Estimating Supply Elasticities for Corn in the United States:

Accounting for Prospective Plantings

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Abstract: *We propose adding USDA-reported prospective plantings to conventional acreage observations to estimate agricultural supply elasticities. Using past yield shocks as instruments to endogenous futures prices, we estimate a supply elasticity for corn at 0.26 percent (with a 95 percent confidence interval that ranges from 0.14 to 0.38 percent). Using three closely-related methods, we show that this elasticity implies the COVID-19 pandemic generated welfare losses to domestic corn producers of about $5.4 billion. Through its Coronavirus Food Assistance Program (CFAP) the federal government compensated producers with payments of $ 6.9 billion.*

1. Introduction

Practitioners use commodity demand and supply elasticities to conduct agricultural policy analysis because policy makers and firms often request an understanding of the implications of sudden and unexpected supply (e.g., weather changes, natural disasters, pest infestations, and crop diseases) and demand shocks (recession, terrorist attacks, epidemics, and pandemics). In most years, commodity price variation is dominated by supply shifts. Consequently, Tomek (1979), Gray (1974), Chua and Tomek (2010), Adjemian and Smith (2012), and several other researchers have estimated demand elasticities and (their related) price flexibilities for agricultural commodities. Econometricians, however, need demand-induced price variations to study the shape of the commodity supply curve. Hendricks et al. (2014) show that estimating supply elasticities for agricultural commodities is complicated by the fact that demand shifters are difficult to observe, and their explanatory power with respect to price variation is limited, relative to supply shocks like weather events.

Recent volatility in commodity prices invited the attention of economists (Kim and Moschini, 2018; Carter, Rausser, and Smith, 2016; Roberts and Schlenker, 2013; Mallory, Hayes, and Babcock, 2011), who link the increases in commodity prices to the adoption of the Renewable Fuel Standard (RFS). RFS was established under the 2005 Energy Policy Act and expanded under the 2007 Energy Independence and Security Act. Post RFS adoption, ethanol consumption increased from 0.5% of total oil consumption in 2008 to 5.37% in 2018 (Schmitz, Moss, and Schmitz, 2020). Moreover, ethanol production accounts for 40% of total corn usage (2021) in the United States (USDA, ERS).

The onset of the COVID-19 pandemic and the ensuing lockdowns and closure of non-essential business reduced the demand for fuel (and therefore the corn used to generate ethanol). From March through November 2020, ethanol production declined by 2 billion gallons (a year-on-year decrease of 2% from 2018 to 2019 and 12% from 2019 to 2020), decreasing corn usage by 700 million bushels (RFA, 2020). Therefore, the COVID-19 pandemic is a large-scale demand shock, raising the question of its impact on farmers' land allocation decisions. This becomes even more important to study because the United States Department of Agriculture (USDA) launched the Coronavirus Food Assistance Program (CFAP) to compensate farmers based on their expected losses.

Roberts and Schlenker (2013) measure supply elasticities by instrumenting prices with the prior-year yield shock. We apply this method to a data set that includes the covid-19 event to estimate and compare supply elasticities used by USDA for policy analysis. Every year USDA releases (1) the Prospective Plantings report containing farmers' planting intentions and (2) the Actual Acreage report. The Prospective Plantings report helps set production expectations and guide market decisions for the coming year. To this point, this information has been left out in the literature when assessing acreage response to price fluctuations. We use the data on prospective plantings, actual plantings, and futures prices to study farmers' responses to price shocks. We also connect this work to policy by using our elasticities to estimate the welfare damage generated by the COVID shock and comparing this to the payments USDA made to domestic corn and soybean producers under CFAP. To do so, we estimate the implied shift in the quantity via three related methods during the year 2020: (1) using the observed price difference from January to April (used by USDA in their calculations), (2) the observed price difference from January to August (harvest month for corn), and (3) the observed price difference from January to November (one month before contract expiration). We find that the supply elasticity for corn is 0.26% (estimates in the literature range between 0.40% and 0.50%). Under all three scenarios, our analysis shows that the USDA was able to entirely compensate farmers for their losses because of the COVID-19 pandemic.

