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by

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Abstract

Considering that Working curve is a well-established stylized fact and that backwardation exists in the grain markets, we build upon the existing literature to explore the nexus between implied volatility (IV) and storage regimes in substitute agricultural commodity markets. We use a substitute-commodity market-setup of corn and soybean to account for any spillovers across their physical-market fundamentals. The impact of commodity fundamentals (production-related information and storage), macroeconomic indicators and financial market-variables is studied on nearby and deferred implied volatility series; the analysis is carried out both at daily and weekly frequency. In fact, we do find the spillovers across the production-related information disappear in the weekly analysis; thus, suggesting the need to account for early-impact of such information on a daily-basis for modeling the uncertainty levels. The distinct reaction of implied volatility of different maturity periods (i.e., nearby and deferred) to the commodity-fundamentals highlights that not only the two IV series behave differently during episodes of contango and backwardation, but also that they behave differently from each other during the two storage-scenarios. Therefore, our study makes crucial additions to the existing works and emphasizes the need to acknowledge the differing behavior of the nearby and far-out IV levels during episodes of contango and backwardation in the grain markets.

Keywords: Backwardation, corn, implied-volatility, soybean, spillover effects.

Introduction

While the theory suggests that the futures price of a storable commodity for any delivery month should be equal to the current spot price plus the cost of storage including interest charges and risk premium, it has been observed that spot prices might exceed nearby futures prices, or near-delivery futures prices might exceed far-delivery futures prices (Working 1933, 1948). This is called "backwardation," and the opposite price pattern, in which more distant prices exceed nearby prices, is called "contango." Working (1933), using the wheat market in the U.S., developed an empirical relationship between storage and the intertemporal price differences, called "Working curve," which is positively sloped and displays storage under negative carrying charges.

Futures contracts also reflect price expectations based on information regarding new and old inventories (Working 1948). However, they cannot reflect the level of uncertainty that the market associates with these price expectations. Implied volatility, on the other hand, measures the degree of uncertainty the market puts on the futures price at the expiration of the option contract (McNew and Espinosa 1994). Analyzing the dynamics of implied volatility can be crucial as they can better predict realized volatility (Szakmary et al. 2003; Haugom et al. 2014).

There are studies that explored these dynamics between implied volatility and commodity-specific physical-market fundamentals in the oil market as well as grain markets. For instance, the relationship among production, storage conditions, and volatility has been investigated in oil markets showing that oil production is inversely related and backwardation is positively related to implied volatility (Litzenberger and Rabinowitz 1995). More recently, Robe and Wallen (2016) find that the relation between crude oil implied volatility and the slope of futures term structure is stronger in periods of contango compared to the periods of backwardation. For the grain markets, Adjemian et al. (2016) use a structural vector autoregressive (SVAR) model to establish that inventory conditions tend to boost nearby implied volatilities. We build upon these works to investigate how dynamics of implied volatility (IV) series for different maturities depend on market fundamentals, macroeconomic indicators, and financial market indicators for a specific commodity, and to ascertain if spillover effects from a substitute commodity market could also be crucial in understanding the patterns of IV series. To this end, we conduct an MGARCH DCC analysis of the corn and soybean IV series using macroeconomic, financial and physical-market fundamentals as variables that depict own effects while using physical market fundamental indicators as variables for spillover effects. The analysis is conducted both at daily and weekly frequency to observe if the IV levels are more prone to immediate impact of fundamentals and other indicators on a daily basis rather than on a weekly basis.

Our findings suggest a strong relationship when backwardation is found to play a key role in boosting uncertainty levels in corn, which contrasts with the oil-markets where a strong relationship is established for contango to be boosting uncertainty levels in the oil-markets (Robe and Wallen 2016). These results are similar to what is found for the grain markets when a strong relationship is established between nearby-implied volatility and the inventory conditions (Adjemian et.al 2016). But our regression analysis and a series of Kolmogorov-Smirnov tests along with a set of kernel-density plots also elaborate on the behavior of implied volatility that differs during episodes of contango and backwardation depending upon if it is nearby or far out in the future in terms of maturity. In the daily analysis spillovers persist across the physical-market fundamentals especially for the deferred IV series. Thus, in many ways our study intends to add valuable insights into understanding how the behavioral pattern of implied volatility differs across maturity periods due to crucial factors that characterize macroeconomic conditions and fundamentals of substitute-commodity markets.

