted by pandemic-related disruptions.

Economic disruptions

Despite a series of severe economic disruptions, the US economy has several layers of protection in place to deal with the mounting challenges of the pandemic's economic and financial disruptions: First, one of the implicit insurances against the spillover effect of these disruptions to food consumption (or, food sales) is the ability of the US economy to resume economic growth, as highlighted in the context of US natural disasters by Anbarci et al. (2005) and confirmed by Kellenberg and Mobarak (2008). Second, as Kahn (2005) and Toya and Skidmore (2007) discovered, the quality of institutions provides an effective barrier to the spread of disruptions and shocks throughout the economy. Third, with effective policy interventions, the short-term adverse effects of such disruptions can be avoided from becoming long-term problems. However, it is also understood that recovery is not always guaranteed (see Noy 2009; Cavallo et al. 2013). The present study introduces the US *WEI* as a proxy for economic disruptions caused by the pandemic. In the context of the COVID-19 pandemic, several papers have used *WEI* to track the economic disruptions caused by the pandemic. Some of the key papers are Aprigliano et al. (2022), Ashraf (2020), Baumeister et al. (2022), Carriero et al. (2022), Koop et al. (2022), and Lewis et al. (2021a, 2021b).

Similarly, as we will see in the following subsection, we use the Chicago Board Options Exchange (CBOE) *VIX* as a proxy for financial market disruptions. Our research is based on examining the relationship between food sales and the *VIX* and *WEI*.

Financial disruptions and roles of non-fundamentals

Besides economic disruptions, pandemic-related news and reports spread people's panic and increase investor anxiety. The fear of investors had a significant impact on

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[4] Both ARDL and NARDL methodologies have a common shortcoming since both methodologies examine the relationship between food sales (Z_1) vis-à-vis *WEI* and *VIX* only at the conditional mean and, thereby, ignore an important possibility that food sales might bear fundamentally heterogeneous relationships with its determinants across different quantiles of the conditional distribution Z_1. If the postulated relationship is meaningfully heterogeneous across quantiles, then our findings NARDL will be untenable (see Section "Quantile autoregressive distributed lag model: fluctuations cointegrating relationships across quantiles").

[5] The major weakness of the ARDL estimation is the potential endogeneity created by the lagged dependent variables. We apply the Bewley transformation to assess the relationship between food sales and other variables—after controlling for potential endogeneity (see Section "Endogeneity problems for the proposed models and insights from the Bewley transformation: a robustness check").

commodity prices (Atri et al. 2021). Since the 2008 financial crisis, the impacts of non-fundamentals, such as participants' expectations, anxiety, and market sentiments, on financial markets have been thoroughly examined (see Joo et al. 2020). Baker et al. (2016) also emphasized the role of policy uncertainty in influencing participants' beliefs, macroeconomic activities, and thus financial markets (Aloui et al. 2016). Therefore, the increasing anxiety among investors in financial markets, resulted in rising "investor fear," which is measured by the CBOE *VIX*. COVID-19's impact on food sales can be seen through its effect on *VIX*. This aspect has remained relatively unexplored despite its potentially devastating short- and long-term consequences for human security. We intend to fill this void by investigating potential nonlinear and asymmetric relationships between food sales and explanatory variables (*WEI* and *VIX*). It is critical to note that market sentiment can be measured using a volatility index derived from the GARCH model. Our results using the volatility index are roughly in conformity with CBOE indicator of *VIX*. Alternatively, the economic sentiment index developed by Shapiro et al. (2022) can be used to assess the news sentiment of the pandemic. Because our focus is not the news sentiment in this work, we choose not to use the economic sentiment index.

COVID-19 and commodity markets

The following summarizes the effects of economic disruptions on commodity markets during the pandemic: First, the outbreak lowered most commodity prices, particularly crude oil. For example, oil prices tumbled by two-thirds in the first quarter of 2020, a never-before-seen phenomenon. Such decreases have a wide-ranging impact on the cost of production for most goods and thus on the supply side. However, the demand side also plummeted due to COVID-19 containment measures, which caused a drop in economic activity. Thus, the pandemic caused a unique combination of disruptions in commodity markets, affecting both demand and supply (see Baffes et al. 2020). According to Baffes et al. (2020), disruptions in the food supply chain may have impacted food sales concerns and hoarding by consumers and speculators.

Simultaneously, the pandemic disrupted agricultural commodity production due to shortages of key inputs, such as fertilizers, primarily due to mitigation measures. The labor movement across state and country borders was heavily regulated. Lockdowns also caused severe supply shocks in the food procuring industries. Moreover, trade restrictions exacerbated the food consumption problem (see Glauber et al. 2020; Schmidhuber et al. 2020; World Bank 2020).

Variables and data

This study employs the *WEI*[6] data for the United States and the CBOE *VIX* to model the short- and long-run effects of a pandemic from January 2020 to January 2021. The *WEI* is an index of real economic activity's ten indicators that are scaled to correspond to the four-quarter GDP growth rate. It is a series component that covers consumer behavior,

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[6] More details about the index can be found at https://www.newyorkfed.org/research/policy/weekly-economic-index#/. As discussed before, *WEI* and *VIX* are not contemporaneous movements—*VIX* is lagged by a week to avoid endogeneity.

the labor market, and production (Lewis et al. 2021a, 2021b). Following the extant litera-ture, we know that the supply and demand shocks caused by the COVID-19 pandemic have an impact on commodity markets, but the commodity market is also impounded by non-fundamentals such as participants' expectations (as discussed in Joo et al. 2020; Baker et al. 2016; Aloui et al. 2016; Baumeister and Peersman 2013; Kilian 2009). The CBOE *VIX* is used to capture market expectations, whereas the US *WEI* is used to cap-ture economic disruptions caused by the COVID-19 pandemic.

The CBOE *VIX* is a real-time market index issued by the CBOE as a volatility index to indicate the market's expectations for the relative strengths of near-term price changes (over the next 30 days) (of the S&P 500 index (SPX)). Smales (2014) emphasized the importance of the *VIX* as a measure of investor fear. Thus, increases (decreases) in *VIX* indicate higher (lower) investor fear about the future. Hence, we use *VIX* as an indica-tor of the pandemic's long-term (economic) consequences. It is critical to note that the long-term in the context of a pandemic can be a few weeks due to potential upheavals in economic and financial situations caused by the pandemic. Meanwhile, *WEI* captures the short-run impacts of economic disruption caused by the pandemic.

For the food sales data, we use a weekly series released by the US Department of Agriculture (USDA). The USDA publishes the weekly retail food sales series, which is derived from proprietary scanner data using a nationally representative sample of retail food establishments collected by Information Resources Inc. [see https://www.ers.usda.gov/data-products/weekly-retail-food-sales/]. The USDA also publishes a volume index of retail food sales. We alternately use these two series as dependent variables as indicators of food sales. The N/ARDL and QARDL methodologies are used to detect the effects of *VIX* and *WEI* on *Food Security* (Z_1) in the United States.

Empirical models

Baseline ARDL model

For assessing the impacts of *VIX* and *WEI*, we postulate an empirical relationship using the standard ARDL model. Equation (1) presents the standard ARDL (p, q) model:

$$LnZ_{1t} = \alpha_0 + \pi\, LnZ_{1t-1} + \sum_{i=1}^{p} \alpha_{1i} \Delta LnVIX_{(t-1)-i} + \sum_{i=0}^{q} \alpha_{2i} \Delta LnWEI_{t-i}$$
$$+ \beta_1 LnWEI_{t-1} + \beta_2 LnVIX_{(t-1)-1} + \varepsilon_t \tag{1}$$

where α_0 is the intercept term, π is the error correction term, α_{1i} & α_{2i} is the short-run coefficient for each variable while the parameter β_1 & β_2 is the long-run coefficient. Note that ε_t is the error term and *ln* is the natural logarithmic transformation. The ARDL bounds test enables us to model both I (0) and I (1) variables together. The null hypoth-eses H_0 posits: $\beta_1 = \beta_2 = 0$. As a result, the null hypothesis assumes that there is no coin-tegration, whereas the alternative hypothesis assumes that there is cointegration. As a result, the alternative hypothesis H1 proposes that at least one parameter I is not zero. Using the Wald test, the F-statistics will be calculated to compare with the critical values of Pesaran et al. (2001). The ARDL mechanism detects cointegration if the calculated F-statistics are greater than the upper bound of critical values.