We expand on the literature by adding information on farmers' intended plantings to estimate agricultural supply elasticities using the data on farmers' intended plantings and actual plantings. This offers us more data points, increasing statistical power and improving the precision of our estimates. Ultimately, our analysis will help government and private organizations form effective strategies when facing future demand shocks. In addition, the information on farmers' responses to price changes will assist traders and market participants inform their production and risk management decisions, improving the efficiency of the agricultural supply chain.

2. Background and Literature Review

Supply Elasticities

Nerlove (1958), in a seminal work, studies agricultural supply elasticity analysis using lagged prices as control variables. Roberts and Schlenker (2013) estimate demand and supply elasticities for corn, soybeans, wheat, and rice by aggregating these commodities into calories. The authors construct weather-induced yield shocks as deviations from yield trends and use them as instruments to estimate supply elasticities. Their elasticity estimate lies between 0.08% and 0.1%.

Further, they use these results to assess the US biofuel mandate's impact on food prices between 2005 and 2008, showing that the mandate increased food prices by 30% (~ loss in consumer surplus of 180 billion). On the contrary, Hendricks et al. (2014a) propose using OLS to estimate supply elasticities by regressing planting area on futures prices with the current-year realized yield shock as a control variable. They decompose supply elasticities into changes in deviations from yield trend, the composition of growing area, and total growing area to show that adding the current year yield shock eliminates any sources of endogeneity, making OLS a suitable model choice.

Hendricks et al. (2014b) use satellite data on land use in three corn belt states, Illinois, Indiana, and Iowa, to estimate short and long-run elasticities for corn and soybeans. With roughly over 8 million observations from 2000 to 2010, the authors use first-order Markov transition probabilities and find an elasticity estimate of 0.29 for corn and 0.26 for soybean. Kim and Moschini (2018) argue that price changes from 2005 to 2015 were due to demand factors following RFS adoption. Using price changes (in this period) as exogenous variables, they estimate corn and soybean supply elasticities for 12 midwestern states from 2005 to 2015. The authors report own-price elasticities of 0.38 for soybeans and 0.50 for corn.

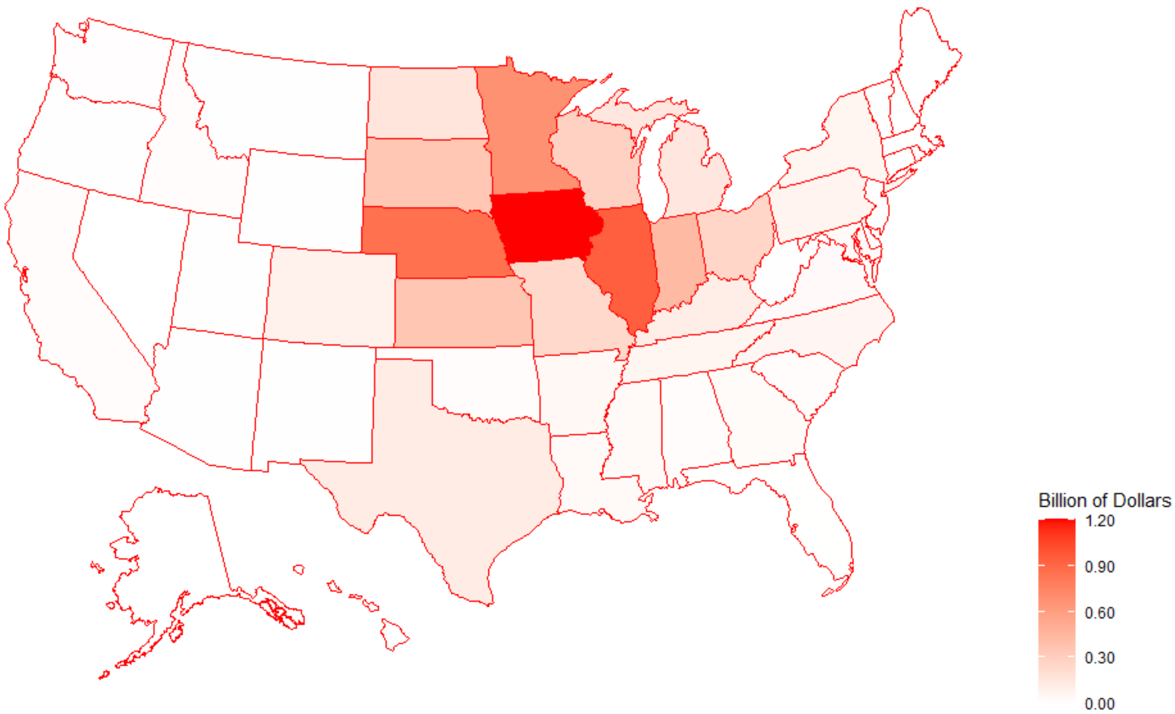
In a recent article, Thompson et al. (2021) study how agricultural supply responds to extreme events such as the global price surge of 2005-07, the African swine fever, the trade war, and the COVID-19 pandemic. These authors evaluate how elasticities from the literature perform under these demand shocks for corn and soybeans. Specifically, they consider the performance of elasticities estimated by Goodwin and Mishra (2006), Hendricks et al. (2014a), and Kim and Moschini (2018). The authors find that the price changes were associated with small area effects; for example, price changes as high as 50% resulted in area changes as low as 3%. They also show that cross-price elasticities are crucial in determining area response to price changes.