Data and Methodology

The series of various macroeconomic, financial, and physical market fundamentals in corn and soybean markets are collected for the period 2009-2018. Each variable is explained in detail below with the expected signs summarized in Table 1.

Macroeconomic variables

We construct a daily series of world economic activity index suggested by Hamilton that performs better than the Kilian index (Hamilton 2018) to replicate world business cycles. From the daily series we also extract a weekly series having observations for every Tuesday for the period 2009-2018. An increase in world economic activity should lower the uncertainty levels in the commodity markets. Thus, we expect it to have a negative sign in the regression analysis.

Financial variables

CBOE's VIX index serves as the 'fear measure' to consider risk aversion and investor sentiments in the market. We take the daily and weekly series for it as we need both for the MGARCH DCC analysis conducted at the daily and weekly frequencies separately. We expect a positive sign for the variable as it should drive up the uncertainty in the commodity markets. We also include the trading volume for both futures and options in the corn and the soybean markets.

Physical market fundamentals

We use nearby and 1-month deferred futures price series along with 3-month Libor interest rate to construct our net cost of carry variable. We expect a negative sign for the net cost of carry under backwardation and a positive sign under contango, implying that both storage regimes boost the uncertainty levels in the grain markets. For substitute commodities, any spillovers across these storage episodes can be important to understand as the uncertainty levels in the market of a commodity might also be prone to the storage-scenario of its substitute commodity.

We use USDA's final annual production numbers to account for the production-related information For substitute commodities, the spillovers across this information-domain become even more crucial to look at as it has been found that corn market reacts to soybean surprises in crop production annual summary whereas the soybean market appears to be more sensitive to corn information in almost all reports except for September crop production and crop production annual summary (Karali et al. 2019). Hence, to simulate market-sentiments about the production scenario pertaining to the two commodities we fit a linear trend to the final production numbers and calculate the deviations from trend interacted with dummy variables indicating good and bad crop years. For own effects, we expect a negative sign for the good crop year (as it brings down the uncertainty) and also a negative sign for the bad crop year (since a negative deviation from the trend along with a negative sign of the coefficient would mean an overall increase the IV levels).

Implied volatility series

Nearby IV series is proxied by the implied volatility series of at-the-money call options and deferred IV series is proxied by the call options with 6-month maturity. The two series have been chosen to see if the impact of the above-mentioned explanatory variables tends to vary according to the maturity periods.

We find that the implied volatility series along with other variables are leptokurtic (Table 2&3); thus, necessitating to consider while conducting any analysis that these time series variables have fatter tails than normal distribution. Our tests for normality confirm that the null for univariate, bivariate, and multivariate normality are rejected for these variables. Langrange multiplier tests confirm the existence of heteroskedasticity in the IV series; thus, making a case for a GARCH (1,1) model for each crop's IV series. We use lagged independent variables to avoid the issue of endogeneity. Augmented-Dickey Fuller tests reject the null hypothesis of a unit root in all the explanatory variable series, except for the Hamilton index. Therefore, we take first difference of Hamilton index.

Multivariate GARCH DCC Model

We fit a multivariate GARCH Dynamic Conditional Correlation (DCC) to model the multivariate IV series of corn and soybean on the respective explanatory variables as follows:

$$IV_t = c + \gamma P_{t-1} + \varepsilon_t \tag{1}$$

where,

IV_t denotes the 2x1 vector of implied volatilities as dependent variables and P_{t-1} is a nx1 vector of lagged independent variables consisting macroeconomic fundamentals, financial and physical-market fundamentals as own effects and spillover effects of physical-market fundamentals from the substitute-market. Let

$$V(\varepsilon_t \,|\Omega_{t-1}) = h_t^2 \tag{2}$$

In a GARCH (1,1) set up:

$$h_t^2 = \beta_0 + \alpha_1 \varepsilon_{t-1}^{\ 2} + \beta_1 h_{t-1}^{\ 2},\ \beta_0 > 0 \tag{3}$$

$$\sigma_t^{\ 2} = \beta_0 + (\alpha_1 + \beta_1)\sigma_{t-1}^{\ 2}, \tag{4}$$

where α_1 and β_1 are the ARCH and GARCH parameters. The time varying conditional correlation matrix can be given as:

$$C_{t-1} = S_{t-1} R_{t-1} S_{t-1} \tag{5}$$

where, S_{t-1} is a 2x2 diagonal matrix with elements $\sigma_{i,t-1}$ and R_{t-1} is the symmetric 2x2 matrix of pair-wise conditional correlations. The decomposition of the conditional covariance matrix C_{t-1} shows how the model accounts for both conditional variances and time-varying conditional covariances. The dynamic nature of MGARCH DCC allows us to model R_{t-1} as:

$$R_{t-1} = (1 - \lambda_1 - \lambda_2)\, R + \lambda_1\, \varepsilon_{t-1} \varepsilon_{t-1}' \lambda_2\, R_{t-2} \tag{6}$$

where R is the unconditional covariance matrix.