Nonlinear autoregressive distributed lag model: an extension

The evolving, albeit limited, literature on the pandemic's effects *implicitly* suggests that the effects of increases and decreases in pandemic-related variables (on other variables) are *symmetric,* with increases and decreases assumed to work along the same functional relationship (see Ashraf 2020; Apergis and Apergis 2021; Bakry et al. 2021; Zaremba et al. 2020). In section "Baseline ARDL model", the ARDL model follows the path of the existing work. In this Section, we consider the possibility of asymmetric relationships between food sales (Z_1) and the *WEI* and *VIX*. We contend that changes in the *WEI* and *VIX* can send specific messages to policymakers about the state of the economy and financial system, to which policymakers may respond asymmetrically. If there are any asymmetries, the symmetric models are incorrectly specified. As a result, we argue that a nonlinear and asymmetric error correction model based on a collection of (nonlinear autoregressive distributed lag) NARDL models will better capture the dependent variable's responses to various shocks in the independent variables of interest when these shocks have underlying asymmetric effects.

To avoid the ARDL model's potential technical inconsistencies, the analysis is performed using the NARDL approach described above. The NARDL model developed by Greenwood-Nimmo and Shin (2013) and Shin et al. (2014) allows us to examine the short-run and long-run responses of Food sales (Z_1) to asymmetric fluctuations in *VIX, WEI.* Furthermore, the NARDL model detects any hidden cointegration that other cointegration models fail to detect. Following the study's motivation, the following nonlinear and asymmetric NARDL model (ignoring short-run dynamics) was applied to the US economy:

$$Z_{1t} = \beta^+ WEI_{t-1}^+ + \beta^- WEI_{t-1}^- + \theta^+ VIX_{(t-1)-1}^+ + \theta^- VIX_{(t-1)-1}^- + \mu_t \qquad (2a)$$

where Z_1 is the chosen measure of food sales, *WEI* is the US weekly economic index, β^+ is the long-run coefficient associated with an increase in *WEI*, WEI_{t-1}^+, which coveys a message of further disruptions of the economy in our model. Similarly, WEI_{t-1}^- conveys the message that (mitigation) disruptions are likely to decrease. This method divides changes in an independent variable's values into positive (+) and negative (-) partial sums, as shown below:

$$WEI_t = WEI_0 + WEI_t^+ + WEI_t^-, \text{ such that } \quad WEI_t^+ = \sum_{i=1}^t \Delta WEI_i^+ = \sum_{i=1}^t \max(\Delta WEI_i, 0)$$

$$\text{and } WEI_t^- = \sum_{i=1}^t \Delta WEI_i^- = \sum_{i=1}^t \min(\Delta WEI_i, 0).$$

Note, β^- is the long-run coefficient associated with the negative change in WEI_{t-1}, WEI_{t-1}^-, which brings the message of decreases in future disruptions to the economy. Note that that β^+ and β^- are the positive partial sum and the negative partial sum of the increases and decreases in WEI_{t-1}, respectively. Similarly, we define the asymmetric change in $VIX_{(t-1)-1}$ as a measure of financial market (investor) fear as follows: an

increase in $VIX_{(t-1)-1}$ carries a message about the rise in future uncertainty, whereas a decrease in $VIX_{(t-1)-1}$ indicates a decrease in investor fear.

To illustrate, consider how the unrestricted linear ARDL (p, q) model of Eq. (1) is reduced to the following nonlinear asymmetric conditional ARDL (Apergis and Gangopadhyay 2020):

$$\Delta LnZ_{1t} = \alpha_0 + \rho LnZ_{1t-1} + a^+ LnWEI_{t-1}^+ + a^- LnWEI_{t-1}^- + b^+ LnVIX_{(t-1)-1}^+$$
$$+ b^- LnVIX_{(t-1)-1}^- + \sum_{i=1}^{p-1} \alpha_i \Delta LnZ_{1t-i} + \sum_{i=0}^{q-1} (b_i^+ \Delta LnVIX_{(t-1)-i}^+$$
$$+ b_i^- \Delta LnVIX_{(t-1)-i}^-) + \sum_{i=0}^{q-1} (a_i^+ \Delta LnWEI_{t-i}^+ + b_i^- \Delta LnWEI_{t-i}^-) + \omega_t \tag{2b}$$

where $\sum_{i=0}^{q-1} b_i^+$ and $\sum_{i=0}^{q-1} b_i^-$ denote the short-run asymmetric dynamics of $LnVIX_{(t-1)-1}$, and ω_t labels the error term. The effects of positive and negative changes in $LnVIX_{(t-1)-1}$, and the asymmetric long-run coefficients of $LnVIX_{(t-1)-1}$, are calculated as $\theta^+ = -\frac{b^+}{\rho}$ and $\theta^- = -\frac{b^-}{\rho}$.

$\sum_{i=0}^{q-1} a_i^+$ and $\sum_{i=0}^{q-1} a_i^-$ denote the short-run asymmetric dynamics of $\Delta LnWEI_{t-1}$. The sums of positive and negative changes in $LnWEI_{t-1}$ and the asymmetric long-run coefficients of $LnWEAI$ are calculated as $\beta^+ = -\frac{a^+}{\rho}$ and $\beta^- = -\frac{a^-}{\rho}$. Now, the error correction model of Eq. (2b) can be presented as:

$$\Delta LnZ_{1t} = \sum_{i=1}^{p-1} \alpha_i \Delta LnZ_{1t-i} + \sum_{i=0}^{q-1} (b_i^+ \Delta LnVIX_{(t-1)-i}^+ + b_i^- \Delta LnVIX_{(t-1)-i}^-)$$
$$+ \sum_{i=0}^{q-1} (a_i^+ \Delta LnWEI_{t-i}^+ + b_i^- \Delta LnWEI_{t-i}^-) +_i ECT_{t-1} + \omega_t \tag{2c}$$

Quantile autoregressive distributed lag model: fluctuations cointegrating relationships across quantiles

Following Cho et al. (2015), we proposed the QARDL model for the postulated ARDL model of (1) as follows:

$$Q(\Delta LnZ_{1t}) = \sigma_0(v) + \sum_{i=1}^{p-1} \delta_i(v) \Delta LnZ_{1t-1} + \sum_{i=0}^{q1-1} \alpha_i(v) \Delta VIX_{(t-1)-1}$$
$$+ \sum_{i=0}^{q2-1} \beta_i(v) \Delta WEI_{t-1} + e_t(v) \tag{3a}$$

In Eq. (3a), $e_t(v) = Q(\Delta LnZ_{1t}) - \Delta LnZ_{1t-i}(v/F_{t-1})$ and $\Delta LnZ_{1t-i}(v/F_{t-1})$ is the v_{th} quantile of ΔLnZ_{1t}, and it is dependent on the F_{t-1} information set.[7] Now, incorporating the long-run dynamics into (1) the QARDL model can be written as follows:

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[7] See Kim and White (2003).

$$Q(\Delta LnZ_{1t}) = \sigma_0(v) + \pi(v)LnZ_{1t-1} + \rho_{VIX}(v)LnVIX_{(t-1)-1} + \omega_{WEI}(v)LnWEI_{t-1}$$
$$+ \sum_{i=1}^{p-1} \delta_i(v)\,\Delta LnZ_{1t-1} + \sum_{i=0}^{q1-1} \alpha_i(v)\Delta LnVIX_{(t-1)-1} + \sum_{i=0}^{q2-1} \beta_i(v)\Delta LnWEI_{t-1} + e_t(v)$$

(3b)

Equation (3b), known as the QARDL error correction model (hereafter QARDL-ECM), posits the parameters of the short-run dynamics for food sales (LnZ_1), $LnVIX$, and $LnWEI$, which are captured by $\delta_i(v)$, $\alpha_i(v)$, and $\beta_i(v)$, respectively. Moreover, the corresponding long-run parameters are given by $\rho_{VIX}(v)$, $\omega_{WEI}(v)$. The cumulative short-run impacts of the independent variables can be calculated using the delta method: $\alpha_{i*}(v) = \sum_{i=0}^{q1-1} \alpha_i (v)$, $\beta_{i*}(v) = \sum_{i=0}^{q2-1} \beta_i (v)$. Moreover, the long-run cointegrating coefficients can be assessed as $\rho_{VIX*}(v) = \rho_{VIX}/\pi$, $\omega_{WEI*}(v) = \omega_{WEI}/\pi$.

The convergence speed toward equilibrium, which must be negative and significant, is given as $\pi^*(v)$.

