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Disentangling Short-Run COVID-19 Price Impact Pathways in the US Corn Market

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Using a data-modified version of the relative-price-of-a-substitute method, we distinguish the consequences of the sharp decline in US automotive fuel demand from the consequences of nonethanol demand changes in the US corn market. Our results suggest that—due to the renewable fuel standard and ethanol-gas price linkages—the COVID-19 pandemic affected corn markets more than it affected other agricultural commodities. The onset of the pandemic reduced Illinois cash prices for corn by approximately 18%. The majority of this impact (approximately 16%) was driven by pandemic-induced reductions in ethanol demand. Ethanol-driven and total impacts were greater in locations farther from terminal markets.

Key words: corn prices, COVID-19, ethanol, stay-at-home order, relative price of a substitute

Introduction

Mitigation efforts associated with the onset of the COVID-19 pandemic induced numerous noteworthy adjustments throughout agricultural supply chains, emphasizing the tangled relationships between many seemingly unrelated production systems (Beckman and Countryman, 2021). From food purchasing behavior to labor safety issues, each disturbance generated systemic short-run consequences throughout agricultural production systems, uniquely impacting commodity prices. To date, most of the empirical literature has focused on food-related agricultural outcomes, with fewer studies exploring the nonfood impacts of COVID-19 mitigation policy on US commodity prices.

Foodservice and other labor-intensive agricultural sectors have been of particular interest as rapid pandemic-related disruptions in food consumption patterns led to consumer price increases and agricultural labor safety issues (Lusk et al., 2020; Peña Lévano, Burney, and Adams, 2020; Ahn and Norwood, 2021; Luckstead and Devadoss, 2021; Malone, Schaefer, and Lusk, 2021; McFadden et al., 2021; Ridley and Devadoss, 2021; Ruan, Cai, and Jin, 2021; Saitone, Schaefer, and Scheitrum, 2021). Despite this focus on pandemic-related supply chain disruptions, fewer empirical studies have sought to isolate short-term price impacts in food and nonfood agricultural commodity markets.[1] Understanding the drivers of short-term commodity price impacts is critical to understanding future susceptibility to major market shocks and to informing policies related to shock mitigation. This article fills this gap by estimating the short-run impacts of the COVID-19 pandemic on US corn prices and disentangling the effects into two components—one due to reductions in demand for ethanol and one due to disruptions in the nonethanol corn supply chain. We find that most of the

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[1] Exceptions include Khanna (2021) and Schnitkey et al. (2021), who utilize COVID-19 to provide narratives describing the likely future of farm profitability as it relates to ethanol markets.

COVID-19 effects on corn prices were driven by reductions in the demand for ethanol, confirming that the growth of ethanol production from corn has made the corn market more susceptible to economy-wide economic shocks.

At the onset of the pandemic, strategies to limit the spread of COVID-19 included “stay-at-home” orders and the slowdown of “nonessential” businesses, dramatically reducing miles driven and leading to sizable declines in gasoline and fuel ethanol demand (Ou et al., 2020; Parr et al., 2020; Malone, Schaefer, and Wu, 2021). Motor gasoline and biofuel consumption decreased considerably, inevitably affecting US corn prices as about 70% of US ethanol facilities were fully idled in April 2020 (Irwin and Hubbs, 2020; Renewable Fuels Association, 2020a). Declines in ethanol production reached an estimated 2 billion gallons lost from March to November 2020, leading to a corresponding decline of 700 million bushels of corn usage and a loss of billions of dollars of ethanol producer surplus (Renewable Fuels Association, 2020b; Schmitz, Moss, and Schmitz, 2020).

This article disentangles the effects of COVID-19 on corn prices into an ethanol and a nonethanol component. To accomplish this task, we use an innovation to a now-standard method (relative-price-of-a-substitute, or RPS) to both estimate the overall impacts of COVID-19 on corn markets and disentangle the drivers of those changes. Corn price impacts are particularly noteworthy because of the size and scope of US corn markets. US growers harvest the largest corn crop in the world, growing 13.6 billion bushels in the marketing year prior to the pandemic, accounting for almost one-third of the global total (US Department of Agriculture, 2021). US farmers rely heavily on ethanol production as a market for their corn; in Michigan, for example, approximately 40% of corn production is processed into ethanol (US Department of Agriculture, 2021).

The prior literature has thoroughly documented linkages between grain and energy markets. McPhail, Du, and Muhammad (2012) conducted a structural vector auto-regression model and variance decomposition to explore the factors explaining corn price variation and found that energy is the most important factor in the long run. Avalos (2014) found that corn prices have been related to oil prices in both the short and long runs since 2006. Many studies have been specifically focused on the impact of corn ethanol expansion in the early twenty-first century on corn prices. Zilberman et al. (2013) found that the introduction of biofuels had an impact on food-commodity prices. Hochman and Zilberman (2018) and Condon, Klemick, and Wolverton (2015) conducted a meta-analysis to integrate the results of multiple related studies and identified the effect of corn ethanol production on corn prices. Results showed that the expansion of corn ethanol led to an average increase of about 14% in corn prices. This percentage was larger, about 30%, during the years right after the implementation of the Renewable Fuel Standard program (2006–2011) (Roberts and Schlenker, 2013). Carter, Rausser, and Smith (2012) found that corn prices were about 30% greater between 2006 and 2011 than they would have been without the Renewable Fuel Standard program.

These prior studies focused on a period of biofuel expansion, while fewer studies have focused on the potential for biofuel market contraction, which is important because many factors—including improvements in transportation energy efficiency, the electrification of vehicles, and the development of advanced biofuels—are likely to decrease future consumption of US corn-based ethanol (International Energy Agency, 2018; Dumortier, Carriquiry, and Elobeid, 2021).[2] Further, while prior studies have estimated price relationships via structural models with limited data availability, our reduced-form estimation strategy considers changes in driving behavior due to COVID-19 as an exogenous shock (Dumortier, Carriquiry, and Elobeid, 2021).