Results

MGARCH DCC model

The MGARCH DCC model not only helps us ascertain the direct impacts of crop-specific explanatory variables on their IVs, but also helps us delineate if there are spillover effects across the substitute crop systems. For this analysis, considering the leptokurtic nature of the probability distribution of variables being used we assume Student's t-distribution for the error terms. We estimate two MGARCH DCC models for the IV series of the two crops: one for daily-analysis and the other for weekly analysis. Kolmogorov-Smirnov test is also performed to observe the behavior of the IV series in the two storage regimes.

The results for the multivariate GARCH DCC models are presented in Table 4 for daily-analysis and in Table 5 for weekly-analysis. As we can observe across the regressions the ARCH and the GARCH effects stay intact at 1% significance level. Moreover, we also check for the relevance of the DCC framework for the model as against a CCC (constant conditional correlation) framework via a Wald test to test the null hypothesis of $\boldsymbol{\lambda}_1 = \boldsymbol{\lambda}_2 = 0$. In all regressions, we reject the null, confirming that the DCC is apt for this analysis as against a CCC. The GARCH effects are higher in the weekly-analysis results which, in turn, hints at higher persistence of past volatility in the weekly analysis. The correlation between corn and soybean IV series (both nearby and deferred) is stronger in the weekly analysis than it is in the daily analysis. The adjustment factor $\boldsymbol{\lambda}_2$ is higher than $\boldsymbol{\lambda}_1$ across daily and weekly analysis; thus, suggesting that the conditional covariances are more dependent on the lagged residual innovations.

The results for own-effects show backwardation to boost the corn IVs (both for nearby and deferred series; Table 4); suggesting a strong relationship between episodes of backwardation and uncertainty in the corn market. We also find some evidence for contango to be boosting daily IV levels in the deferred IV series for corn. The soybean IV series do not show any significant relation with storage regimes. Even for the production-related information, we find significant results only for the nearby soybean IV series (both in daily and weekly-analysis) where a good year in soybean brings down the nearby IVs in soybean. Nearby IV series are found to be significantly impacted by the 'fear measure' more so in the weekly-analysis than in the daily-analysis when the VIX is found to heighten the uncertainty levels for the weekly-nearby corn and soybean series (Table 5). Futures and options trading volumes are found to lower the IV levels for corn in nearby and deferred series respectively, which is in contrast to the oil-markets where any increase in trading volumes is expected to heighten the uncertainty levels (Robe and Wallen 2016). We find very weak evidence for the world economic activity to be impacting the IV levels in the two grain markets. In a nutshell, our analysis for the own-effects suggests that storage-stress is crucial in determining the uncertainty levels where we observe that backwardation tends to heighten the nearby-IV levels by a relatively higher magnitude than they heighten the deferred IV levels. Thus, the impact differs across IVs of different maturity options contracts. Soybean's physical-market fundamentals are found to hardly impact the uncertainty levels in the market. Any of the significant impacts of explanatory variables observed in the results tend to have a higher magnitude for the weekly analysis.

The results for the spillovers suggest significant volatility-spillovers from the corn market to the soybean market. We find significant spillovers across the production-perception measured by the good year and bad year dummies; the perception seems to be impacting mostly the deferred IV series in the daily-analysis. The soybean production-related perception has significant dampening effect on the IV levels in the deferred corn series, whereas a good year in corn tends to dampen the IV levels in soybean (Table 4). Interestingly, our analysis finds the spillover-effects to disappear in the weekly-analysis (Table 5). Backwardation in corn seems to be impacting the IV levels in the deferred series of soybean where we find it to be boosting the uncertainty levels in the soybean market (both in daily and weekly analysis). The nearby series do not witness any spillover-effects across the physical-market fundamentals. As observed for the own-effects earlier, for the spillovers also the coefficients for significant factors are higher in the weekly-analysis.