Following Cho et al. (2015), we used the Wald test to statistically assess the regressors' short- and long-term nonlinear and asymmetric effects on the regressand (LnZ_1). In this context, the null and alternative hypotheses for short-term dynamics are as follows:

H_0: $S\,\alpha_i(v) = s$ against H_1: $S\,\alpha_i(v) \neq s$;
H_0: $S\,\beta_i(v) = s$ against H_1: $S\,\beta_i(v) \neq s$;.

For the cumulative short-run effect, the null and alternative hypotheses can be.

- H_0: $S\,\alpha_{i*}(v) = s$ against H_1: $S\,\alpha_{i*}(v) \neq s$;
- H_0: $S\,\beta_{i*}(v) = s$ against H_1: $S\,\beta_{i*}(v) \neq s$;

Meanwhile, for the long-run parameters and QARDL error correction term (ECT) terms ($\pi(v)$), the null and alternative hypothesis are as follows: $\rho_{lnVIX}(v)$, $\omega_{lnWEI}(v)$,

H_0: $S\,\rho_{lnVIX*}(v) = S\,(\rho_{lnVIXi}/\pi) = s$ against H_1:$S\,\rho_{lnVIX*}(v) = S\,(\rho_{lnVIXi}/\pi) \neq s$;
H_0: $S\,\omega_{lnWEI*}(v) = S\,(\omega_{lnWEI}/\pi) = s$ against H_1: $S\,\omega_{lnWEI*}(v) = S\,(\omega_{lnWEI}/\pi) \neq s$;
H_0: $F\,\pi_*(v) = f$ against H_1: $F\,\pi_*(v) \neq f$.

Here, S and s, and F and f are pre-determined matrices with the h number of restrictions. The Wald test examined all of the nonlinear features of the parameters. The relevant null and alternative hypotheses for the speed of adjustment parameter $\pi_*(v)$, for example, are:

H_0: $\pi_*(0.25) = \pi_*(0.50) = \pi_*(0.75) = \pi_*(0.95)$ and
H_1: $\pi_*(0.25) \neq \pi_*(0.50) \neq \pi_*(0.75) \neq \pi_*(0.95)$ over the four quantiles Q25, Q50, Q75, and Q95.

As the independent variable moves from one quantile to another, QARDL allows us to establish a possible nonlinearity through a data-driven process. This method may be superior to Shin et al.'s (2014) nonlinear ARDL (NARDL), which exogenously

builds nonlinearity by setting the quantile threshold to zero (see Apergis and Gangopadhyay [2020](#)). Once (3b) is estimated, we can apply the Wald test to test the asymmetry hypothesis.

Endogeneity problems for the proposed models and insights from the Bewley transformation: a robustness check

The problem of endogeneity has been noted in the context of ARDL. A simple transformation of the ARDL model known as the Bewley transformation allows for asymptotically valid inference while overcoming estimation issues due to endogeneity using t-statistics on long-run coefficients. This transformation provides an alternative method for estimating the cointegrating relationship, with certain finite sample advantages over the Engel–Granger method. More information in the regression (in this case, via the Bewley transformation) is likely to produce estimators with better features, as simulations in Inder ([1993](#)) demonstrate.

By considering the ARDL (p, q) model from Eq. ([4a](#)), the final form of the same equation under the Bewley transformation can be written as Eq. ([4b](#)).

$$Y_t = \alpha_0 + \sum_{j=0}^{q} \beta_j L^j X_t + \sum_{i=1}^{p} \gamma_i L^i Y_t + \varepsilon_t \tag{4a}$$

$$Y_t = \frac{\alpha_0}{1 - \gamma_1} + \frac{\beta_0 - \beta_1}{1 - \gamma_1} X_t - \frac{\beta_1}{1 - \gamma_1} \Delta X_t - \frac{\gamma_1}{1 - \gamma_1} \Delta Y_t + \frac{\varepsilon_t}{1 - \gamma_1} \tag{4b}$$

Because of the presence of a contemporaneous relationship between the variables in Eq. ([4b](#)), the Bewley transformation necessitates the use of instrumental variables. Generally, Y_{t-1} is used as an instrument for ΔY_t. In this study, we will use Stata's IVREG2 command to extract the Bewley transformation results and test the tenability of our ARDL model.

Results and discussion

Table [7](#) illustrates the descriptive statistics of the data: the mean, median, and standard deviation of LnZ_1. The kurtosis statistics of all series, except *WEI*, are greater than 3. Thus, the NARDL and QARDL models are more suitable. The Jarque–Bera tests find that all of the variables deviated from the normal distribution. Table [8](#) shows that all variables are I(0) or I(1), implying that the ARDL, NARDL, and QARDL models constitute the proper methodology. Tables [1](#), [2](#), [3](#), [4](#), [5](#) and [6](#) show the results of linear ARDL, NARDL, and QARDL model estimation.

In Table [7](#), we explore the fundamental statistics before moving on to the unit root tests, summarized in Table [8](#). Tables [7](#) and [8](#) are available in the appendix. We use the ARDL methodology to explore the cointegrating relationship between variables given by Eq. ([1](#)), and the results are summarized in Table [1](#).

The NARDL methodology is then applied, and the results are presented in Table [2](#). Figure [1](#) depicts the NARDL diagram.

In addition to the preceding tests, we use the QARDL methodology as a robustness check for the ARDL and NARDL methodologies. The possibility of the cointegrating

Table 1 ARDL results

Variable	Dependent variable LnZ_1				
	Long Run			*Short Run*	
	Coeff	**t-value**		**Coeff**	**t-value**
ECT				−1.03***	−7.19
LnVIX	0.12***	4.76			
LnWEI	−0.002	−0.51			
Constant	22.98***	6.38			
ΔLnZ_{1t-1}				0.33***	2.90
R^2	0.46			0.50	
F Stat	12.18***				
Cointegration	Yes				

Notes: *** indicate significant at 1% level of significance

Table 2 NARDL results

NARDL Model: LnZ1 = f (LnVIX, LnWEI)	
C	36.659***
$LnZ1_{t-1}$	−1.576***
$LnVIX_{t-1}^{POS}$	0.436***
$LnVIX_{t-1}^{NEG}$	0.134**
WEI_{t-1}^{POS}	−0.029***
WEI_{t-1}^{NEG}	0.030***
$\Delta LnZ1_{t-1}$	0.403**
$\Delta LnVIX_t^{POS}$	0.053
$\Delta LnVIX_{t-1}^{POS}$	−0.342***
$\Delta LnVIX_t^{NEG}$	0.135*
$\Delta LnVIX_{t-1}^{NEG}$	0.178**
ΔWEI_t^{POS}	0.025
ΔWEI_{t-1}^{POS}	−0.003
ΔWEI_t^{NEG}	−0.013
ΔWEI_{t-1}^{NEG}	0.035**
F_PSS	18.2115***
t_BDM	−6.8854***
Cointegration	**Yes**
Long-run effect	
L_{LnVIX}^{POS}	0.276***
L_{LnVIX}^{NEG}	−0.085**
L_{WEI}^{POS}	−0.018***
L_{WEI}^{NEG}	−0.019***
Asymmetry effect	

Long-run asymmetry F-stat		*Short-run asymmetry F-stat*	
LnVIX	37.75***	*LnVIX*	13.01***
WEI	35.80***	*LnWEI*	0.0000133
J-B test		0.851	
Ramssey RESET test		0.621	
Portmanteay test		13.380	
Breusch-Pegan test		0.054	

Notes: ***, **, and * indicate significant at 1%, 5%, and 10% significance levels

Table 3 QARDL results

Parameters	Quantile v = 0.25		Quantile v = 0.50		Quantile v = 0.75		Quantile v = 0.95	
	Coef	p value	Coef	p value	Coef	p value	Coef	p value
π_* (v)	-1.062^a	0.000	-0.961^a	0.002	-0.919^b	0.042	-1.250^b	0.044
ρ_{VIX*} (v)	0.060	0.429	0.100	0.150	0.363^a	0.000	0.254^a	0.002
ω_{WEI*} (v)	−0.004	0.190	−0.005	0.329	0.013^b	0.041	0.009	0.175
$\eth\,\delta_1$(v)	0.183	0.452	0.109	0.712	0.120	0.660	0.318	0.417
$\eth\,\alpha_0$(v)	−0.022	0.649	0.009	0.860	0.121	0.216	0.181^c	0.096
$\eth\,\alpha_1$(v)	0.008	0.923	−0.012	0.885	−0.150	0.144	−0.082	0.494
$\eth\,\beta_0$(v)	−0.005	0.839	−0.005	0.864	0.018	0.480	0.033	0.211
$\eth\,\beta_1$(v)	0.013	0.552	−0.001	0.956	0.023	0.251	−0.035	0.288
$\eth\,\beta_2$ (v)	−0.009	0.661	0.008	0.654	0.021	0.184	0.043^a	0.007
σ_*(v)	24.593^a	0.000	22.149^a	0.002	20.503^b	0.044	28.339^b	0.047