[2] We expect that the biofuel market contraction would not just have the opposite effects of a similar-sized expansion since the system now is very different from what it was in the ethanol boom period. The expansion of ethanol was accompanied by the construction of ethanol capacity, and it was a very rapid process incentivized mainly by policies. Currently, significant ethanol production capacity already exists, and the contraction was caused by economic reasons. In addition, many existing studies (e.g., Goodwin and Holt, 1999; Tappata, 2009) have shown asymmetric price adjustments to positive and negative shocks.

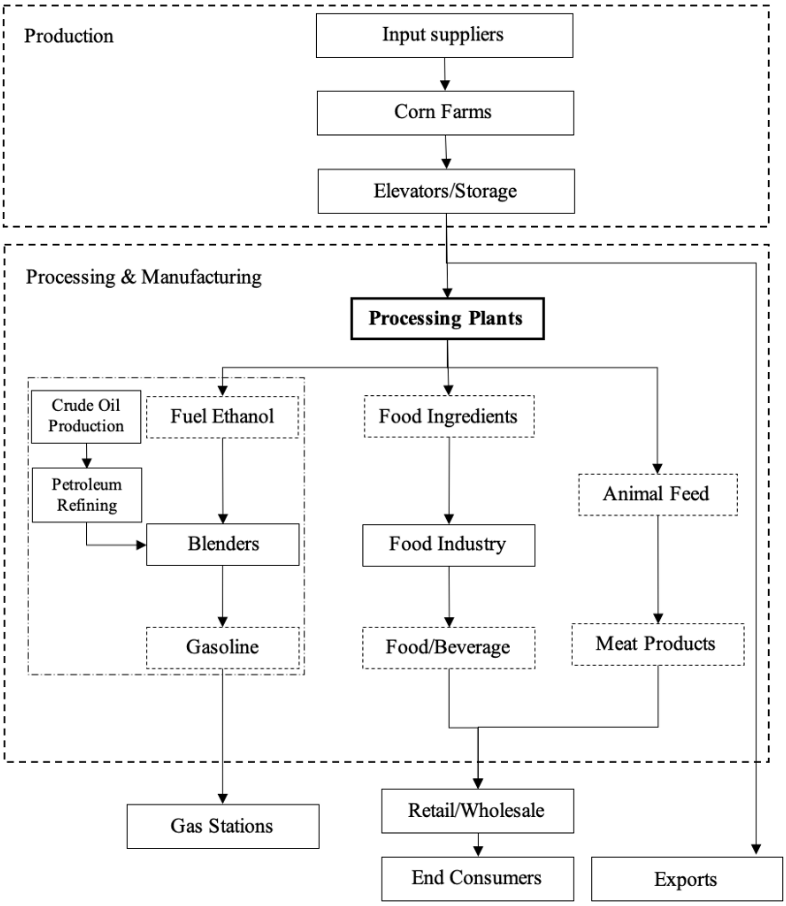

Figure 1. The US Corn Supply Chain

Notes: Ethanol, meat products, and other food are exported. Corn is also processed to produce other industrial products. For simplicity, we decided not to draw these flows as they fall outside the scope of our analysis.

Background

Our empirical analysis distinguishes between ethanol and nonethanol COVID-19 supply chain disruptions. Figure 1 presents a production, processing, manufacturing, and distribution supply chain map for US corn markets. The corn supply chain begins on the farm where corn is harvested; farmers can either sell or store their corn. Most is sold either to local grain elevators or to local processors (e.g., ethanol plants and livestock feed producers). In the marketing year prior to the pandemic, roughly 40% of US domestic corn use went to fuel ethanol production and almost half was dedicated to animal feed and residual use, including distiller's grains left over from ethanol production. The remaining 12% was used for food ingredients and industrial uses other than ethanol.

COVID-19 Ethanol Disruptions

Although the COVID-19 pandemic affected the corn market through many channels, reduced ethanol demand represents the most direct and noteworthy channel (Hart et al., 2020). Increases in corn-based ethanol production that started in 2005 have linked agricultural commodity prices and energy markets as US ethanol production increased rapidly from 3.9 billion gallons in 2005 to 13.3 billion by 2010 and 15.8 billion by 2019 (Chakravorty, Hubert, and Nøstbakken, 2009;

Wright, 2011; Roberts and Schlenker, 2013; Asgari, Saghaian, and Reed, 2020; US Department of Agriculture, 2021). Many existing studies have shown that the expansion of biofuels explains a significant portion of corn price increases (Babcock and Fabiosa, 2011; Hochman and Zilberman, 2018). It is reasonable to expect that reductions in ethanol demand would have a negative impact on corn prices, though the size of this impact remains an open question.

Beginning in March 2020, US states and territories issued mitigation policies to reduce the transmission of COVID-19, including stay-at-home orders and other social-distancing rules. Much of the US labor force began working remotely and student classrooms pivoted to online learning. Car travel was also limited due to contemporaneous interstate travel restrictions. These control policies substantially disrupted population mobility and transportation. The average Apple Maps routing requests for driving in March, April, and May 2020 were 30% lower than they had been in February 2020 (Apple, 2020). Indeed, compared with the corresponding month in 2019, the US Department of Transportation (2020) reported that travel (vehicle miles) on all roads and streets was reduced by 18.6%, 39.8%, and 25.5% for March, April, and May 2020, respectively.

This huge reduction in mobility led to a considerable contraction in gasoline demand. In March, April, and May 2020, US demand for motor gasoline was 10%, 41%, and 23% lower than it had been in the corresponding months in 2019 (US Energy Information Administrationb, 2020). Given that over 90% of US ethanol is used in mixtures of E10 gasoline and the US market reached a 10% "blend wall" in 2016, any reduction in gasoline use will cause proportional decreases in ethanol use (US Energy Information Administrationa, 2020; US Department of Agriculture, 2021). Further, given that 94% of the US ethanol is produced from corn (Center for Sustainable Systems, 2020), ethanol use reduction induced by COVID-19 had a sizable impact on corn demand and corn prices, though the size of the impact on corn prices has been relatively understudied.