Kolmogorov-Smirnov tests and kernel-density plots

As observed in the regression results that the extent to which backwardation impacts nearby and deferred corn IV levels differs in magnitude which is also supported by a series of Kolmogorov-Smirnov tests (Table 6&7) and k-density plots (Figure 1&2). The non-parametric KS test suggests that the pattern observed for the IV differs not only across episodes of contango and backwardation, but the behavior shown by the nearby IVs is found to be opposite to that observed in the deferred IVs during the two episodes (Table 6&7). The nearby corn and soybean IVs are found to be higher during episodes of backwardation than contango while the opposite is true for the deferred IV series.

Conclusions

The study establishes a close relation between episodes of backwardation and the uncertainty levels, whereas contango is not found to be that closely linked to the uncertainty in the grain markets. Spillovers across the physical market-fundamentals such as production-related information highlights the importance of the nature of information contained in USDA production reports. The market-perception of such a report and the uncertainty-level seems to be closely linked in a substitute-commodity set up of corn and soybean; this necessitates to study similar dynamics further for other commodities as well. The dynamics observed for the daily analysis do not necessarily persist for the weekly analysis except for backwardation to be consistently linked to the IV levels in corn; thus, hinting at the importance of modeling the dynamics on a daily basis rather than on a weekly basis. The dynamics of nearby IVs seem to differ from the dynamics of the far-out IV levels; a point to be considered while modeling implied volatility, especially when it comes to observe how the physical-market fundamentals impact the uncertainty in the grain markets.

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Table 1: Expected Impacts on Implied Volatility

Lagged Variables	Expected Signs (for own-effects)
IV	positive
VIX	positive
Change in Hamilton	negative
Good crop year	negative
Bad crop year	negative
Net cost of carry-contango	positive
Net cost of carry-backwardation	negative

Table 2: Summary Statistics for Corn

	Mean	Std. Dev.	Max.	Min.	Skewness	Kurtosis
VIX	17.991	6.708	48.000	9.140	1.473	5.228
Hamilton	-0.682	0.748	0.836	-2.656	-0.451	2.514
Nearby IV	26.726	9.220	90.810	6.200	0.765	4.072
Deferred IV	28.506	11.215	62.430	3.810	0.421	2.796
Deviation from trend in production	-1.442	10.294	10.242	-24.300	-0.857	2.951
Net cost of carry	1.058	3.247	4.522	-26.068	-3.786	22.216
Futures volume (in hundred thousand)	1.161	0.760	5.382	0.000	0.495	3.969
Options volume (in hundred thousand)	0.476	0.278	2.430	0.000	1.644	7.021

Table 3: Summary Statistics for Soybean

	Mean	Std. Dev.	Max.	Min.	Skewness	Kurtosis
Nearby IV-	21.952	6.722	49.900	0.900	0.973	4.475
Deferred IV	19.169	6.846	34.890	1.010	-0.107	3.124
Deviation from trend in production	4.550	9.053	21.608	-9.703	0.118	2.323
Net cost of carry	-0.720	2.394	1.546	-17.103	-2.539	10.452
Futures volume (in hundred thousand)	0.642	0.539	3.276	0.000	0.435	2.562
Options volume (in hundred thousand)	0.306	0.175	1.526	0.000	1.873	8.367