Notes: The coefficients in bold-italics with a, b, and c indicates level of significance at 1%, 5%, and 10%, respectively

Table 4 Wald test results

Parameters	Coefficient	F-Stat
π_* (v)	0.24	0.8685
ρ_{VIX*} (v)	8.45^b	0.0374
ω_{WEI*} (v)	5.56	0.1353
$\eth\,\delta_1$(v)	0.40	0.7558
$\eth\,\alpha_0$(v)	1.12	0.3516
$\eth\,\alpha_1$(v)	0.56	0.6420
$\eth\,\beta_0$(v)	0.63	0.5966
$\eth\,\beta_1$(v)	4.11^b	0.0112
$\eth\,\beta_2$ (v)	1.76	0.1687
Short-run Cumulative Effect		
$\eth\,\alpha_*$	0.96	0.8115
$\eth\,\beta_*$	3.16	0.3673

Notes: The coefficients in bold-italics with a, b, and c indicates level of significance at 1%, 5%, and 10%, respectively

relationship fluctuating across quantiles is central to the QARDL methodology. If this relationship fluctuates, the ARDL and NARDL results are not reliable. Table 3 displays the results of the QARDL model. Meanwhile, Table 4 displays the Wald statistics for the QARDL model.

The heterogeneity of coefficients across different quantiles is captured in Fig. 1, as we note that the relationship between *Food Security* (LnZ_1) vis-à-vis *LnVIX* and *WEI* fluctuates from quantiles to quantiles.

We discuss the QARDL model results in light of the ARDL and NARDL results presented in Section "Results and discussion". Finally, one of the shortcomings of using autoregressive methodology is addressed by employing the Bewley transformation to examine endogeneity issues. We present the results from the Bewley transformation in Section "Findings from the Bewley transformation after controlling for endogeneity".

Table 5 Results from first stage regressions of Bewley transformation

ΔLnZ_{1t-1}	Coefficient	*p* value
LnZ_{1t-1}	−0.772	0.000
$LnVIX$	0.120	0.000
WEI	0.001	0.617
Cons	17.682	0.000

Sanderson-Windmeijer multivariate F test of excluded instruments: F (1, 51) = 34.17, Prob > F = 0.0000

Under identification Test: Anderson canon. corr. LM statistic: Chi-sq(1) = 22.07, *p* value = 0.0000

Weak identification Test: Cragg-Donald Wald F statistic 34.17***

Weak-instrument-robust inference
Anderson-Rubin Wald test F(1,51) = 2.97 *p* value = 0.0907
Anderson-Rubin Wald test Chi-sq(1) = 3.21 *p* value = 0.0733
Stock-Wright LM S statistic Chi-sq(1) = 3.03 *p* value = 0.0817

Number of observations N = 55
Number of regressors K = 4
Number of endogenous regressors $K_1 = 1$
Number of instruments L = 4
Number of excluded instruments $L_1 = 1$

Notes: *** indicate significant at 1% level of significance

Table 6 Results of Bewley transformation from instrument variable estimation

$LnZ1$	Coefficient	*p* value
ΔLnZ_1	−0.295	0.167
$LnVIX$	0.156	0.000
WEI	0.002	0.612
Cons	22.899	0.000

Number of obs = 55
F(3, 51) = 7.89
Prob > F = 0.0002
Total (centered) SS = 0.3189746795
Total (uncentered) SS = 30,134.53036
Residual SS = 0.3008455664
Centered R2 = 0.0568
Uncentered R2 = 1.0000
Root MSE = 0.07396

Under identification test (Anderson canon. corr. LM statistic): 22.065
Chi-sq(1) *p* value = 0.0000
Weak identification test (Cragg-Donald Wald F statistic): 34.168
Stock-Yogo weak ID test critical values: 10% maximal IV size 16.38
15% maximal IV size 8.96
20% maximal IV size 6.66
25% maximal IV size 5.53
Sargan statistic (overidentification test of all instruments): 0.000
(Equation exactly identified)

Findings from the Baseline ARDL Model

The ARDL results (Table 1) reveal a long-term causality running from the chosen variables (*WEI* and *VIX*) to food sales (Z_1), as the ECT, which indicates the speed of adjustment toward the long-run equilibrium after a shock, is negative and statistically significant at the 1% level. However, there is some evidence of overcorrection
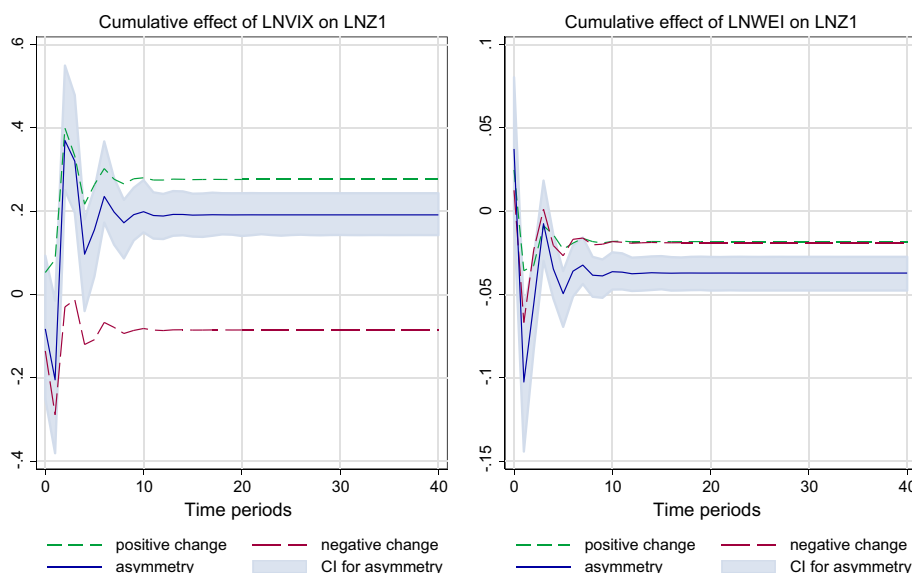
Fig. 1 Cumulative effects of *LNVIX* and *WEI* on Food Insecurity (LNZ_1)

(ECT $= \pi = -1.03$). Second, we find that the F statistic confirms cointegration between food sales and the regressors at the 1% significance level for the ARDL model. Third, none of the control variables have long-term relationships with food sales: we find clear evidence that *VIX* positively impacts food sales (Z_1) at the 1% significance level. However, the effect of *VIX* on Z_1 is inelastic: a 1% increase (decrease) in *VIX*, or a 1% increase (decrease) in investor fear, increases (decreases) food sales (Z_1) by 0.12%. Moreover, *WEI* did not exert any statistically significant long-term impact on food sales (Z_1). In the short-run, we find that ΔLnZ_{1t-1} has a statistically significant and positive impact on $\Delta LnZ_{1t,}$ though inelastic, implying some sort of buyers' panic to hoard food items: a 1% increase in ΔZ_{1t-1} increases ΔZ_{1t} by 0.34% and the effect is statistically significant at the 1% level. Finally, the proposed model is confirmed to have a long-run relationship, or cointegration, as evidenced by the bound test results provided by actual values of F_PSS in Table 1. As previously discussed, the model establishes causality running from the model's explanatory variables to food sales, as evidenced by the error correction terms in Table 1.

Since the ARDL model assumes symmetric changes, it cannot detect asymmetric effects and, as a result, cannot detect hidden cointegration and nonlinearities. If there is hidden cointegration between food sales and the *VIX* and *WEI*, the ARDL model results are not credible. In what follows, we present the NARDL model results and find evidence of hidden cointegration, confirming that the baseline ARDL model results are not tenable.

Findings from the NARDL model: is there evidence of hidden cointegration?

Table 2 shows that the positive partial sum of an increase in *LnVIX* (θ^+) has a positive long-term effect on LnZ_1 and is statistically significant at the 1% level. The effect is inelastic, implying a 1% increase in *VIX—ceteris paribus—*will increase Z_1 by 0.27%.