Thompson et al. (2021), however, do not estimate supply elasticities; they only assess the values measured in the literature. This article fills this gap by estimating supply elasticities for corn and soybeans using recently advanced techniques and methods. Furthermore, although most supply work relies on a single, annual observation of price and plantings, we expand the dataset by accessing one additional source of data: information on planting expectations that the USDA releases in its Prospective Plantings report in March before planting is complete.

Coronavirus Food Assistance Program

The United States government announced Coronavirus Food Assistance Program in April 2020. USDA allocated $16 billion to assist farmers and ranchers based on pandemic-associated losses. Producers who have suffered a price decline of 5% or greater were eligible for the program. Applications were accepted from May 26, 2020, to September 11, 2020. Later USDA offered a second round of payments (CFAP2) and received applications from April 2021 through October 2021. USDA made a total payment of $11.8 billion under CFAP1, and $19.2 billion under CFAP2, summing to $31 billion. Figure 1 shows the total CFAP payments made for corn (~$6.86 billion) across different states. As expected, disbursements are higher in corn belt states (Iowa, Illinois, Nebraska) compared to other regions.

Figure 1: Total CFAP Payments for Corn



Source: USDA Data

3. Data

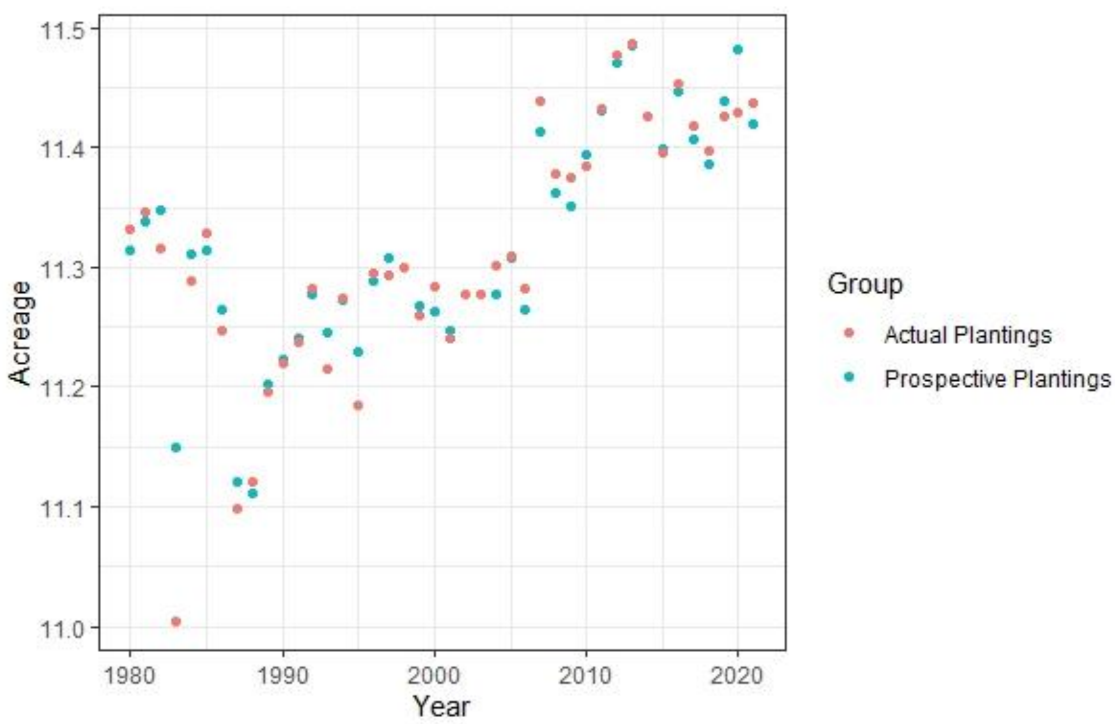
End of March every year, USDA releases the Prospective Plantings report containing information on farmers' planting intentions for that marketing year. The organization conducts farmer surveys towards the end of February and early March (March Agricultural Survey) and provides markets with an indication of the expected crop size (Good and Irwin, 2011). A total of 78,900 farm operators were included in this survey in 2021 (Lofthus, 2021). In addition, every year in June, USDA publishes the Crop Acreage report presenting information on planted