Table 4: MGARCH DCC Results with Daily Series

	Nearby IV		Deferred IV	
	Corn	Soybean	Corn	Soybean
Own-effects				
IV	0.983***	0.948***	1.003***	0.992***
	(0.000)	(0.000)	(0.000)	(0.000)
VIX	0.008	0.009**	0.002	-0.001
	(0.156)	(0.039)	(0.435)	(0.628)
Change in Hamilton	0.374	0.893	0.721**	0.351
	(0.565)	(0.102)	(0.037)	(0.213)
Good crop year	0.008	-0.007**	0.003	-0.0004
	(0.315)	(0.026)	(0.486)	(0.812)
Bad crop year	-0.007	-0.007	-0.007	0.01
	(0.454)	(0.688)	(0.137)	(0.242)
Net cost of carry contango	-0.014	-0.100	0.025**	0.013
	(0.579)	(0.101)	(0.049)	(0.684)
Net cost of carry backwardation	-0.039***	-0.015	-0.023**	0.008
	(0.007)	(0.247)	(0.026)	(0.329)
Futures volume	-0.061**	0.018	-0.009	-0.012
	(0.037)	(0.592)	(0.523)	(0.492)
Options volume	-0.121	-0.153	-0.115**	-0.069
	(0.21)	(0.201)	(0.013)	(0.249)
Spillovers				
IV	0.006	0.019***	-0.003	0.004***
	(0.535)	(0.000)	(0.369)	(0.007)
Good crop year	-0.004	0.004	-0.004**	-0.006*
	(0.260)	(0.523)	(0.050)	(0.087)
Bad crop year	0.019	0.004	0.031***	0.003
	(0.406)	(0.625)	(0.006)	(0.426)
Net cost of carry contango	-0.112	0.027	-0.062	0.008
	(0.158)	(0.168)	(0.122)	(0.437)
Net cost of carry backwardation	0.018	0.005	0.008	-0.025***
	(0.229)	(0.703)	(0.402)	(0.002)
constant	0.322*	0.404***	0.022	0.064
	(0.051)	(0.002)	(0.772)	(0.277)
Other statistics				
ARCH	0.723***	0.641***	0.346***	0.295***
	(0.001)	(0.002)	(0.000)	(0.000)
GARCH	0.603***	0.665***	0.613***	0.795***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.081***	0.542***	0.195***	0.036***
	(0.003)	(0.005)	(0.000)	(0.000)
Corr(corn-iv,soybean-iv)	0.421***		0.536***	
	(0.000)		(0.000)	
Lambda1	0.050**		0.0003	
	(0.026)		(0.605)	
Lambda 2	0.830***		0.996***	
	(0.000)		(0.000)	
df	2.328***		0.536***	
	(0.000)		(0.000)	
N	2413		2413	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; p-value in parenthesis

Table 5:MGARCH DCC Results with Weekly Series

	Nearby IV		Deferred IV	
	Corn	Soybean	Corn	Soybean
Own effects				
IV	0.826***	0.734***	0.996***	0.958***
	(0.000)	(0.000)	(0.000)	(0.000)
VIX	0.079**	0.070***	0.007	0.001
	(0.014)	(0.003)	(0.689)	(0.908)
Change in Hamilton	0.443	0.582	0.882	0.347
	(0.630)	(0.446)	(0.135)	(0.433)
Good crop year	0.041	-0.037**	0.010	0.001
	(0.301)	(0.036)	(0.707)	(0.886)
Bad crop year	-0.062	-0.054	0.017	0.018
	(0.252)	(0.533)	(0.632)	(0.708)
Net cost of carry contango	-0.088	0.058	0.025	0.175
	(0.520)	(0.860)	(0.768)	(0.352)
Net cost of carry backwardation	-0.320***	-0.097	-0.188***	-0.011
	(0.000)	(0.159)	(0.001)	(0.791)
Futures volume	-0.322**	-0.010	0.031	-0.017
	(0.012)	(0.951)	(0.711)	(0.856)
Options volume	0.310	0.478	-0.640***	-0.139
	(0.417)	(0.363)	(0.003)	(0.670)
Spillovers				
IV	0.061	0.085***	0.007	0.020**
	(0.219)	(0.001)	(0.697)	(0.043)
Good crop year	0.003	0.047	-0.006	-0.027
	(0.899)	(0.167)	(0.668)	(0.193)
Bad crop year	0.114	0.014	0.033	0.023
	(0.367)	(0.729)	(0.675)	(0.321)
Net cost of carry contango	-0.270	0.015	-0.064	0.038
	(0.504)	(0.892)	(0.781)	(0.526)
Net cost of carry backwardation	0.0004	-0.074	0.035	-0.120***
	(0.996)	(0.237)	(0.466)	(0.006)
Constant	1.477*	1.598**	0.090	0.213
	(0.090)	(0.014)	(0.844)	(0.518)
Other Statistics				
ARCH	0.184***	0.210***	0.042**	0.249**
	(0.004)	(0.001)	(0.032)	(0.032)
GARCH	0.838***	0.790***	0.961***	0.691***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.552*	0.666**	0.060	0.535**
	(0.063)	(0.023)	(0.184)	(0.033)
Corr(corn-iv,soybean-iv)	0.629***		0.743***	
	(0.000)		(0.001)	
Lambda 1	0.054**		0.004	
	(0.023)		(0.569)	
Lambda2	0.910***		0.986***	
	(0.000)		(0.000)	
df	3.268***		2.918***	
	(0.000)		(0.000)	
N	490		490	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; p-value in parenthesis