Furthermore, the negative partial sum of a decrease in *VIX* (θ^-) has a long-term negative effect on LnZ_1 and is statistically significant at the 1% level. The effect is inelastic once more. We find that the value implies that a 1% decrease in *VIX* increases demand for food sales (Z_1) by 0.085%. Thus, there is evidence of asymmetry for *VIX*'s effect on Z_1. In other words, there is evidence of hidden cointegration that the ARDL model failed to detect. However, the absolute values of the positive effect, θ^+, is stronger than the corresponding values of the negative effects, or θ^-. The positive effect is approximately three (3) times greater than the negative effect, in absolute value. Thus, the effect of *VIX* increases outweigh the effect of *VIX* decreases during the COVID-19 pandemic. The Wald test results (Table 4) confirm the long-term asymmetries of both effects of θ^+ and θ^-.

Turning our attention to the asymmetric relationship between Z_1 and *WEI*, we find that the positive partial sum of an increase in *WEI* (β^+), has a negative long-term effect on food sales (Z_1) and is statistically significant at the 1% level. The inelastic effect implies that a 1% increase in *WEI* will reduce food sales (Z_1) by 0.018%. Moreover, the negative partial sum of a reduction in *WEI* (β^-) has no statistically significant effect on Z_1. In other words, there is significant asymmetry in the positive effect (β^+) vis-à-vis the negative effect (β^-) on food sales (Z_1). The Wald test results (see Table 4) confirm the long-term asymmetries of both effects of β^+ and β^-.

For the short-term asymmetries, from the Wald test in Table 4, we find evidence of statistically significant asymmetries for *VIX*. As *VIX* rose by 1%, food sales (Z_1) declined by 0.34%, at the 1% significance level. However, as *VIX* decreased by 1%, food sales (Z_1) declined by 0.18%, at the 1% significance level. We did not find any evidence of short-run asymmetries for the effects of *WEI* on food sales (Z_1).

The adequacy of the dynamic specification is first assessed using a variety of diagnostics, including the Jarque–Bera (J-B) statistic for error normality, the Portmanteau test statistic for model fit, the Breusch-Pagan test for autoregressive conditional heteroskedasticity up to order 2, and the Ramsey RESET statistics for regression specification error test. The results are shown in the lower panel of Table 4. The models pass key diagnostics, indicating error normality, the absence of autocorrelation and the ARCH effect, and overall parameter stability. Accordingly, the dynamics of COVID-19 indicators are sufficiently specified.

Finally, the postulated model is confirmed to have a long-run relationship, or cointegration, as evidenced by the bound test results provided by actual values of F_PSS in Table 2. As previously discussed, the model establishes causality running from the model's explanatory variables to food sales, as indicated by the ECT in Table 2. The presence of hidden cointegration, as confirmed by the asymmetric effects of *VIX* and *WEI* on LnZ_1, renders the ARDL findings untenable, while the NARDL model results are meaningful. In what follows, we apply the QARDL model to test the robustness of the NARDL model. One of the NARDL model's central assumptions is that the coefficients remained stable across quantiles. The tenability of the NARDL model breaks down when coefficients fluctuate from one quantile to another. In the following subsection, the QARDL model will test the robustness of the NARDL model.
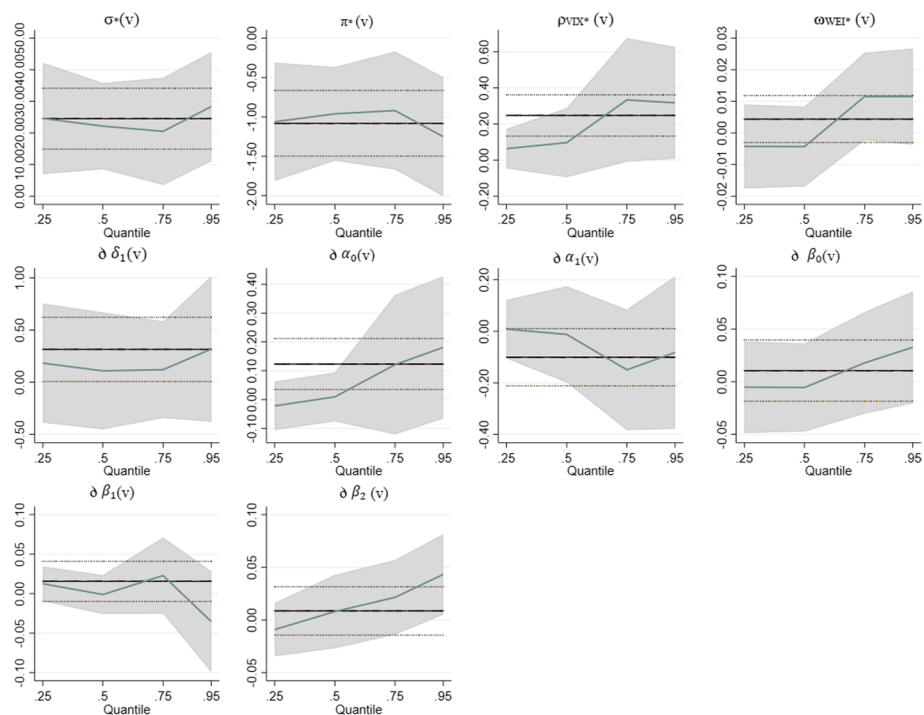
Fig. 2 95% confidence intervals of the QARDL model parameters. Horizontal axis indicates the quantile levels (v < 0.5, 0.5 < v < 0.75, 0.75 < v < 0.95). Vertical axis indicates coefficient estimates of parameters

Findings from the QARDL model to test fluctuations of coefficients across quantiles: robustness check of NARDL model

We estimated the model using four quantiles (Q25, Q50, Q75, and Q95). The speed of adjustment parameter π_* is not only negative but also significant across the four quantiles, indicating the presence of long-run cointegrating relationships. This demonstrates that long-run cointegrating relationships are valid with both basic ARDL estimation and the QARDL model.

The long-run coefficients of the *VIX* index [$\rho_{\text{VIX}_*}(v)$] have significant positive impacts on food units sold [Z_1] in the 0.95 quantile, whereas weekly economic activity [$\omega_{\text{WEI}_*}(v)$] has insignificant impact across the quantiles.

The short-run parameters show that, among the regressors, the lag difference of food sales [$\partial \delta_1(v)$], *VIX* [$\partial \alpha_0(v)$], and *WEI* [$\partial \beta_2(v)$] exhibits a significant positive effect on food sales only in the fourth quantile [$v = 0.95$].

We discovered that the constant term [$\sigma_*(v)$] is significant across all four quantiles. Figure 2 shows a graphical representation of the results.

Wald tests for null of linearity were performed to test for the consistency of parameter estimates across quantiles, and the results are shown in Table 3. For the speed of adjustment parameter π_*, the *p* value of 0.418 shows that the null of linearity cannot be rejected, confirming that the parameter is consistent across quantiles. This conclusion is reached with the remaining parameters in both the long and short runs.

After applying the QARDL methodology for the same relationship between food sales and the control variables, we find important insights into the long-run relationships across various quantiles, that is, contingent on the conditional distribution of the dependent variables. It is important to note that the QARDL model findings do not support the NARDL model findings, but the Wald tests of the QARDL model show no evidence of parameter fluctuations or fluctuations in cointegration across quantiles. Thus, the NARDL model is robust.

Table 3 shows that the error correction terms across quantiles are negative and significant for all QARDL model quantiles. Hence, for all quantiles of the dependent variable, the causality runs from the chosen variables (*WEI* and *VIX*) to food sales (Z_1). This is an important finding because both ARDL and NARDL results showed that causality runs from the selected variables to food sales at the 1% significance level. Thus, the unbundling of the relationship across quantiles—using the QARDL methodology—confirms the NARDL models' causality findings for all quantiles.

Findings from the Bewley transformation after controlling for endogeneity

It is critical to explain the causal identification strategy that we have chosen to address potential endogeneity in the current *WEI* and *VIX* measures. First, we avoided concurrent movements in *WEI* and *VIX* by delaying the *VIX* variable by one week. As a result, unknown future *WEI* values do not affect current or historical *VIX* values. Second, we checked the correlation between *WEI* and *VIX* (lagged by a year), and the correlation is in the safe zone. Finally, we check the reverse causality of *VIX* (expectations about the future) on current and future *WEI*. Then, we ran the ARDL estimation and found the absence of any long-run causality running from *VIX* to (future) *WEI*.