acreage for major crops across different states. The data on yield is available in the annual crop production summary published every year in January. The Cornell University Library maintains these data from 1980 through 2020. In addition, we also collect data on ethanol production from the U.S. Department of Energy. Table 1 provides summary statistics for each of the above series we use in our analysis.

Table 1: Summary Statistics

Variable	Time Period	Mean	Standard Error
Prospective Plantings (1,000 acres)	1980-2020	82635.5	1191.4
Planted Acreage (1,000 acres)		82340.6	1300.6
Yield (per acre)		136.58	4.06
Ethanol Production (Million gallons)	2000-2020	9870	1206.02

Source: USDA Reports

Figure 2: Corn Acreage over Time



Source: USDA reports

Domestic prospective and planted corn acreage increased from 1980 to 2020, as shown in figure 2. In most years, prospective and actual plantings are fairly close. Their mean within-year difference over the period of observation is 0.36%. In 1983 prospective plantings exceeded actual acreage by 9.4 million acres—the largest difference observed in our dataset—potentially due to a drought in the mid-west that year. The next largest difference occurred in 2020, where planted acreage was about 5 million fewer acres than expected. This difference is most likely due to the reduced demand for ethanol and therefore corn as a result of the COVID-19 pandemic. Moreover, the pandemic also disrupted an increasing ethanol production trend in 2020 (a decrease of 1.8 billion gallons). For the analysis we use harvest contract futures closing prices traded on the day prospective and acreage plantings reports are released. We draw these prices from Bloomberg.

4. Methodology

We follow the approach of Roberts and Schlenker (2013) to estimate agricultural supply elasticities. In their model, quantity is specified as a function of price and other covariates:

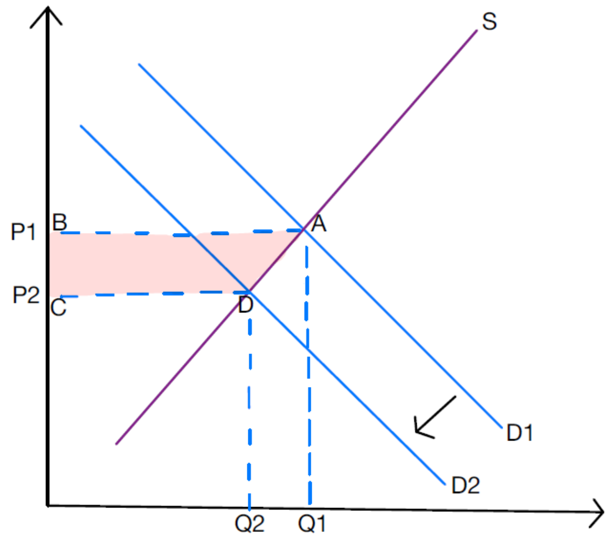
$$q_{st} = \alpha_s + \beta_s p_{st} + \gamma_s \omega_t + f_s(t) + u_t \qquad (1)$$

