Market Stress in Agricultural Markets: Can Alternative Implied Volatility Measures Predict It?

Mahendra Kumar Singh, Iowa State University, mahenks1@iastate.edu
Sergio Lence, Iowa State University, shlence@iastate.edu

Selected Paper prepared for presentation at the 2023 Agricultural & Applied Economics Association Annual Meeting, Washington DC; July 23-25, 2023

Market Stress in Agricultural Markets: Can Alternative Implied Volatility Measures Predict It?

Mahendra Kumar Singh
mahenks1@iastate.edu

Sergio Lence
shlence@iastate.edu

Department of Economics
Iowa State University

1. Introduction

Asset pricing theory has a long tradition of inquiry into the tradeoff between expected return and risk, as measured by variance or volatility. The predictability of return and volatility has paramount financial implications for risk management, portfolio allocations, and investments. Martin (2017) recently derived a lower bound for the equity premium (i.e., the expected excess return on the market) using an implied volatility index named SVIX. SVIX is computed from the observed premiums on stock options and the observed prices of their underlying stocks. Martin (2017) showed how one could use SVIX as a real-time measure of the equity premium. This feature is a distinctive advantage of SVIX compared to alternatives that need infrequently updated accounting data to make such predictions. Another suitable implied volatility measure to assess risk in equity markets is VIX, often called the “fear gauge” (Demeterfi et al. 1999). Like SVIX, VIX is calculated using the observed premiums on stock options and the observed prices of their underlying stocks. VIX has become quite popular as a gauge of risk in equity markets, to a large extent because the Chicago Board of Options Exchange (CBOE) provides a real-time VIX index (up to minutes) for several asset classes traded.[1] Mathematically, one can express the SVIX and VIX measures as follows:

$$SVIX_{t\to T}^{2}=\frac{2R_{f,t}}{(T-t)F_{t}^{2}}\left[\int_{0}^{F_{t,T}} put_{t,T}(K)dK+\int_{F_{t,T}}^{\infty} call_{t,T}\,(K)dK\right] \qquad \ldots (1)$$

$$VIX_{t\to T}^{2}=\frac{2R_{f,t}}{(T-t)}\left[\int_{0}^{F_{t,T}}\frac{1}{K^{2}} put_{t,T}(K)dK+\int_{F_{t,T}}^{\infty}\frac{1}{K^{2}} call_{t,T}\,(K)dK\right] \qquad \ldots (2)$$

where t and T denote the current time period and option maturity date, R_f is the risk-free interest rate between the time periods t and T, and $F_{t,T}$ is the underlying asset's current forward/futures price which expires on date T. The call and option prices are denoted as $call_{t,T}$, and $put_{t,T}$. Lastly, K indicates the traded option's strike price on the underlying asset.

Option price theory deals with measures like VIX and SVIX under the implied volatility paradigm. Implied volatility measures are calculated from the observed premiums on options traded, and are indicators of expected realized volatility over the period preceding the options' maturity date. Unlike the standard calculation of implied volatility which relies on the Black and Scholes' option pricing model (Black and Scholes, 1973), VIX and SVIX are "model-free", in that they only rely on the assumption of no arbitrage. Martin (2017) provides an intuitive interpretation of VIX and SVIX. He demonstrates that SVIX is the risk-neutral volatility of the return on the market, whereas VIX is the risk-neutral entropy of the return on the market. Importantly, both measures are driven by the expected variation of the underlying asset's returns. Furthermore, Martin (2017) analytically shows–under the assumption that the stochastic discount factor (SDF) and returns are conditionally jointly log-normal–that SVIX should always be greater than VIX and that the magnitude of the gap between these two implied volatility measures should not be large.

[1] https://cdn.cboe.com/api/global/us_indices/governance/Volatility_Index_Methodology_Cboe_Volatility_Index.pdf

On the contrary, Martin (2017) finds that VIX is higher than SVIX for the S&P500 index during the period 1996–2012. Furthermore, he finds a large gap between VIX and SVIX, and that such gap becomes even larger during times of market stress, i.e., periods of high volatility. Martin (2017) interprets these empirical facts as strong evidence that the joint conditional log-normality assumption for the SDF and returns is highly unlikely to hold in real-world asset prices, and that such an assumption becomes even less likely to hold during periods of extreme volatility, i.e., market stress or market crash. In other words, the gap between VIX and SVIX can thus be interpreted as direct model-free evidence that SDF and returns are not log-normally distributed, at least in the equity market.