This subsection addresses the additional endogeneity problem by estimating the postulated model's Bewley equation using the ARDL instrumental variable (IV). This will allow us to determine whether the proposed ARDL models are robust in extracting short and long-run relationships by using the lag of the dependent variable as the independent variable (Stučka 2004). The Bewley transformation allows us to find whether a change in the ARDL model's dependent variable should correlate with any of the variables in question (see Inder 1993).

This transformation methodology uses the lagged dependent variable as the instrument. Tables 5 and 6 summarize the results of the instrumental variable regression using the IVREG2 command of Stata. Our findings are two-fold:

 (i) As shown in Table 6, the Cragg–Donald Wald F statistic is greater than the Stock–Yogo weak ID test critical values. Hence, the instrument of the Bewley transformation is valid.

 (ii) Z_1 bears a (statistically significant) positive relationship with *VIX* (Table 6). Thus, increases (decreases) in the financial uncertainty, or disruptions, will increase (decrease) food sales (Z_1). We find a positive relationship between Z_1 and *WEI*, but it is not statistically significant. Note that the relationship between *WEI* and Z_1 is expected to hold because these are concurrent movements within the same week. *WEI* is likely to take a little longer to influence food sales Z_1. Thus, once the Bewley transformation controls the potential endogeneity, there is clear evidence that financial market disruptions or the *VIX* impacts food sales. After controlling for

endogeneity, we determined that economic disruptions have no statistically signifi-
cant effect on food sales in the same week. The standard ARDL results confirmed
this. Hence, our identification strategy to lag *VIX* effectively avoids the endogeneity
trap.

Direct vis-à-vis indirect effects of the pandemic on food sales

One of our analysis's obvious flaws is that the direct effect of the pandemic on food sales
cannot be clinically separated from the indirect effect of the pandemic due to economic
dislocations.[8] We tested the addition of a variable to capture pandemic intensity as an
additional regressor. However, as highlighted in the literature, any attempt to capture the
intensity of the pandemic will create serious estimation problems. Our model's appar-
ent weakness stems from one of the primary requirements of any variant of the ARDL
methodology: the regressors are truly exogenous (see Cho et al. 2021, p. 1). It is well-
recognized that a large number of studies have ignored this key requirement and drawn
incorrect conclusions. Sam et al. (2019) succinctly argued that "However, as pointed out
by McNown et al. (2018), these assumptions were sometimes ignored by researchers,
possibly leading to misleading conclusions" (p. 130).

In all ARDL variants, including ARDL, NARDL, QARDL models, and other exten-
sions, the explanatory variables must be exogenous; hence, we chose our model after
carefully checking that the chosen explanatory variables are exogenous. To assess the
feasibility of incorporating the pandemic variable, we chose a variable $X_{Pandemic}$, defined
as the weekly COVID-19 infection rate, as a possible explanatory variable to capture the
intensity of the pandemic in the United States.

The results from a vector autoregressive (VAR) model establishes that $X_{Pandemic}$ can-
not be used simultaneously with *WEI* due to endogeneity problems, as highlighted by
Cho et al. (2021). Table 9 in the appendix confirms that *WEI* and *VIX* can be used safely
as exogenous explanatory variables. However, including $X_{Pandemic}$ in the ARDL method-
ology will lead to incorrect estimation. Several other pandemic-related variables were
investigated. We found that none of them can be used with *WEI* and *VIX* without violat-
ing the requirement of exogenous explanatory variables.

However, the cost of this weakness in the ARDL methodology is relatively minor, if not
non-existent. As shown in Table 10 in the appendix, $X_{Pandemic}$ (from ARDL results after
dropping *WEI*) has no cointegration with, or causal effect, on *Food Sales* (Z_1) based on
the bound test results. Hence, the results of our paper, which are based on several vari-
ants of the ARDL methodology, are robust because they have little weakness from the
failure to separate the overall effect of the pandemic into direct and indirect effects (via
WEI).

Therefore, we can say that the COVID-19 pandemic caused unprecedented shocks in
global economic and financial markets. The collapse of economic and financial markets
created downside risks. Because downside risks are a major concern in asset pricing and

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[8] We are grateful to one of our referees for raising this inseparability of direct and indirect effects.

corporate finance, several important papers in finance have investigated this issue (see Wen et al. 2019). Traditionally, during an economic and financial turmoil, such as the COVID-19 pandemic, downside risk is measured by stock price crash risk. This risk, which will have long-term negative effects on the development of the capital market and economic growth, will jeopardize shareholder value. The problem is exacerbated by managers' incentives to send biased signals to investors by withholding information (see Jin and Myers 2006). Firm-specific shocks do not emerge until a critical point and, more often than not, trigger a crash when the information becomes public (see, Habib et al. 2018; Callen and Fang 2013; Hutton et al. 2009).[9] Note that the COVID-19 pandemic sent shockwaves through the entire economy, leaving little room for information asymmetry. Even if there are reasonable grounds to believe that the pandemic has created information asymmetry, retail investor attention can mitigate the problem of information withholding and asymmetry, as highlighted by Gao et al. (2018). According to Gao et al. (2018), retail investor attention can help overcome the problem of information withholding caused by asymmetric information because individual investors can glean information about a company from retail investor attention. Additional signals, such as retail investor attention, can help mitigate the asymmetric information problem (see Ding and Hou 2015). Consequently, the severity of crash becomes much less pronounced with retail investor attention.

The pandemic also caused significant changes in buyer behavior, particularly for food items, which can pose significant risks (see Li et al. 2022). Li et al. (2022) emphasized the emergence of market and financial risks due to changing buyer behavior. Li et al. (2022) have highlighted clustering in this context to better understand the role of unknown sub-patterns in data aggregation in local areas. Our focus on the US food market, rather than the global market or aggregate consumer spending, stems from the need for data aggregation in local areas.

During the pandemic, decision-making problems have become complex processes even for households. As Kou et al. (2021) highlighted, there is a need to develop more accurate and effective results for any complex decision-making problem. In this paper, we develop a quantile dependence structure as a more accurate model to explore food purchasing patterns across quantiles during unprecedented downside risks.

Conclusion

From the baseline ARDL model, we find that the US food sales (Z_1), during the first phase of the pandemic, had a long-run relationship (or cointegration) with both *VIX* and *WEI* and the causality runs from *VIX* and *WEI* to Z_1. The baseline ARDL model suggests that *VIX* impacted Z_1; however, there is no evidence that *WEI* had any statistically significant effect on Z_1. To avoid the potential endogeneity between *VIX* and *WEI*, we have used the lagged value of *VIX* by a week in the regressions. We also used the Bewley transformation to overcome endogeneity problems. As a result, economic disruptions

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[9] The extant literature considered various factors responsible for the severity of stock price crash risk: as examples, opaque financial reports (Hutton et al. 2009; Kim and Zhang 2014), corporate tax avoidance (Kim et al. 2011b), CFO equity incentives (Kim et al. 2011a), analyst optimism (Xu et al. 2013), institutional investor stability (Callen and Fang 2013), corporate social responsibility (Kim et al. 2014), religion (Callen and Fang 2015), CEO overconfidence (Kim et al. 2016), and social trust (Li et al. 2017).

caused by mitigation strategies did not reduce US food consumption on its own. We find that investor apprehension, or fear, in financial markets (*VIX*), spilled over to US food market sales: *ceteris paribus*, a 1% increase in *VIX* (rising investor anxiety) increased weekly food sales by 0.12% in the long-run. The ARDL methodology assumes that this effect is symmetric: a 1% decrease in *VIX* reduces weekly food sales by 0.12%. The Bewley transformation estimation confirmed the ARDL findings.

As a robustness check, we used the nonlinear ARDL (NARDL) methodology to test the ARDL findings' robustness by capturing the asymmetric effects of *WEI* and *VIX* on Z_1. The NARDL results revealed a *hidden cointegration*, or long-run relationship, between Z_1 and changes in *WEI* and *VIX*. Hence, the ARDL model results are found to be untenable. Using the NARDL methodology, we discovered significant long-run and short-run asymmetries: increases in *WEI* have adverse long-run effect on food sales, which is statistically significant at the 1% level. However, reductions in *WEI* had no statistically significant (long-run) effect on food sales. Thus, there is no evidence of food insecurity in the United States due to COVID-19 economic disruptions. We found that a 1% increase in the *VIX*, indicating increased investor fear, increased food sales by 0.27% in the long-run. This rise, driven by rising investor fear, could be explained as speculative hoarding/panic buying by buyers. By contrast, a 1% drop in the *VIX* resulted in a 0.088% increase in (long-run) food sales. Thus, there is no evidence that any positive or negative shocks to financial markets have harmed food sales in the United States in the long-run. Although increases (decreases) in *VIX* reduced (increased) food sales in the short-run, fluctuations in *WEI* had no statistically significant (asymmetric) effects on food sales.