Nonethanol COVID Disruptions

In addition to ethanol disruptions, the onset of the COVID-19 pandemic affected US corn markets through other channels, including food ingredients, animal feed, and export markets. Food ingredients such as corn starch and corn oil are processed for food and beverage markets, and corn-based animal feed is fed to livestock by meat and dairy producers. The final products, including food, beverage, meat, and dairy products, are provided to consumers through wholesalers and retailers.

The animal feed market is another large channel through which COVID-19 could have affected corn prices in the United States. With the reduction of ethanol production, the production of distillers' grain, a coproduct of ethanol, also decreased sharply (Gertner and Dennis, 2020a). Since corn is used as a substitute for distillers' grain as animal feed, this substantial reduction in distillers' grain production immediately after the outbreak of the pandemic may have boosted corn use to some extent (Gertner and Dennis, 2020b). On the other hand, feed corn demand was also affected by the curtailed capacity or shutdown of slaughterhouses and meat processing plants due to COVID-19. In April, many US meat processing and packaging plants experienced temporary closures due to COVID-19 outbreaks in the workforce. Slaughter and processing capacities were also limited at plants that stayed open or reopened after the temporary closure because of labor shortages and social-distancing rules (Malone, Schaefer, and Wu, 2021). Livestock farmers had to hold onto animals for longer, and some tried to slow the growth of the livestock. In this way, demand for corn feed declined, also leading to corn price reductions (Schnitkey et al., 2021).

Finally, COVID-19 also influenced commodity exports, as approximately 15% of US corn production is exported (US Department of Agriculture, 2021). During the two quarters after the outbreak of COVID-19, US corn exports increased by 3.3% and 5.8% year over year, respectively. Further, the growth rate from Quarter 2 to Quarter 3 in the 2019/20 marketing year exceeded the pace in 2018/19 and 2016/17 marketing years, indicating that corn exports during the COVID-19 period increased. Mallory (2021) found that US corn exports were almost at the top of the seasonal range

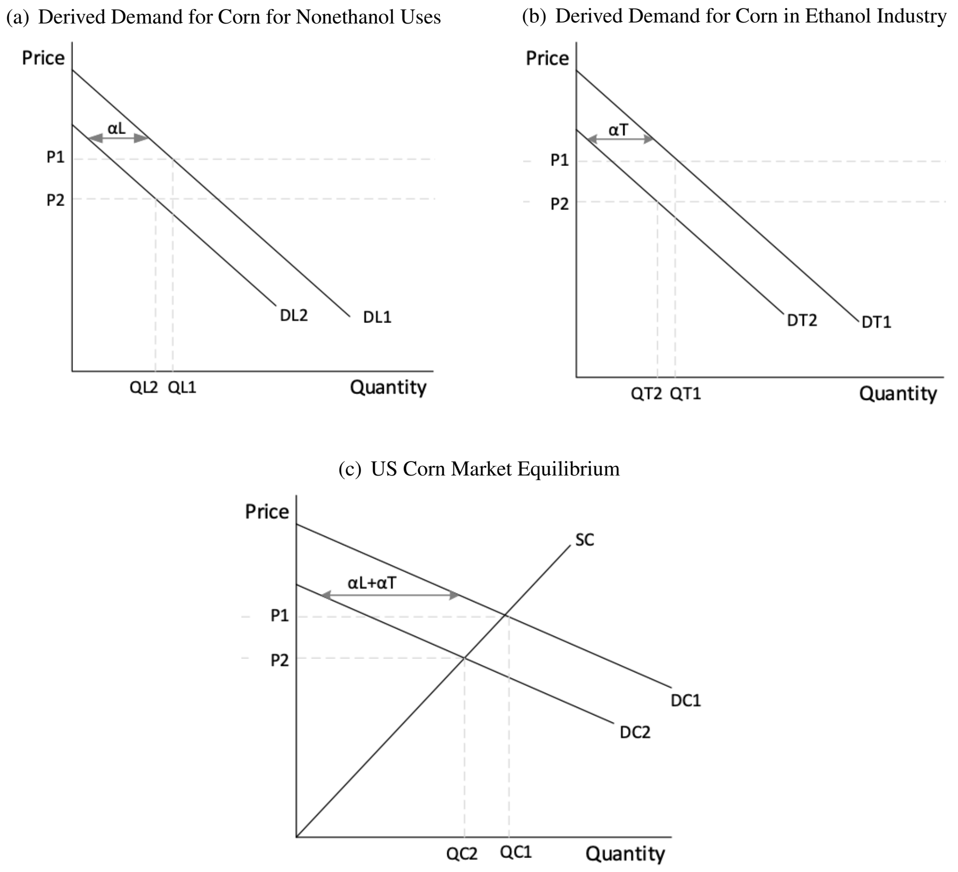

Figure 2. Disentangling the Impacts of COVID-19 on the US Corn Market

in April 2020. This is reasonable given that marine transportation used for corn export experienced limited COVID-19 disruptions (Johansson, 2020).

Conceptual Framework

The conceptual framework in Figure 2 represents the short-run price impact pathways we estimate in this paper. Figure 2(a) represents the short-run derived demand for corn to be used in nonethanol channels, which accounts for about 60% of US corn use and includes corn demand in livestock feed and residual use, food ingredients and industrial use, and exports. Schedule DL1 represents prepandemic nonethanol derived demand. We represent the effects of the pandemic as an inward shift of αL in nonethanol demand. That is, αL is the nonethanol channel demand shift. Schedule DL2 represents short-run nonethanol demand for corn during the pandemic. As discussed above, although we have represented the nonethanol channel effects as an inward shift in Figure 2, the effect is not necessarily negative. The increase in export demand and the reduction in distillers' grain production could generate an outward shift in the schedule. Indeed, the fact that livestock farmers were required to hold on to animals for longer, and their attempts to slow livestock growth, could shift the schedule DL1 to the right. We can expect the same conceptual framework represented in Figure 2(a) to also apply to the sorghum market.