Table 6: Kolmogorov-Smirnov Test for Corn IV Series

	Nearby IV		Deferred IV	
Smaller Group[a]	Difference between distribution functions	P-value	Difference between distribution functions	P-value
Contango	0.300***	0.000	0.000	1.000
Backwardation	-0.005	0.986	-0.325***	0.000
Combined K-S	0.300***	0.000	0.325***	0.000
	1675 unique values out of 2415		1792 unique values out of 2415	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, [a] indicates which of the two groups have smaller values

Table 7: Kolmogorov-Smirnov Test for Soybean IV series

	Nearby IV		Deferred IV	
Smaller Group	Difference between distribution functions	P-value	Difference between distribution functions	P-value
Contango	0.195***	0.000	0.029	0.378
Backwardation	-0.000	1.000	-0.277***	0.000
Combined K-S	0.195***	0.000	0.277***	0.000
	1468 unique values out of 2415		1420 unique values out of 2415	

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, [a] indicates which of the two groups have smaller values

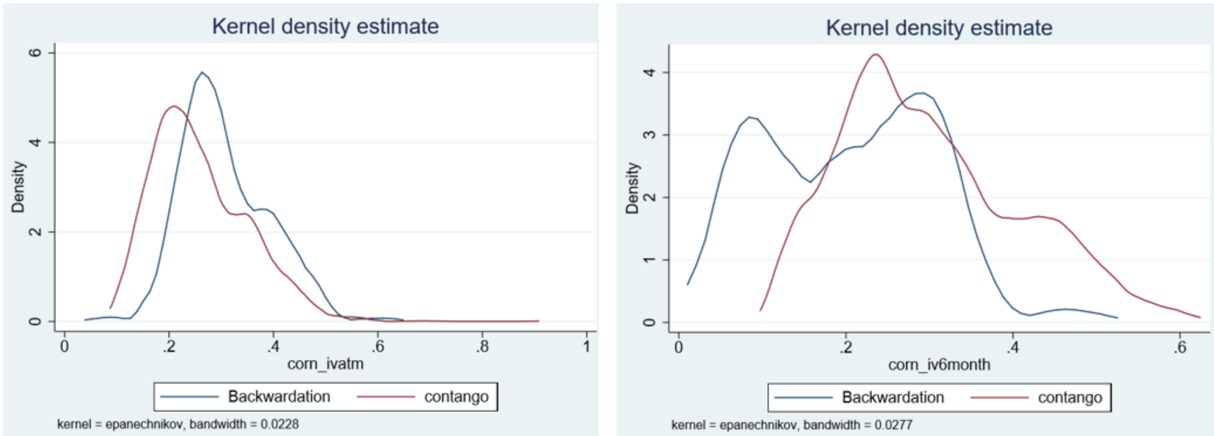

Figure 1: Kernel density plots for corn IV series

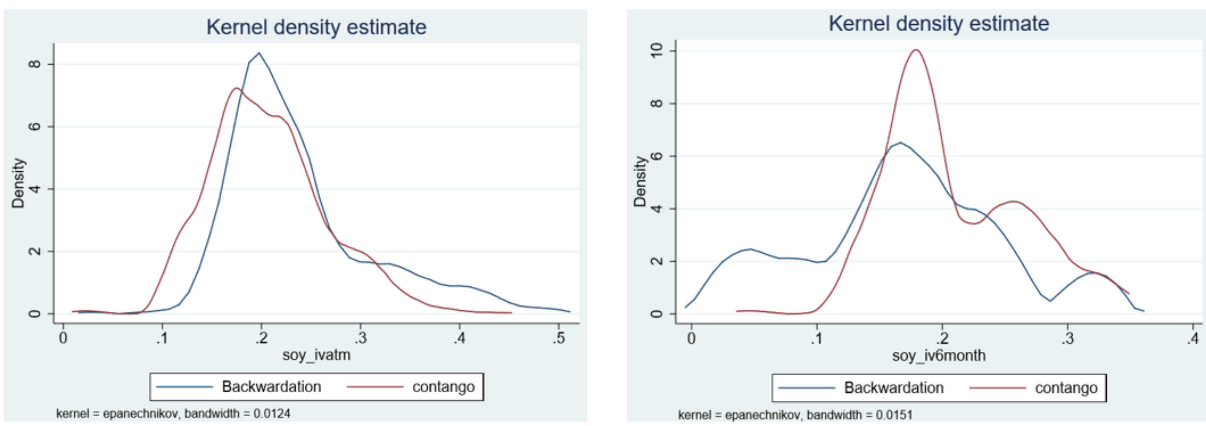

Figure 2: Kernel-density plots for soybean IV series