When applying the QARDL methodology for testing the tenability of NARDL results, we find that the cointegrating coefficients in the long-run relationship between food sales and regressors have some fluctuations across different quantiles. However, except for the top quantile, the effects are not statistically significant. Thus, the NARDL results are robust when we consider the possibility of fluctuations in the postulated cointegrating relationship across quantiles. Therefore, despite nontrivial COVID-19-induced economic and financial disruptions, we conclude that US food sales remained relatively immune to such massive economic and financial disruptions.

Appendix

See Tables .

Table 7 Descriptive statistics

Tests	Food sales (LnZ₁)	LnVIX	LnWEI
Mean	23.40402	3.308548	−4.53375
Median	23.39508	3.276573	−4.175
Maximum	23.7092	4.336637	2.01
Minimum	23.23164	2.558002	−11.43
Std. Dev	0.079684	0.345731	3.885991
Skewness	1.376243	0.578612	−0.07226
Kurtosis	7.683862	4.173201	2.082183

Table 8 Unit root tests

Variables	Intercept				Trend & intercept			
	I (0)		I (1)		I (0)		I (1)	
	t-value	Prob	t-value	Prob	t-value	Prob	t-value	Prob
ADF Test Results								
LnZ_1	−4.464664	0.0007	−7.958035	0.0000	−4.451689	0.0041	−7.939127	0.0000
LnVIX	−2.800662	0.0647	−7.136504	0.0000	−3.083342	0.1205	−4.780847	0.0016
LnWEI	−2.363666	0.1568	−3.798901	0.0051	−2.767857	0.2153	−4.111416	0.0107
PP Test Results								
LnZ_1	−4.240205	0.0014	−16.13667	0.0000	−4.170083	0.0091	−18.04663	0.0000
LnVIX	−2.954826	0.0457	−7.151691	0.0000	−3.127007	0.1104	−7.184270	0.0000
LnWEI	−1.805652	0.3741	−3.779356	0.0054	−1.950793	0.6145	−4.100376	0.0110

Table 9 Vector autoregressive model of *LnVIX* and *LnWEI* with $X_{Pandemic}$ as an exogenous variable

Variable	Dependent variable			
	LnWEI		*LnVIX*	
	Coeff	t-value	Coeff	t-value
$X_{Pandemic}$	−5.07***	−3.23	−0.15	−0.45
LnVIX	0.31	0.55	0.80***	6.59
LnWEI	−0.41***	−3.90	0.03	1.57
Constant	0.57	0.43	0.75**	2.61

Notes: *** indicate significant at 1% level of significance

Table 10 ARDL results with pandemic intensity ($X_{Pandemic}$) as a regressor

Variable	Dependent variable LnZ_1			
	Long run		Short run	
	Coeff	t-value	Coeff	t-value
ECT			−0.35*	−1.62
LnVIX	−0.14	−1.03	0.07*	1.76
$X_{Pandemic}$	1.42*	1.94	−0.18	−0.90
Constant			8.36	1.64
ΔLnZ_{1t-1}			−0.53***	−2.78
R^2	0.73		0.73	
F Stat	3.28			
Cointegration	NO			

Notes: *** and * indicate significant at 1% and 10% significance levels

Author contributions
ND: Conceptualization, Data curation, Methodology, Software, Formal analysis, Project administration, Roles/Writing—original draft; Writing—review & editing. PG: Conceptualization, Data curation, Methodology, Software, Formal analysis, Project administration, Roles/Writing—original draft; Writing—review & editing. Both the authors have read and approved the final version of the manuscript.

Declarations

References
Aloui R, Gupta R, Miller SM (2016) Uncertainty and crude oil returns. Energy Economics 55:92–100. https://doi.org/10.1016/j.eneco.2016.01.012

Anbarci N, Escaleras M, Register CA (2005) Earthquake fatalities: the interaction of nature and political economy. J Public Econ 89(16):1907–1933. https://doi.org/10.1016/j.jpubeco.2004.08.002

Apergis E, Apergis N (2021) The impact of COVID-19 on economic growth: evidence from a Bayesian Panel Vector Autoregressive (BPVAR) model. Appl Econ. https://doi.org/10.1080/00036846.2021.1946479

Apergis N, Hayat T, Saeed T (2021) Us partisan conflict uncertainty and oil prices. Energy Policy 150:112–118. https://doi.org/10.1016/j.enpol.2020.112118

Apergis N, Gangopadhyay P (2020) The asymmetric relationships between pollution, energy use and oil prices in Vietnam: some behavioural implications for energy policy-making. Energy Policy 140:111430

Aprigliano V, Emiliozzi S, Guaitoli G, Luciani A, Marcucci J, Monteforte L (2022) The power of text-based indicators in forecasting Italian economic activity. Int J Forecast. https://doi.org/10.1016/j.ijforecast.2022.02.006

Ashraf BN (2020) Economic impact of government interventions during the COVID-19 pandemic: International evidence from financial markets. J Behav Exp Financ 27:100371–100371. https://doi.org/10.1016/j.jbef.2020.100371

Atri H, Kouki S, Gallali M (2021) The impact of covid-19 news, panic and media coverage on the oil and gold prices: an ardl approach. Resour Policy 72:102061

Baffes J et al (2020) The role of income and substitution in commodity demand. Policy Research Working Paper 8495. World Bank, Washinton, DC

Baker SR, Bloom N, Davis SJ (2016) Measuring economic policy uncertainty. Q J Econ 131:1593–1636. https://doi.org/10.1093/qje/qjw024

Baker M, Wurgler J (2007) Investor sentiment in the stock market. J Econ Perspect 21(2):129–152. https://doi.org/10.1257/jep.21.2.129

Bakry W, Kavalmthara PJ, Saverimuttu V, Liu Y, Cyril S (2021) Response of stock market volatility to COVID-19 announcements and stringency measures: a comparison of developed and emerging markets. Finance Res Lett 46:102350. https://doi.org/10.1016/j.frl.2021.102350

Baumeister C, Leiva-León D, Sims E (2022) Tracking weekly state-level economic conditions. Rev Econ Stat. https://doi.org/10.1162/rest_a_01171

Baumeister C, Peersman G (2013) Time-varying effects of oil supply shocks on the US economy. Am Econ J Macroecon 5:1–28

Benkraiem R, Lahiani A, Miloudi A, Shahbaz M (2018) New insights into the us stock market reactions to energy price shocks. J Int Finan Markets Inst Money 56:169–187. https://doi.org/10.1016/j.intfin.2018.02.004

Callen JL, Fang X (2013) Institutional investor stability and crash risk: Monitoring versus short-termism? J Bank Finance 37(8):3047–3063. https://doi.org/10.1016/j.jbankfin.2013.02.018

Callen JL, Fang X (2015) Religion and Stock Price Crash Risk. J Financ Quantit Anal 50(1–2):169–195. https://doi.org/10.1017/S0022109015000046

Carriero A, Clark TE, Marcellino M (2022) Nowcasting tail risk to economic activity at a weekly frequency. J Appl Econom 37(5):843–866. https://doi.org/10.1002/jae.2903

Carvalho VM, Nirei M, Saito Y, Tahbaz-Salehi A (2016) Supply chain disruptions: evidence from the Great East Japan earthquake. Columbia Business School Research Paper, No. 5

Cashin P, Mohaddes K, Raissi M, Raissi M (2014) The differential effects of oil demand and supply shocks on the global economy. Energy Econ 44(1):113–134. https://doi.org/10.1016/j.eneco.2014.03.014

Cavallo E, Galliani S, Nov I, Pantano J (2013) Catastrophic natural disasters and economic growth. Rev Econ Stat 95(14):1549–1561. https://doi.org/10.1162/REST_a_00413

Cho JS, Greenwood-Nimmo M, Shin YC (2021) Recent developments of the autoregressive distributed lag modelling framework. J Econ Surv. https://doi.org/10.1111/joes.12450