To build upon this discussion, we conjecture that there is no a priory reason for the standard log-normality assumption to hold in agricultural commodity markets. Hence, it remains an empirical question whether gaps between VIX and SVIX do exist in agricultural markets. Notably, unlike options defined on the S&P500 index, options on agricultural commodities (e.g., corn, soybean, and wheat) are defined on their corresponding futures contracts. Therefore, of necessity the gaps between VIX and SVIX for such commodities must be analyzed using the observed premiums of futures options contracts and their underlying futures prices.

In addition, there exists a plethora of studies that investigate the ability of implied volatility measures to predict realized volatility. For instance, Christensen and Prabhala (1998) provide seminal empirical evidence that implied volatility measures based on Black and Scholes' option pricing model contain forward-looking investors' sentiment about the market conditions. Thus, such implied volatility measures can predict the (future) realized volatility. Furthermore, Kanas (2013) documents that incorporating VIX into the GARCH model improves the ability to forecast the realized volatility of the S&P500 index. Pan et al. (2019) utilize a volatility spillover GARCH model and report that adding VIX to their model significantly improves the forecast for the S&P500 index's realized volatility. In other words, VIX computed from today's option prices contains information about subsequent market conditions, and models incorporating it have greater predictive power than the ones relying only on the historical realized volatility.

Embarking on this strand of literature, we hypothesize that the gap between VIX and SVIX (which originates due to the violation of the log-normality assumption) contains extra embedded information about future conditions in agricultural commodity markets. In particular, in this study we seek to examine the ability of the VIX-SVIX gap to predict the realized volatility of corn/soybean/wheat futures prices. In a nutshell, we explicitly ask this research question: does the divergence between VIX and SVIX measures forecast market stress in agricultural commodity derivatives markets? To the best of the authors' knowledge, this study will be the first one to employ SVIX (risk-neutral volatility of the return on the market) to predict future realized volatility for agricultural commodity derivatives. Surprisingly, Hollstein et al. (2020) is the only paper in the literature that explicitly uses VIX and SVIX measure for commodities to study their volatility term structures, however, a different goal from the objective of the present paper.

On a similar note, Bollerslev et al. (2018) provide a very intuitive mean-variance framework that signifies the need for volatility forecasting in general. In their framework, there is a representative agent with mean-variance preferences. The agent faces an optimal wealth allocation problem with two assets: (i) a risk-free asset and (ii) a risky asset with time-varying return volatility. Therefore, we can write the time-t expected utility as follows: $E_t\big(U(W_{t+1})\big) = E_t(W_{t+1}) - \frac{1}{2}\gamma^A Var_t(W_{t+1})$, where γ^A is the investor's absolute risk aversion. Also, the budget constraint can be written as $W_{t+1} = W_t(1 + x_t r_{t+1} + (1 - x_t)r_t^f)$, where W_t denotes initial wealth; x_t is the fraction of wealth invested into a risky asset, and $r_{t+1}$is the interest accrued on the risky asset. Now, one can define the excess return as $r_{t+1}^e = r_{t+1} - r_t^f$ and drop the constant terms from the optimization problem to arrive at the objective function as: $U(x_t) = W_t\left(x_t E_t(r_{t+1}^e) - \frac{\gamma}{2} x_t^2 Var_t(r_{t+1}^e)\right)$. Here, $\gamma = \gamma^A W_t$ is the investor's relative risk aversion. Now, one can replace the expected realized volatility as: $U(x_t) = W_t\left(x_t E_t(r_{t+1}^e) - \frac{\gamma}{2} x_t^2 E_t(RV_{t+1})\right)$. Bollerslev et al. (2018) argue that it is very common among investors to target the Sharpe ratio for their investments as $SR = \frac{E_t(r_{t+1}^e)}{\sqrt{E_t(RV_{t+1})}}$. Thus, one can modify the objective function as: $U(x_t) = W_t(x_t SR\sqrt{E_t(RV_{t+1})} - \frac{\gamma}{2} x_t^2 E_t(RV_{t+1}))$ and get the optimal wealth allocation $x_t^* = \frac{SR/\gamma}{\sqrt{E_t(RV_{t+1})}}$ and achieve the highest utility level as $U(x_t^*) = \frac{SR^2}{2\gamma} W_t$. For illustration, we can take some reasonable numbers $SR = 0.4$ and $\gamma = 2$ to arrive at $U(x_t^*) = 4\% W_t$. Therefore, if one could perfectly forecast next period's volatility, then the representative investor in the model could attain the highest level of utility, i.e., 4% of his/her initial wealth. Thus, we resort to this simple illustration to motivate this article to investigate the extant issue of empirical forecasting of realized volatilities using the information embedded in the VIX and SVIX gap. This issue has been largely ignored in the existing literature to the best of authors' knowledge.