where q_{st} is the log corn supply (prospective and actuals) at time *t*. The log futures price is denoted by p_{st}, ω_t refers to the yield shock at time *t*, and the time trend is captured by $f_s(t)$. However, farmers might make acreage decisions based on futures prices, and simultaneously acreage might determine futures prices, resulting in endogenous prices negatively biasing the elasticity coefficient. We follow Roberts and Schlenker (2013) and use the lagged yield shock as an instrument to address the concern of endogenous prices. Yield shocks are unexpected deviations from yield trends that occur due to random weather shocks. We approximate these shocks by calculating Jackknife residuals by fitting a yield trend using a restricted cubic spline with three knots (Roberts and Schlenker, 2013; Hendricks et al., 2014a). We also perform a robustness test by repeating the procedure using four and five knots. More specifically, the first stage of the 2-SLS method is given by:

$$p_{st} = \delta_s + \mu_{s0}\omega_t + \mu_{s1}\omega_{t-1} + f_s(t) + \epsilon_t \tag{2}$$

Lagged yield shock (ω_{t-1}) is an excluded instrument. Before conducting our analysis, we deflate futures prices with the seasonally adjusted consumer price index (CPI).

Figure 3: Demand and Supply Movements due to COVID-19



As shown in figure 3, because of the COVID-19 pandemic, the demand curve shifted inward, resulting in losses for farmers and ranchers; in the figure, it moved from D1 to D2. In the short run, because the supply technology hasn't changed the supply curve remains constant.[2] Therefore, we use our estimated elasticities from equation (1) to approximate the welfare damage—or the loss in producer welfare—resulting from this shift in the demand curve (trapezoid ABCD in the figure).[3] To assess this, we use the following equation:

$$\text{Welfare Loss} = \frac{1}{2}\left(P_{January-P'}\right)\left(\frac{Q_{Acreage\ 2020}}{1+\beta_s\frac{\left(P' - P_{January}\right)}{P_{January}}} + Q_{Acreage\ 2020}\right) \tag{3}$$

[2] Planting harvest of field crops isn't affected by covid lockdown restrictions

[3] We assume that the demand and supply curves are linear.

Where, $P_{January}$ is the average futures price for the December 2020 corn contract in January 2020, and $Q_{Acreage\ 2020}$ is the actual corn acreage planted in 2020 (from the June Acreage report). The supply elasticity estimate is given by β_s (from equation (1)). We use three different estimates for P': (1) the harvest futures contract price in April (used by USDA in their calculations), (2) in August (harvest month), and (3) in November (one month before contract expiration).

5. Results

In Table 2, we report the 2-stage least squares (2-SLS) model estimated using equations (1) and (2) using the data from 1980 to 2020. Column (A) corresponds to our base specification with yield shock and time trend (fitted using a cubic spline with three knots) as controls and lagged yield shock as an instrument. Our result implies that, on average, a 1% increase in corn's harvest futures prices, increases acreage by 0.27%. In columns (B) and (C), we fit the time trend using a cubic spline with four and five knots, respectively. The supply elasticity varies between 0.26% – 0.28% with overlapping confidence intervals, indicating the robustness of our results.

Elasticity coefficients are statistically significant at a 5% significance level across all regression models. Column (B) is our preferred model because it has the lowest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values.[4] Figure 4 compares our estimated corn elasticity to the results in the literature. It is important to note that Hendricks et al. (2014) use data from 2000 to 2010, and Kim and Moschini use data from 2005 to 2015; our results are based on the information from 1980 to 2020. Moreover, none of these papers instruments for futures prices.