Figure 2(b) represents the derived demand for corn for use in transportation fuel. Schedule DT1 represents prepandemic demand, and DT2 represents demand in during the pandemic. Thus, the onset of the pandemic generates an αT inward shift in ethanol demand for corn. That is, αT denotes the ethanol channel demand shift. We do not draw the short-run marginal cost curve in this graph, but it is likely that the reduction in ethanol demand and then corn demand would lead to a price reduction in corn, which is the ethanol-driven price impact we estimate in this paper. Figure 2(c) depicts equilibrium changes in US corn prices and usage resulting from the pandemic. Schedule SC describes the short-run marginal cost curve for US corn. Schedule DC1 represents the total corn demand and COVID-19 shifts the curve to DC2. The observed reduction in equilibrium price from P1 to P2 is the aggregate result of the αL shift in derived demand for corn for nonethanol uses and the αT inward shift in the derived demand for corn used in the transportation sector. The difference between P2 and P1 is the full price impact that we estimate.

Empirical Method

In this section, we present a modified version of the RPS method to simultaneously estimate the total effect of the onset of COVID-19 on US corn prices (i.e., $\alpha L + \alpha T$ in Figure 2) and to disentangle ethanol-driven impacts (αT) from nonethanol impact pathways (αL).[3] The RPS method is used to estimate the price impact of a market event using the relative-price relationship between a commodity of interest and a close substitute (Carter and Smith, 2007). Consistent with Carter and Smith (2007), our focus is on the US corn market, with US grain sorghum as the substitute commodity. A typical application of the RPS method assumes the event impacts the commodity of interest but has little or no impact on the price of the substitute product (Carter and Smith, 2007; Schmitz, 2018; McKendree, Saitone, and Schaefer, 2021). In contrast, to disentangle the impact pathways of the onset of COVID-19, we make use of the fact that the pandemic affected both US corn and sorghum prices, but that the sorghum market was predominantly impacted through nonethanol channels.[4] The RPS method still applies when both prices are affected by the event but are affected differently.

Modified Relative Price of a Substitute

The RPS method identifies the price impact of a market event using a reduced-form approach without estimating a structural supply and demand model (McKendree, Saitone, and Schaefer, 2021). The impact of the event is estimated using a cointegration model of the corn and sorghum prices. Inference under the RPS framework requires a stationary relative-price relationship between the two goods prior to the event date. To assess the cointegrating relationship between corn and sorghum prices, we first test the log of the two prices individually for a unit root, using both the Augmented Dickey–Fuller (ADF) and the Phillips–Perron tests.[5]

Following Carter and Smith (2007), we then test for a long-run cointegrating relationship of the form

$$p_t - s_t = \mu + z_t, \tag{1}$$

where p_t and s_t are log prices of corn and sorghum at time t,[6] μ is the long-run mean-stable relative price, and z_t is a stationary error term. We use the Bai and Perron (1998) to test for the

[3] We also conduct a similar analysis using a vector autoregression model (VAR) as a robustness check. The model specification, data sources, and main results are reported in the Online Supplement (see www.jareonline.org).

[4] While 94% of the ethanol produced in the United States is derived from corn, we use the word "predominantly" because a small share is derived from grain sorghum. To the extent that ethanol demand shocks affected the grain sorghum price, our estimates of αT may be slightly overestimated.

[5] Both tests have a null hypothesis that a unit root exists. The optimal number of lags for the ADF test is decided according to Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and the HQIC.

[6] A more general expression of the RPS cointegrating relationship is $p_t - s_t = \mu + \beta' \boldsymbol{X_t} + z_t$, where $\boldsymbol{X_t}$ is supply and demand shifters (including, e.g., income, factor prices, and prices of substitute or complement goods) and z_t is a stationary error term. As discussed in Carter and Smith (2007), however, if the shifters have permanent impacts on the relative price, then the shifters are required in the estimation equation. But if the two prices are cointegrated before the event, then the impact of the shifters is transitory and it is unnecessary to include them in the estimation.

existence and timing of an unknown number of structural breaks in the mean relative price (μ) over our sample period.[7] Although the pandemic was declared on March 11, 2020, the impact of COVID-19 on agricultural markets is more ambiguous. The exact date when the pandemic hit the market depends on market expectations, the timing of response policies, and the observed case rates (Castillo, Staguhn, and Weston-Farber, 2020). This procedure allows us to identify the date on which COVID-19 began affecting US grain markets and to select a pre-event sample for which cointegrating parameters are stable.

Once the number and location of structural breaks are determined, we estimate the following error-correction model (ECM) on the pre-event sample using Johansen's MLE method:

$$\Delta p_t = \beta_c z_{t-1} + \sum_{i=1}^{I} (\gamma_{ci} \Delta p_{t-i} + \delta_{ci} \Delta s_{t-i}) + \varepsilon_{ct}; \tag{2}$$

$$\Delta s_t = \beta_s z_{t-1} + \sum_{i=1}^{I} (\gamma_{si} \Delta s_{t-i} + \delta_{si} \Delta p_{t-i}) + \varepsilon_{st}; \tag{3}$$

where Δp_t denotes the first difference of log corn price, Δs_t denotes the first difference of log sorghum price, and z_t is the error-correction term from equation (1). Model lag length I is chosen according to the Hannan and Quinn information criterion (HQIC).

We use the ECM parameters estimated in equations (2) and (3) to forecast counterfactual post-event prices for the two goods, assuming the event did not occur. The total impact of the pandemic in the US corn market (denoted PI^C and equal to $\alpha L + \alpha T$ from Figure 2) is estimated as the average forecast corn price error over the post-event period. Standard errors for $\widehat{PI}^C$ are calculated as in Carter and Smith (2007).[8]

Because the onset of the pandemic affected the sorghum market primarily through the nonethanol channel, we can isolate the effects of the ethanol and nonethanol impact pathways in the corn market as $\widehat{PI}^C - \left(\widehat{PI}^S + \hat{\mu}\right)$ and $\widehat{PI}^S + \hat{\mu}$, respectively, where $\widehat{PI}^S$ is the total impact of the pandemic in the sorghum market and $\hat{\mu}$ is the pre-event mean-stable relative price estimated in equation (1). These expressions are based on the assumption that the relative-price relationship between corn and sorghum prices would have remained constant in the face of the pandemic if not for the ethanol impact; thus, PI^S and PI^C would have been equivalent. The standard error for the ethanol-driven impact—conditional on the realized sorghum impact (PI^S)—is the standard error for the pre-event relative price, $\hat{\mu}$.