One of the recent empirical pieces of evidence for commodity price volatility and the underlying determinants is available in Algieri (2021). She specifically analyzes the crop futures (wheat/corn/rice/soybean) and WTI crude oil futures traded in the U.S. from January 4, 2000, to October 27, 2017. She investigates the role of behavioral factors like economic policy uncertainty, price risks (captured by commodity-specific implied volatility measures), and the extent of regulation in the U.S. financial markets. Employing the Generalized Autoregressive Conditional

Heteroskedasticity (GARCH) type modeling, Algieri (2021) finds empirical support for the following: (i) economic policy uncertainty and price risks (implied volatility) positively impact the (future) realized volatility; and (ii) the period of 2000–2009, which was less regulated and promoted high liberalization in commodity markets witnessed high volatility as compared to the 2010–2018 (Dodd-Frank Act) era which had more stringent financial regulations.

Similarly, Giot (2003) reports one of the earliest such evidence from the agricultural commodity markets. Giot (2003) considers the sample of cocoa, coffee, and sugar futures and options prices and concludes that under the GARCH setup, option-based implied volatility measures provide one of the most relevant short-term forecasting information content. So much so that the past return volatility adds a minuscule predictive power once the implied volatility has been incorporated into the GARCH regression model. Recently, Triantafyllou et al. (2015) contributed to this discussion by assessing the predictive power of option-implied volatility and risk-neutral option-implied skewness to forecast the future realized volatility for wheat, corn, and soybean futures market. They analyze the data set for crop futures traded on the CBOT for January 1990 to December 2011. Triantafyllou et al. (2015) report that risk-neutral option implied volatility and skewness have far superior predictive accuracy than the model based on historical volatility. Also, Triantafyllou et al. (2015) find significant predictive power of the variance risk premium to forecast the returns in these crop futures markets.

Furthermore, Triantafyllou et al. (2020) contribute to this discussion by analyzing implied volatility measures to predict the sudden price jumps in the agricultural commodity markets, not only the price volatility. Triantafyllou et al. (2020) utilize daily futures and options data for corn/wheat/soybeans traded on the CBOT from January 1990 to December 2011. Triantafyllou et al. (2020) model the probability of price jumps in a probit model and find the following: (i) more negative forward spreads (futures and spot price spread) indicate a higher probability of price jumps in the agricultural commodity markets, and (ii) higher option-implied measures (tail-risk measure; risk-neutral variance, i.e., implied volatility; variance risk premium) are associated with higher probability of price jumps. Triantafyllou et al. (2020) interpret that the negative forward spread is more like a convenience yield in the theory of storage that causes higher returns in the next period or price jumps in their analysis.

Moreover, Trujillo-Barrera et al. (2018) provide another interesting evidence of how option-implied volatility measures predict the ex-ante lean hog futures price density (not only standard point forecast). Note that these ex-ante price densities are the future conditional probability of price distribution. Trujillo-Barrera et al. (2018) consider daily settlement prices of lean hog futures and options contracts traded on the Chicago Mercantile Exchange (CME) from February 2002 to February 2017 and perform the forecasting exercise at a 2-week time horizon. Trujillo-Barrera et al. (2018) conclude that the risk-neutral and risk-adjusted forward-looking option-implied measures always outperform the traditional GARCH model with historical volatilities in predicting future price densities.