[4] AIC measures the relative distance between the fitted and the true (unknown) likelihood function, whereas BIC estimates the probability of the estimated model being true; lower AIC and BIC values are preferred.

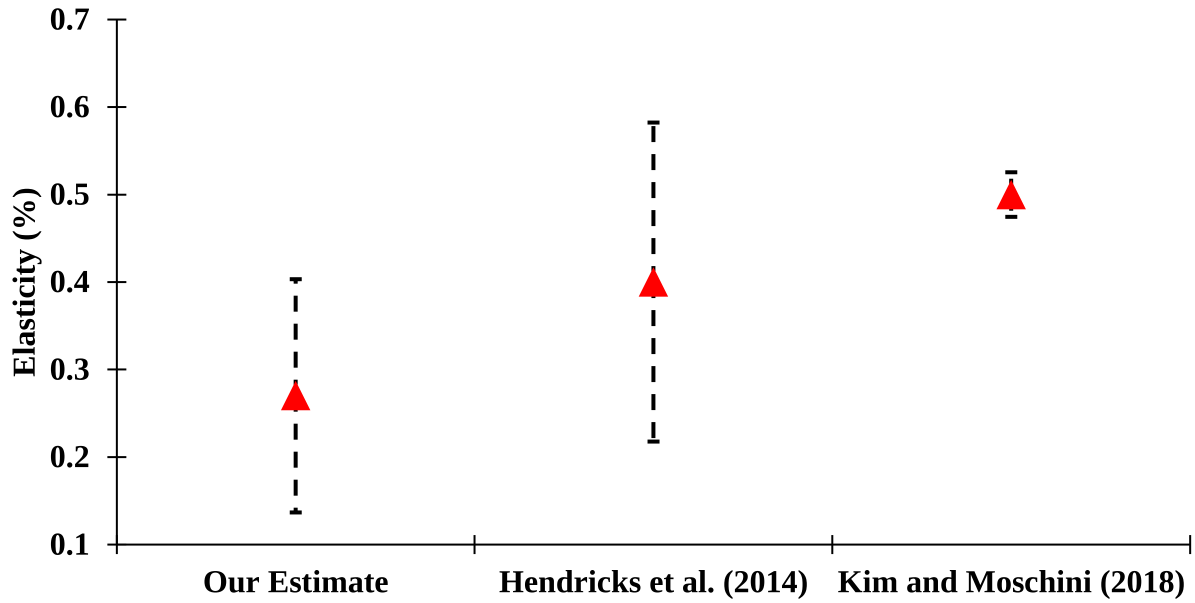
Table 2: 2-SLS Regression Results for Corn

	Dependent variable:		
	Log Acreage		
	3 knots (A)	**4 knots (B)**	**5 knots (C)**
Log Price (β_s)	0.276^{***}	0.264^{***}	0.284^{***}
	(0.068)	(0.062)	(0.070)
Yield Shock	0.025^{***}	0.026^{***}	0.024^{***}
	(0.008)	(0.008)	(0.008)
			(0.098)
Constant	-6.61	-10.19	-1.9
	(6.957)	(12.329)	(12.178)
Weak instruments	0	0	0
Wu-Hausman	0.11	0.04	0.03
Observations	82	82	82
R^2	0.696	0.716	0.702

Note: Robust standard errors are reported in parentheses. Asterisks *,**, and *** denote statistical significance at the 10%, 5%, and 1%, respectively.
Source: Authors

Next, we assess the welfare damages to corn producers because of the pandemic by estimating equation (3) with $\beta_s = 0.264\%$. Based on price changes from January to April (the period used by USDA in their calculations), we estimate that the pandemic generated $5.4 billion (95% CI: [$5.35 bn, $5.45 bn]) in damages for corn producers due to an inward shift in the demand curve. In addition, our results project an estimated loss of $5.76 billion (95%CI: [$5.71 bn, $ 5.82 bn]) when using price changes from January to August. However, when using price changes from January to November (one month before the 2020 harvest contract expires), our analysis projects that corn producers would have instead gained during the pandemic. However, it is important to note that increasing our period (January – November) might be adding noise and diluting the pandemic's impact since the country was adapting and moving towards normalcy. Figure 5 documents the welfare damages in three different scenarios and compares them to the USDA's payments under CFAP 1 and 2 – all our estimates indicate that the USDA was able to fully compensate farmers for their damages due to the pandemic.