Our baseline model measures the effects for cash bids at ethanol plants in Illinois. We then re-estimate the model for a number of different corn delivery locations to assess the geospatial sensitivity of our findings.

Data

Our data include weekly cash prices for corn and sorghum from April 2018 to December 2020. Sorghum prices are from the Kansas City market, sourced from the US Department of Agriculture

[7] The null hypothesis of the Bai and Perron (1998) sequential test of L versus $L + 1$ breaks is that L breaks exist, and the alternative is that an additional unknown break exists. The testing procedure begins with a null of zero breaks against the alternative of an unknown break. If the null hypothesis is rejected the first break is then taken as given and the null of one break is tested against the alternative of two breaks. The procedure repeats until the evidence fails to reject the null hypothesis. All test statistics are sup-F tests and are denoted as sup-$F(L + 1|L)$.

[8] These standard errors are calculated using pre-event forecast errors as follows: Let h be the number of weeks during the post-event period (i.e., the forecast steps), l be the total number of pre-event weeks, and q be the number of lags in the ECM above. Based on the pre-event data, $l - h - p$ h-period-ahead forecasts can be made using each start time. An $(l - h - p) \times 2h$ dimensional matrix is generated, with the first h columns being the forecast errors for corn and the next h columns being the forecast errors for sorghum. This matrix is used to compute the $2h \times 2h$ variance–covariance matrix. The main diagonal of this variance–covariance matrix provides the variance of the price impact.

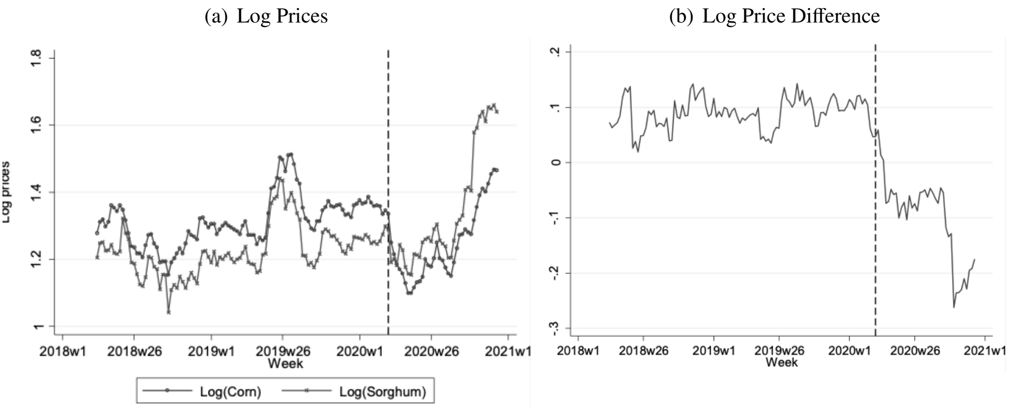

Figure 3. Corn and Sorghum Prices

Notes: The vertical line is the week in which the World Health Organization labeled the COVID-19 outbreak as a pandemic.

(2020b). Illinois weekly corn prices are average cash bids at state ethanol plants, obtained from the Agricultural Marketing Resource Center (2021). Corn prices for Nebraska, South Dakota, Wisconsin, and Iowa are also obtained from the Agricultural Marketing Resource Center (2021). Michigan corn prices (obtained from DTN, Inc.) are the average cash bids across all the elevators in different counties in Michigan.

Figure 3(a) displays weekly corn and sorghum prices from April 2018 to December 2020. The vertical line is the week when the World Health Organization (WHO) declared the COVID-19 outbreak to be a pandemic (World Health Organization, 2020). Before the outbreak of COVID-19 in the United States in March 2020, corn prices were slightly, but consistently, higher than sorghum prices. After the outbreak, corn prices plummeted and remained much lower than sorghum prices for the remainder of the sample horizon. Figure 3(b) shows the weekly log price difference between corn and sorghum, which hovered around 0.1 before the outbreak and dropped to an average of −0.1 after the outbreak. This decline in the relative price indicates that COVID-19 had a smaller impact on sorghum prices relative to corn prices.

Results

Pre-Event Cointegration Test

Table 1 reports the results of prepandemic stationarity tests for the individual corn and sorghum prices and the log relative price.[9] Results from both the ADF and Phillips–Perron tests fail to reject the null of a unit root for both corn and sorghum prices. We reject the null hypothesis of nonstationarity for the log relative price at the 1% significance level. In other words, both the corn and sorghum prices have a unit root, while the log relative price is stationary. Thus, we can conclude that the two prices were cointegrated before the pandemic, as required for the RPS method.

Structural Break Test

Table 2 reports the results of the sequential Bai–Perron test on the number and location of breaks in the log relative price. As shown in Table 2, the statistic from the sup-$F(1|0)$ test is significant at the 5% level and the statistic from the sup-$F(2|1)$ fails to reject the null of one break, which suggests

[9] Note that—for the purposes of the stationarity tests—we select March 11, 2020, as the breakpoint. This is the date when the World Health Organization labeled COVID-19 as a pandemic.

Table 1. Cointegration Tests

Augmented Dickey–Fuller Test	Optimal Lag	Test Statistic	p-Value	Conclusion
Corn	1	2.19	0.21	Unit root
Sorghum	1	−2.37	0.15	Unit root
Log relative price	1	−4.02	< 0.01	Cointegration

Phillips–Perron Test	Optimal Lag	Z(ρ) Test Statistic	Z(t) Test Statistic	p-Value	Conclusion
Corn	4	−10.10	−2.26	0.18	Unit root
Sorghum	4	−12.76	−2.54	0.11	Unit root
Log relative price	4	−34.96	−4.50	< 0.01	Cointegration

Notes: Tests are conducted for pre-event period (i.e., April 2018–June 2020). The 5% critical value for the augmented Dickey–Fuller test is −2.89. Prices for corn and sorghum are in log scales. Log relative price means the difference between the log corn and log sorghum prices. Optimal lags are determined by Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and the the Hannan and Quinn information criterion..
[a]Selection-order criteria suggested four lags. If we run the corn prices on four lags, it is stationary. According to Carter and Smith (2007) and the results of Phillips–Perron test, corn prices are nonstationary. We decided to use one lag, which is consistent with the sorghum price.