Adding another dimension to the context, it becomes quintessential to analyze the volatility spillover from other closely related assets. For instance, in the era of commodity financialization, risks can spill-over between closely related commodities. Marfatia et al. (2022) provide very recent evidence of such spillover of volatility between agricultural commodities. In particular, Marfatia et al. (2022) examine the role of co-volatility among China's agricultural futures (corn, cotton, palm, wheat, and soybean) and the role of volatility in the global oil market. Marfatia et al. (2022) argue that recently there has been a very close nexus between the energy sector and agriculture for several reasons, particularly the push toward bio-renewable fuels in several countries. Marfatia et al. (2022) utilize high-frequency data (5-minutes interval, intraday) from January 2013 to May 2018 in a multivariate heterogeneous autoregressive regression (MHAR) model that allows for co-volatility error dependence structure to conclude the following: (i) global oil volatility has almost no incremental information to forecast the volatility in the agricultural commodities, and (ii) MHAR model performs reasonably well for forecasting at 5-day ahead or 22-day ahead horizons. However, we don't account for such spillover mechanisms among commodities to focus on the main research objective of this study.

Stochastic volatility models have been another main strand of the literature to model the price returns and examine the underlying volatility process. Koekebakker and Lien (2004) follow this model suite to investigate the sudden and discontinuous price changes in the wheat futures market in the U.S. Koekebakker and Lien (2004) argue that these prices follow a jump-diffusion process and incorporate seasonality and maturity effects in their stochastic volatility model. They apply this framework to the CBOT wheat futures data for January 1989 to December 1999 and find that neglecting jump process, seasonality, and maturity effect led to severe mispricing of the wheat futures. Similarly, Wu et al. (2015) propose a risk-adjusted measure of implied volatility based on a jump-diffusion process. Wu et al. (2015) apply their model to the corn futures and options data for February 25, 1987, to June 30, 2010, and find that risk-adjusted model-free option-implied volatility measures are unbiased predictors with superior forecasting ability for the future realized volatility in the corn futures market.

Furthermore, Koopman et al. (2005) provide crucial empirical evidence using both time-series and stochastic volatility suite of models to forecast the daily variability of the S&P100 index. Koopman et al. (2005) argue that the more frequent data helps recover the underlying volatility process accurately; thus, it should have better forecasting ability for the future volatility. They consider three volatility measures to make such predictions: (i) historical volatility (calculated from the daily return series), (ii) implied volatility (calculated from the option data), and (iii) realized volatility (sum of the square of high-frequency returns within a day). They employ a daily tick-by-tick data set for January 1997 to November 2003 in four different models: (i) autoregressive fractional integrated moving average, (ii) unobserved component model based on Ornstein-Uhlenbeck process, (iii) stochastic volatility model, and (iv) GARCH model. Koopman et al. (2005) report that any model (either time-series based or stochastic volatility) with realized volatility as the explanatory variable has a higher prediction accuracy. Their findings can be of crucial significance to the present work as well. Given the data availability, this work can be extended to have the measure of realized volatility (i.e., the sum of the square of high-frequency returns within a day) as the dependent variable and investigate the efficacy of the gap between VIX and SVIX to forecast it. A dependent variable with less measurement error or less noise could help improve the forecasting exercise overall.

Similar evidence regarding informational efficiency was found in New Zealand's dairy industry. Fernandez-Perez et al. (2019) construct a dairy implied volatility index using the options traded on the New Zealand exchange on the whole milk powder futures. They utilize a dataset consisting of daily observations on futures and options for November 30, 2011, to January 8, 2018. Fernandez-Perez et al. (2019) find that implied volatility measures, along with the historical measures, have superior forecasting ability in both GARCH setup and the predictive regressions. Lastly, Liang et al. (2020) provide empirical evidence about the superior performance of implied volatility measures from the international stock market. In particular, Liang et al. (2020) consider eight international stock markets, namely: (i) SPX (U.S.), (ii) GDAXI (Germany), (iii) FCHI (France), (iv) FTSE (UK), (v) SMSI (Switzerland), (vi) N225 (Japan), (vii) KS11 (South Korea), and (viii) HIS (Hong Kong) from October 24, 2006 to December 31, 2018. Liang et al. (2020) employ the heterogeneous autoregressive framework and substantiate the following findings: (i) implied volatility measures have better forecasting abilities at any forecasting horizon from 1 day to 22 days, and (ii) the market's own implied volatility and first principal component of international markets' implied volatilities produce a superior forecasting performance.

The remainder of the article proceeds as follows: Section 2 describes the dataset utilized, section 3 presents the empirical methodology employed, section 4 briefly discusses the empirical results, and, finally, section 5 concludes with some policy implications.