Figure 4: Comparison of Corn Elasticities

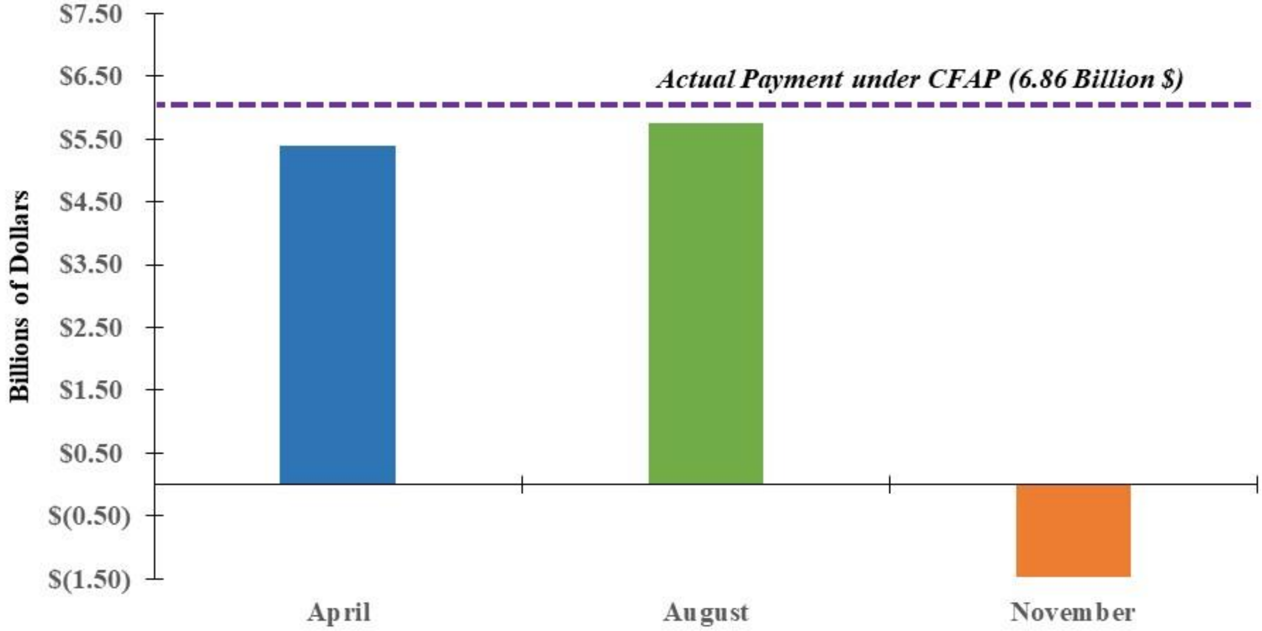


Source: Authors

6. Conclusions

Previous literature addresses the concern of endogenous futures prices by using lagged yield shocks as instruments. However, these papers only use planted acreage as a dependent variable. USDA publishes prospective plantings and acreage in two separate reports published three months apart. We take advantage of this information and use both expected plantings and actual plantings to estimate agricultural supply elasticity for corn from 1980 to 2020. Our results show consistency across different model specifications, with a mean elasticity estimate of 0.26%.

Figure 5: Estimated Corn Producer Surplus Effects of COVID-19



Source: Authors

Recently, due to the COVID-19 pandemic, demand for ethanol plummeted – resulting in an inward shift in the demand curve for corn. Consequently, our analysis shows that corn producers suffered losses worth $5.4 billion (using price changes from January to April), 27% lower compared to the actual payments USDA made under CFAP. Moreover, all our estimates suggest that the USDA was able to fully compensate producers for any losses they faced due to demand reduction.

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