Table 2. Results of Structural Break Tests

Test	Statistic	5% Critical Value[a]	Date of Maximal F-Statistic	Conclusion
Bai–Perron Test				
sup-F(1|0)	555.6**	8.6	April 10, 2020	At least one break
sup-F(2|1)	3.7	10.1	-	One break
LWZ criterion	–	–	-	One break
Schwarz criterion	–	–	-	One break

	Statistic	p-value	Conclusion
Wald Test	555.6	< 0.001	One break on April 10, 2020
LR Test	226.8	< 0.001	One break on April 10, 2020

Notes: Double asterisks indicate significance at the 5% level. We allowed up to five breaks and used a trimming of 0.15.
[a] Bai and Perron (2003) critical values. Liu, Wu, and Zidek (LWZ) criterion and Schwarz criterion are shown for a robustness check.

there is just one break in the relative price. The test identifies April 10, 2020, as the most likely break date.

As a robustness check, we take this structural breakpoint (April 10, 2020) as given and conduct the Wald and likelihood-ratio (LR) tests to test the null hypothesis of no structural break against the alternative of a known break. As shown in Table 2, both tests reject the null hypothesis. The results of the Bai–Perron, Wald, and LR tests on the log relative price constitute strong evidence that the pandemic affected corn and sorghum markets in different ways, suggesting that both the ethanol and nonethanol pathways had meaningful effects on these grain markets.

Price Impact Estimates

Because our ADF and Philipps–Perron results suggest that corn and sorghum prices were cointegrated prior to the pandemic, we proceed to estimate the ECM based on the pre-event observations. We run the model on observations from April 2018 to February 2020 with a single lag as suggested by the AIC and the HQIC.

Table 3 reports the estimation results. The estimated coefficient for the error correction term for the sorghum, β_S, is 0.281, statistically significant at the 5% level. This indicates that on average the

Table 3. Error-Correction Model Estimation Results (*N* = 99)

Parameter	Corn	Sorghum
β	−0.052	0.281**
	(0.092)	(0.116)
γ_1	0.449***	0.575***
	(0.153)	(0.194)
δ_1	−0.236	−0.234
	(0.121)	(0.153)
Constant	0.000023	−0.000004
	(0.0025)	(0.00317)

Notes: Values in parentheses are standard errors. Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% level. The sample period is from April 2018 to February 2020.

weekly sorghum price adjusts to correct 28.1% of any deviation from the long-run equilibrium. As suggested by Madhavan and Smidt (1993), we calculated the half-life of the mean reversion process, which is the expected number of periods required to achieve half of the adjustment back to long-run equilibrium after a shock. The estimated half-life is 2.8 weeks. The error correction coefficient for corn is −0.052 and is not significantly different from 0. This implies that the sorghum price incurs most of the adjustment when there is a shock to the long-run equilibrium relationship prior to the pandemic.

Based on estimates from the ECM, we forecast the log prices of corn and sorghum from March to December 2020 using the standard RPS.[10] Figure 4(a) reports the forecast errors (difference between the observed prices and the forecasts) of the log prices for corn, sorghum, and the relative price. The vertical dashed line represents the breakpoint selected by the Bai–Perron test (April 10, 2020). These results suggest that COVID-19 had an immediate impact on corn prices and continued to have an impact through the end of the impact window.

Figure 4(b) shows the full price impacts with 95% confidence intervals over the 11-week event window. COVID-19 had a large and immediate impact on corn prices. We find that the pandemic led to a 17.2% reduction in corn prices within the first week of the event window (2020w16). This impact increased to a 23.1% reduction in the fourth week of the event window (2020w19). The average impact is an 18.7% reduction over the entire event window.

Figure 4(c) shows this total impact alongside the ethanol-only price impacts (with corresponding 95% confidence interval), obtained using the modified RPS approach. As shown in the figure, the full COVID price impact is larger in magnitude than the ethanol-driven impact. However, the reduction in corn prices at the onset of the pandemic was primarily driven by the huge drop in ethanol demand. The decrease in ethanol demand induced by COVID-19 reduced corn prices by 16.1% immediately, with a 95% confidence interval of (15.5%, 16.6%). Over the entire 11-week impact window, the ethanol-driven price impact for corn is a 15.9% reduction with a 95% confidence interval of (−15.4%, −16.5%). In contrast, by comparing point estimates for the total and ethanol-only impact, we deduce that—on average over the impact window—nonethanol impact pathways generated an additional 2.7-percentage-point reduction in corn prices. This is consistent with *a priori* expectations. As discussed previously, the nonethanol impact pathway involves aspects that we anticipate having a negative short-term effect on corn prices and aspects that we anticipate having a positive effect, including reduced animal slaughter, longer rearing times for livestock, and reduced availability of other feed sources (such as dried distiller's grains). In contrast, the ethanol pathway corresponds to a huge and immediate reduction in the demand for ethanol. Thus, we expect those impacts to hit the market quickly.

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[10] When we forecast prices through the end of our post-pandemic sample (December 2020), we observe a sudden drop in the log relative price due to a surge of the forecast error for sorghum around week 35. This suggests that another exogenous shock may exist in the post-event period. The surge of the actual sorghum price was likely caused by the strong export demand from China (US Department of Agriculture, 2020a). Accordingly, we define the impact window as the period from April 17 to the end of June, even though the COVID-19 pandemic may have a persistent impact on corn prices.