2. Data

We source the daily settlement prices of corn and soybean futures and options contracts of different maturities from IVolatility.[2] We consider December 2, 2025 to January 31, 2023 as the time period of analysis in this study. We consider corn, soybean, and wheat futures and options contracts traded on the Chicago Mercantile Exchange (CME).[3] There are five standard futures contracts for corn (and wheat) traded on CME that expire in March, May, July, September, and December. There are several option contracts defined on these corn futures contracts as underlying assets[4]. Similarly, there are seven futures contracts available for soybeans on CME, which expire in January, March, May, July, August, September, and November[5]. Furthermore, one should note corn and soybean futures expire typically on the 14th day of the respective expiration month (or the previous trading date if the 14th of that month is not a trading day). Similarly, corn options

[2] https://www.ivolatility.com/home.j
[3] In the next revision, we plan to analyze nine more commodities: Soybean Oil, Soybean Meal, Cocoa, Light Sweet Crude Oil, Cotton No. 2, Live Cattle, Lean Hog, Henry Hub Natural Gas, and Sugar No. 11.
[4] Corn contract specification: https://www.cmegroup.com/markets/agriculture/grains/corn.contractSpecs.html
[5] Soybean contract specification: https://www.cmegroup.com/markets/agriculture/oilseeds/soybean.contractSpecs.options.html

contracts on a particular futures contract typically mature on the 3rd Friday of the month preceding the underlying futures maturity month. For instance, the May 2022 futures contract for corn expires on May 13, 2022, whereas the option contract that takes this May 2022 corn futures contract as underlying expires on April 22, 2022. One can access the detailed calendar for these grain futures and options contracts at Barchart[6]. One has to be very careful about assigning the exact expiration dates and IVolatility provides daily options premium data along with the underlying futures price. Recently, the CME has allowed weekly options trading on the agricultural futures, however, we remove all those weekly options from the analysis. Also, for all the following VIX and SVIX computations, we deal with out-of-the-money options with strike prices not too distant from the underlying futures price. For instance, if the underlying futures price is 100 cents then we only use options with strike prices between 90 and 110 cents to compute VIX or SVIX.

Furthermore, we need a risk-free interest rate until the options maturity date to compute VIX and SVIX. Given the data availability, we utilize the market yield on U.S. Treasury Securities at 3-month constant maturity (available daily for the relevant time period of this study) as the risk-free interest rate to expiration[7]. In an ideal world, one would like to get the risk-free interest at any time to the expiration date precisely. Such a risk-free interest rate will require interpolation (like a cubic spline) between 1-month and 3-month constant maturity rates. However, for brevity, we use 3-month constant maturity rates as the risk-free interest rates for the VIX and SVIX computations. Since we compute VIX and SVIX for the next thirty days, this assumption about the risk-free interest rate does not pose a severe threat to the empirical computational exercise. Lastly, we adopt the discrete method of VIX computation from the CBOE VIX white paper[8]. Similarly, we follow

[6] (i) Future expiration calendar: https://www.barchart.com/futures/futures-expirations/grains
(ii) Futures-option expiration calendar: https://www.barchart.com/futures/options-expirations/grains
[7] Downloaded from this link: https://fred.stlouisfed.org/series/DGS3MO
[8] https://cdn.cboe.com/resources/vix/vixwhite.pdf

Martin (2017) to compute SVIX discretely, as we don't observe continuous strike prices (K) in the real-world data.

3. Empirical Method

We follow a simple econometric regression framework proposed by Christiansen et al. (2012) to investigate the role, if any, of incremental information embedded in the gap between VIX and SVIX to forecast the realized volatility in the corn, soybean, and wheat futures markets. We measure realized annual volatility[9] as $RV_t = \sqrt{12} \times (\sqrt{\sum_{t=t+1}^{t+T} r_t^2})$, where T denotes the number of trading days in a month; r_t indicates the daily returns computed as $r_t = (\frac{F_t}{F_{t-1}} - 1) \times 100$. Note, F_t is the settlement price in the futures market on a particular trading date t. More specifically, this (slightly-different) specification of the realized-volatility graphically enables us to make a direct comparison with the forward looking implied volatility measures. At any trading date t, the realized-volatility constructed in this way captures the variation in the futures prices for the next 30-days. Similarly, VIX and SVIX measures also quantify the expected variation of underlying futures prices for a one-month ahead time period using premiums on options. In other words, we don’t need to introduce lead-lag structure between realized volatility and VIX or SVIX measures. Therefore, one can specify the following empirical regression framework to investigate the research objective of the present study:

$$RV_t = \alpha + \rho RV_{t-30} + \beta(VIX_t - SVIX_t) + \epsilon_t \qquad \dots (3)$$