Cho JS, Kim TH, Shin Y (2015) Quantile cointegration in the autoregressive distributed-lag modeling framework. J Econom 188:281–300

Ding R, Hou W (2015) Retail investor attention and stock liquidity. J Int Finan Markets Inst Money 37:12–26. https://doi.org/10.1016/j.intfin.2015.04.001

Glauber J et al (2020) COVID-19 trade restrictions are the worst possible responses to safeguard food sales. IFPRI Blog Post, March 27. IFPRI, Washington, DC

Greenwood-Nimmo M, Shin Y (2013) Taxation and the asymmetric adjustment of selected retail energy prices in the UK. Econ Lett 121(3):411–416. https://doi.org/10.1016/j.econlet.2013.09.020

Gao GX, Fan ZP, Fang X, Lim FY (2018) Optimal Stackelberg strategies for financing a supply chain through online peer-to-peer lending. Eur J Oper Res 267(2):585–597. https://doi.org/10.1016/j.ejor.2017.12.006

Habib A, Hasan MM, Jiang H (2018) Stock price crash risk: review of the empirical literature. Account Financ 58:211–251. https://doi.org/10.1111/acfi.12278

Hutton AP, Marcus AJ, Tehranian H (2009) Opaque financial reports R2 and crash risk. J Financ Econ 94(1):67–86. https://doi.org/10.1016/j.jfineco.2008.10.003

Inder B (1993) Estimating long-run relationships in economics: a comparison of different approaches. J Econom 57:53–68

International Food Policy Research Institute (2020) COVID-19 policy response (CPR) portal. IFPRI, Washington, DC. Retrieved June 20, 2020 from https://www.ifpri.org/project/covid-19-policy-response-cpr-portal

Jin L, Myers S (2006) R2 around the world: New theory and new tests. J Financ Econ 79(2):257–292. https://doi.org/10.1016/j.jfineco.2004.11.003

Joo K, Suh JH, Lee D, Ahn K (2020) Impact of the global financial crisis on the crude oil market. Energy Strategy Rev 30:100516. https://doi.org/10.1016/j.esr.2020.100516

Kahn ME (2005) The death toll from natural disasters: the role of income, geography, and institutions. Rev Econ Stat 87(2):271–284. https://doi.org/10.1162/0034653053970339

Kellenberg DK, Mobarak AM (2008) Does rising income increase or decrease damage risk from natural disasters? J Urban Econ 63(4):788–802. https://doi.org/10.1016/j.jue.2007.05.003

Kilian L (2009) Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. Am Econ Rev 99:1053–1069. https://doi.org/10.1257/aer.99.3.1053

Kim TH, White H (2003) Estimation, inference, and specification testing for possibly misspecified quantile regression. Emerald Group Publishing Limited. https://doi.org/10.1016/S0731-9053(03)17005-3

Kim JB, Zhang L (2014) Financial reporting opacity and expected crash risk: evidence from implied volatility smirks. Contemp. Account Res 31(3):851–875. https://doi.org/10.1111/1911-3846.12048

Kim JB, Li Y, Zhang L (2011a) CFOs versus CEOs: equity incentives and crashes. J Financ Econ 101(3):713–730. https://doi.org/10.1016/j.jfineco.2011.03.013

Kim, JB, Li Y, Zhang L (2011b) Corporate tax avoidance and stock price crash risk: Firm-level analysis. J Financ Econ 100(3):639–662. https://doi.org/10.1016/j.jfineco.2010.07.007

Kim Y, Li H, Li S (2014) Corporate social responsibility and stock price crash risk. J Bank Finance 43:1–13. https://doi.org/10.1016/j.jbankfin.2014.02.013

Kim JB, Wang Z, Zhang L (2016) CEO Overconfidence and Stock Price Crash Risk. Contemp Account Res 33(4):1720–1749. https://doi.org/10.1111/1911-3846.12217

Koop G, McIntyre S, Mitchell J, Poon A (2022) Reconciled estimates of monthly GDP in the United States. J Bus Econ Stat. https://doi.org/10.1080/07350015.2022.2044336

Kou G, Olgu Akdeniz Ö, Dinçer H, Yüksel S (2021) Fintech investments in European banks: a hybrid IT2 fuzzy multidimensional decision-making approach. Financ Innov 7(1):39. https://doi.org/10.1186/s40854-021-00256-y

Lewis DJ, Mertens K, Stock JH, Trivedi M (2021a) Measuring real activity using a weekly economic index. Am Econ Rev AEA Pap Proc 111:326–330. https://doi.org/10.1257/pandp.20211050

Lewis D, Mertens K, Stock JH, Trivedi M (2021b) Measuring real activity using a weekly economic index. J Appl Economet. https://doi.org/10.1002/jae.2873

Li X, Wang SS, Wang, X (2017) Trust and stock price crash risk: Evidence from China. J Bank Finance 76:74–91. https://doi.org/10.1016/j.jbankfin.2016.12.003

Li T, Kou G, Peng Y, Philip SY (2021) Integrated Cluster Detection Optimization and Interpretation Approach for Financial Data. IEEE Trans Cybern 52(12):13848–13861. https://doi.org/10.1109/TCYB.2021.3109066

McNown R, Sam CY, Goh SK (2018) Bootstrapping the autoregressive distributed lag test for cointegration. Appl Econ 50(13):1509–1521. https://doi.org/10.1080/00036846.2017.1366643

Mensi W, Rehman MU, Al-Yahyaee KH (2020a) Time-frequency co-movements between oil prices and interest rates: evidence from a wavelet-based approach. North Am J Econ Finance 51:100836. https://doi.org/10.1016/j.najef.2018.08.019

Mensi W, Sensoy A, Vo XV, Kang SH (2020b) Impact of covid-19 outbreak on asymmetric multifractality of gold and oil prices. Resour Policy 69:101829. https://doi.org/10.1016/j.resourpol.2020.101829

Mogues T (2020). Food markets during COVID-19 Pandemic. Fiscal Affairs, Special Series by the International Monetary Fund

Noy I (2009) The macroeconomic consequences of disasters. J Dev Econ 88(2):221–231. https://doi.org/10.1016/j.jdeveco.2008.02.005

Pesaran MH, Shin Y, Smith RJ (2001) Bounds testing approaches to the analysis of level relationships. J Appl Economet 16(3):289–326. https://doi.org/10.1002/jae.616

Sam CY, McNown R, Goh SK (2019) An augmented autoregressive distributed lag bounds test for cointegration. Econ Model 80:130–141. https://doi.org/10.1016/j.econmod.2018.11.001

Schmidhuber J et al (2020) COVID-19: Channels of transmission to food and agriculture. FAO, Rome

Shapiro AH, Sudhof M, Wilson DJ (2022) Measuring news sentiment. J Economet 228:221–243

Shin Y, Yu B, Greenwood-Nimmo M (2014) Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In: Sickles R, Horrace W (eds) Festschrift in Honor of Peter Schmidt. Springer, New York. https://doi.org/10.1007/978-1-4899-8008-3_9

Singh DR, Ghimire S, Upadhayay SR, Singh S, Ghimire U (2020) Food insecurity and dietary diversity among lactating mothers in the urban municipality in the mountains of Nepal. PLoS ONE 15(1):e0227873. https://doi.org/10.1371/journal.pone.0227873

Smales LA (2014) News sentiment and the investor fear gauge. Financ Res Lett 11(2):122–130. https://doi.org/10.1016/j.frl.2013.07.003

Stučka T (2004) The effects of exchange rate change on the trade balance in Croatia. IMF Working Paper, WP 04/65

Toya H, Skidmore M (2007) Economic development and the impacts of natural disasters. Econ Lett 94(1):20–25. https://doi.org/10.1016/j.econlet.2006.06.020

Wen F, Xu L, Ouyang G, Kou G (2019) Retail investor attention and stock price crash risk: Evidence from China. Int Rev Financ Anal 65:101376. https://doi.org/10.1016/j.irfa.2019.101376

World Bank (2020) Three impediments to keep food moving in a time of fear and confusion. World Bank Blog

Xu N, Jiang X, Chan KC, Yi Z (2013) Analyst coverage optimism and stock price crash risk: Evidence from China. Pac Basin Financ J 25:217–239. https://doi.org/10.1016/j.pacfin.2013.09.001

Zaremba A, Kizys R, Aharon DY, Demir E (2020) Infected markets: novel coronavirus, government interventions, and stock return volatility around the globe. Financ Res Lett 35:101597–101597. https://doi.org/10.1016/j.frl.2020.101597

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