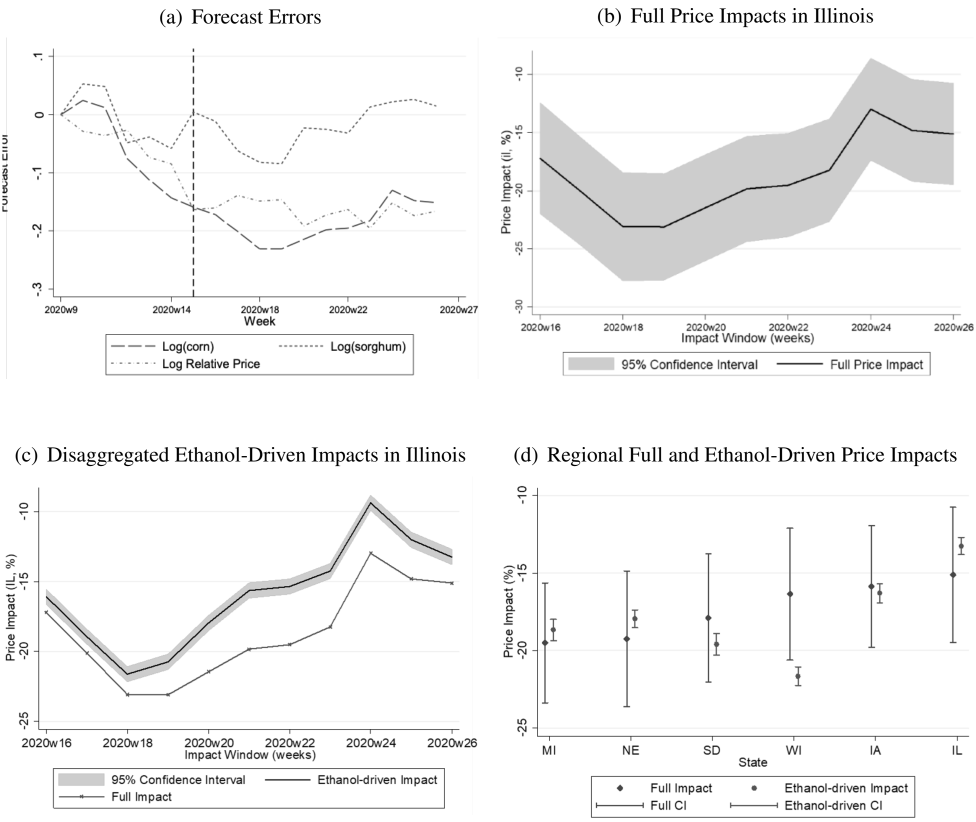

Figure 4. Forecast Errors and Price Impacts

Notes: The vertical line in Figure 4a is the breakpoint (2020w15, April 10, 2020) selected by the Bai–Perron test. MI = Michigan, NE = Nebraska, SD = South Dakota, WI = Wisconsin, IA = Iowa, IL = Illinois, CI = confidence interval.

Model Robustness—Geospatial Price Impacts

We repeat the estimation procedures above using corn prices from Michigan, Nebraska, South Dakota, Wisconsin, and Iowa. Figure 4(d) reports the full and ethanol-driven price impacts at the end of June and the corresponding 95% confidence intervals. All states experienced large negative price impacts on corn as a result of COVID-19. Michigan experienced the largest full price impact (−19.5%), while Illinois had the smallest full impact (−15.1%). Wisconsin had the largest ethanol-driven price impact (−21.6%), followed by South Dakota (−19.6%), Michigan (−18.7%), Nebraska (−17.9%), Iowa (−16.3%), and Illinois (−13.3%). The full price impacts in Michigan, Nebraska, and Illinois were higher than the ethanol-driven price impacts. In the remaining states, the ethanol-driven price impacts were larger, which indicates that the nonethanol channel boosted corn prices to some extent in these states.

These results tell an interesting story about the spatial dimensions of corn price impacts. Generally speaking, it appears that locations lying farther from terminal markets (e.g., South Dakota and Nebraska) experienced the largest total impact. This is not surprising considering the disruptions to the transportation sector. Perhaps more interesting with respect to these spatial impacts are the results in Wisconsin. We observe a very large ethanol-channel price impact (approximately −22%), whereas the nonethanol impact is positive (approximately 5%). In light of the substantial amount of high-value dairy production in the state, it is reasonable to assume that the increased need for corn as a feed source outweighed other nonethanol impact pathways in Wisconsin.

Conclusion

While many studies have focused on the food-related impacts of COVID-19 control measures on US commodity prices, less attention has been paid to nonfood agricultural channels. This article focuses on one such channel (ethanol demand) to explore the impact pathways of COVID-19 on US corn prices. Given the high proportion of corn used for ethanol production, knowing the size of the price impact of reductions in ethanol demand is critical for understanding the vulnerability of corn markets to economy-wide shocks and for designing appropriate policy to mitigate the effects of such shocks. Using a modified version of the relative price of a substitute method, we estimated the overall corn price impact of COVID-19 and then disentangled the ethanol-driven impact.

Our findings have important policy implications. Linkages between corn and biofuel markets have made energy policy an essential factor affecting on-farm crop decisions. The potential for stabilized gasoline demand, limited flex-fuel vehicles, and the commercialization/support of advanced ethanol suggest a possible reduction of corn-based ethanol in the future. Further, the small refinery exemptions have effectively reduced corn-based ethanol demand (Irwin, 2018; Coppess, 2021). Our results suggest expansion of small refinery exemptions could have a significant short-run impact on corn prices. Our results also will help policy makers understand the consequences of economy-wide shocks that cause large reductions in ethanol demand. In turn, this has important implications for rural economic growth (Nkolo, Motel, and Djimeli, 2018).

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Online Supplement: Disentangling Short-Run COVID-19 Price Impact Pathways in the US Corn Market

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We also conduct a similar analysis using a vector autoregression model (VAR) as a robustness check. The model specification, data sources, and main results are reported below.

Method and Data

We use the relative number of visits to gas stations, which is defined as the difference between the current level and the pre-COVID level, to proxy the effect of COVID-19. The VAR model is specified as:

$$X_t = \alpha_0 + \sum_{i=1}^{I} A_i X_{t-i} + \alpha_1 Z_t + \epsilon_t$$

where $X_t = [v_t\ g_t\ e_t\ c_t]^T$, v_t is the change in the number of visits to gas stations in Michigan[1] at week t, g_t is the gasoline price in the Midwest at week t, e_t is the ethanol price in Iowa at week t, c_t is the corn price in Michigan at week t. α_0 is a vector of constants, and A_i is a 4×4 coefficient matrix for the lagged endogenous variables. Model lag length I is chosen according to the Hannan and Quinn information criterion (HQIC). X_t denotes exogenous variables and includes month dummies.