It is a simple univariate autoregressive framework that is suitable for univariate forecasting. One can interpret this regression as follows: at each trading day t, a measure of realized volatility is

[9] This realized volatility RV_t is annualized to make it time-unit consistent with VIX and SVIX measure. These two implied measures are annualized in their construction.

available using the next 30 days' futures settlement prices, and we need to forecast or predict it using the gap between forward-looking implied volatility measures computed at date t. Here, the parameter β is of main interest, and given the findings of Martin (2017), we hypothesize it to be significantly different from zero. In other words, we test the hypothesis, $H_0: \beta = 0.$ Moreover, to make the analysis more robust, we also regress the following specification to assess the predictive ability of the gap between VIX and SVIX measures:

$$RV_t = \alpha + \rho RV_{t-30} + \gamma(|VIX_t - SVIX_t|) + \epsilon_t \qquad \dots (4)$$

This restricted specification enables us capture the predictive performance of the gap between VIX and SVIX measures by avoiding directional change of it. Similarly, we expect the parameter of interest γ to be statistically different from zero (i.e., $H_0: \gamma = 0$). Lastly, we also check for the incremental predictive performance of the gap between VIX and SVIX measures, if any, after accounting for the historical volatility and VIX (or SVIX) in the regression models as follows:

$$RV_t = \alpha + \rho RV_{t-30} + \beta(VIX_t) + \phi(VIX_t - SVIX_t) + \epsilon_t \qquad \dots (5)$$

$$RV_t = \alpha + \rho RV_{t-30} + \beta(VIX_t) + \delta(|VIX_t - SVIX_t|) + \epsilon_t \qquad \dots (6)$$

The above two regression models make the analysis even more interesting as the predictive abilities of the historical volatility and VIX have been very well documented in the recent literature. The statistical significance of ϕ ($H_0: \phi = 0$) and δ ($H_0: \delta = 0$) would indicate even superior predictive performance of the incremental information imbedded in the difference of VIX and SVIX measures.

4. Results

Table 1 reports the summary statistics of the variables used in the analysis. For corn, over the sample period, the average of (30-days ahead) realized volatility is 25.76% (annualized). Figure 2 provides a clear visualization of it. Similarly, average of the VIX and SVIX measure for corn is estimated to be 25.84% and 25.88% (Figures 3 and 4). Moreover, the variable of the main interest, mean of the gap between VIX and SVIX measures is -0.04 and with -0.64 and 1.00 as minimum and maximum values respectively (Figure 5). Notably, this is a contrasting finding from Martin (2017) as he obtains VIX greater than SVIX throughout the sample period (Figure 1). We find similar observations for soybean and wheat as well. For instance, the absolute maximum values of VIX-SVIX are estimated as 0.45 and 1.55 for soybean and wheat respectively.

Furthermore, Tables 2, 3, and 4 present the regression results for corn, soybean, and wheat respectively. In all these tables, we find that the VIX and SVIX measures have statistically significant predictive power to forecast the realized volatility even after accounting for the historical realized volatility term. This finding is in line with the literature discussed above. Most importantly, the coefficient of the gap between VIX and SVIX measures (VIX-SVIX) turns out to be statistically significant for soybean and wheat, but insignificant for corn. However, the coefficient on the absolute value of the gap between VIX and SVIX ($|VIX - SVIX|$) is estimated to have statistically significant predictive power to forecast 30-day ahead realized volatility, that too after accounting for the lagged historical realized volatility. Furthermore, after accounting for the lagged realized volatility and VIX or SVIX, the incremental predictive ability of the gap between VIX and SVIX shows some promising predictive performances for corn and wheat. For instance, in Table 2 (columns 6 and 8), the absolute gap measure ($|VIX - SVIX|$) is strongly statistically significant for corn. Similarly, in Table 4 (columns 5 and 7), the gap between VIX and

SVIX (VIX-SVIX) shows superior predictive performance for wheat. However, in Table 3, the incremental predictive power of (VIX-SVIX) or ($|VIX - SVIX|$) vanishes after accounting for the lagged realized volatility and VIX or SVIX for soybean. In other words, these findings seem to be a modest contribution to the literature pertaining to the option-implied information.