The sample period is from January 2019 to November 2020. The period from January 2019 to February 2020 is defined as the pre-COVID period for the calculation of the relative number of visits to gas stations.

Michigan corn prices are sourced from DTN Inc. Ethanol prices in Iowa are obtained from the Agricultural Marketing Resources Center (2021). The gasoline prices in Midwest are from US Energy Information Administration (2021). The weekly visit counts to gas stations in Michigan are obtained from Safegraph Inc.

This reduced-form VAR model is estimated and then the estimated dynamic relationship is used to simulate the prices for corn, ethanol, and gasoline without the impact of COVID-19. The main point in the simulation is that the relative number of visits to gas stations can be positive, negative, or zero and it takes the value zero during the pre-COVID period. If its value in the post-COVID period was set to zero, the market would operate in the absence of COVID-19. The full price impacts are the difference between the actual realized prices and the simulated prices.

Results

Table S1 reports the estimation results from the VAR model. Figure S1 and Table S2 illustrate the historical and simulated corn prices. Results show that COVID-19 reduced Michigan corn prices

The material contained herein is supplementary to the article named in the title and published in the *Journal of Agricultural and Resource Economics* (*JARE*).

[1] Our VAR analysis is based on Michigan corn prices due to data availability.

by 24.2% during the same impact window, which is close to the 19.5% from our study. Also, we find that COVID-19 reduced the ethanol and gasoline prices by 17.9%, and 11.3% respectively. The VAR method does not allow disentangling the effects into ethanol and nonethanol channels.

Table S1. Estimation Results

	Visit Count Equation 1	**Gasoline Price Equation 2**	**Ethanol Price Equation 3**	**Corn Price Equation 4**
Visit count, lag 1	0.0622	0.0003	0.00120*	0.0021
	(0.0999)	(0.0006)	(0.0005)	(0.0014)
Visit count, lag 2	0.0443	-0.0004	0.0005	0.00328*
	(0.1050)	(0.0006)	(0.0005)	(0.0014)
Gasoline price, lag 1	46.52**	1.219***	0.339***	0.28
	(17.55)	(0.11)	(0.09)	(0.24)
Gasoline price, lag 2	-35.18*	-0.279**	-0.273**	-0.29
	(17.12)	(0.10)	(0.09)	(0.24)
Ethanol price, lag 1	9.09	0.230*	0.780***	-0.28
	(18.15)	(0.11)	(0.09)	(0.25)
Ethanol price, lag 2	22.71	-0.06	-0.230**	0.28
	(17.34)	(0.10)	(0.09)	(0.24)
Corn price, lag 1	3.47	0.08	0.202***	0.745***
	(7.30)	(0.04)	(0.04)	(0.10)
Corn price, lag 2	-15.15*	-0.104*	-0.167***	0.221*
	(7.61)	(0.05)	(0.04)	(0.10)
R^2	0.56	0.98	0.94	0.95

Notes: Month dummies included.

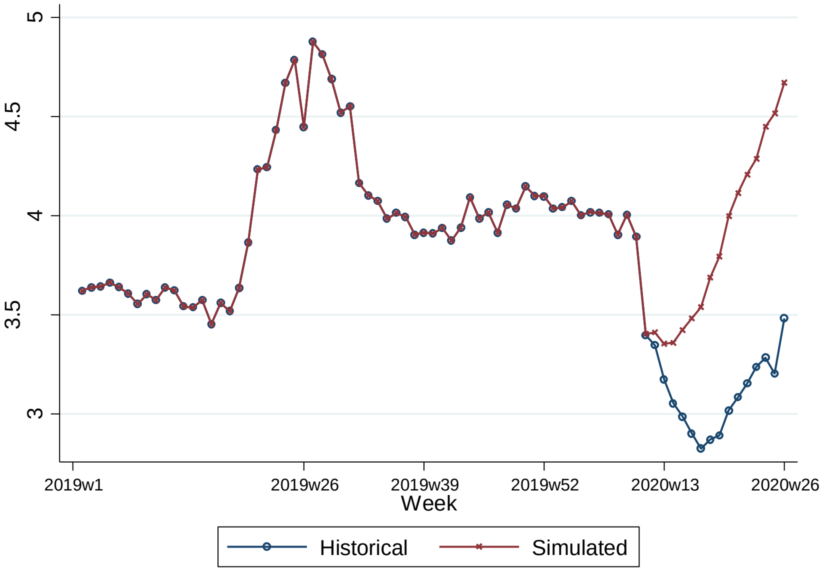

Figure S1. Historical and Simulated Corn Prices

Table S2. Historical and Simulated Prices for Corn, Ethanol, and Gasoline

Period	Corn ($/bushel) Hist.	Corn ($/bushel) Sim.	Corn ($/bushel) Diff. (%)	Ethanol ($/gallon) Hist.	Ethanol ($/gallon) Sim.	Ethanol ($/gallon) Diff. (%)	Gasoline ($/gallon) Hist.	Gasoline ($/gallon) Sim.	Gasoline ($/gallon) Diff. (%)
January 2019–February 2020 (pre-COVID period)									
Mean	3.99	3.99	0	1.33	1.33	0	2.47	2.47	0
Std. dev.	0.35	0.35	0	0.11	0.11	0	0.19	0.19	0
March 11, 2020–June 30, 2020									
Mean	3.16	3.86	–18.1	1.01	1.19	-15.1	1.83	1.99	–8.0
Std. dev.	0.27	0.45	–40.0	0.18	0.2	-10.0	0.23	0.27	–14.8
April 17, 2020–June 30, 2020 (impact window)									
Mean	3.09	4.07	–24.2	1.06	1.29	-17.9	1.82	2.06	–11.3
Std. dev.	0.21	0.40	–48.6	0.16	0.15	9.1	0.22	0.27	–17.0