5. Conclusion

The predictive ability of the implied volatility measures has been well documented in the previously discussed literature. However, the predictive ability of the information content embedded in the difference of alternative implied volatility measures (VIX minus SVIX) seems to be worthwhile avenue to be explore. This study attempts to shed a light on the information content embedded in the gap between VIX and SVIX. Martin (2017) interprets VIX and SVIX as risk-neutral entropy and risk-neutral volatility of the underlying assets return respectively. Martin (2017) analytically shows–under the assumption that the stochastic discount factor (SDF) and returns are conditionally jointly log-normal–that SVIX should always be greater than VIX and that the magnitude of the gap between these two implied volatility measures should not be large. Indeed in this study, we find that the gap between VIX and SVIX is not very large for corn, soybean and wheat. However, SVIX is not always greater than VIX for all three commodities. Furthermore, the differences between these two implied measures are found to be statistically significant predictor of the future realized volatility for corn, soybean, and wheat futures market. Future work can make similar investigation for other commodities market like soybean oil, soybean meal, live cattle, lean hog, sugar, cotton, cocoa, crude oil and natural gas. A future research avenue could be to explore an important caveat of the present study, namely, that premiums used to compute VIX or SVIX are based on American style futures options. Notably, one can approximate European prices from the American option premiums and subsequently estimate implied volatility measures (see Martin and Wagner, 2019).

References

Algieri, B. 2021. “Fast & furious: Do psychological and legal factors affect commodity price volatility?.” *The World Economy*, *44*(4): 980-1017.

Andersen, T.G., T. Bollerslev, P.F. Christoffersen, and F.X. Diebold. 2006. “Volatility and correlation forecasting.” *Handbook of Economic Forecasting 1*:777-878.

Black, F. 1976. “The pricing of commodity contracts.” *Journal of Financial Economics 3*(1-2): 167-179.

Black, F. and M. Scholes. 1973. “The Pricing of Options and Corporate Liabilities.” *Journal of Political Economy 81*(3):637-654.

Bollerslev, T., B. Hood, J. Huss, and L. H. Pedersen. 2018. “Risk everywhere: Modeling and managing volatility.” *The Review of Financial Studies*, *31*(7): 2729-2773.

Christensen, B.J. and N.R. Prabhala. 1998. “The Relation Between Implied and Realized Volatility.” Journal of Financial Economics 50(2):125-150.

Christiansen, C., M. Schmeling, and A. Schrimpf. 2012. “A comprehensive look at financial volatility prediction by economic variables.” *Journal of Applied Econometrics*, *27*(6):956-977.

Demeterfi, K., E. Derman, M. Kamal, and J. Zou. 1999. “More Than You Ever Wanted to Know About Volatility Swaps.” Goldman Sachs Quantitative Strategies Research Notes.

Fernandez-Perez, A., B. Frijns, WE. Gafiatullina and A. Tourani-Rad. 2019. “Properties and the predictive power of implied volatility in the New Zealand dairy market.” *Journal of Futures Markets*, *39*(5): 612-631.

Giot, P. (2003). “The information content of implied volatility in agricultural commodity markets.” *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, *23*(5): 441-454.

Hollstein, F., M. Prokopczuk, and C. Würsig. 2020. Volatility term structures in commodity markets. *Journal of Futures Markets*, *40*(4):527-555.

Kanas, A. 2013. “The risk-return relation and VIX: evidence from the S&P 500.” *Empirical Economics*, *44*:1291-1314.

Koekebakker, S. and G. Lien. 2004. “Volatility and price jumps in agricultural futures prices—evidence from wheat options.” *American Journal of Agricultural Economics*, *86*(4):1018-1031.

Koopman, S. J., B. Jungbacker, and E. Hol. 2005. “Forecasting daily variability of the S&P 100 stock index using historical, realized, and implied volatility measurements.” *Journal of Empirical Finance*, *12*(3):445-475.

Liang, C., Y. Wei, and Y. Zhang. 2020. "Is implied volatility more informative for forecasting realized volatility: An international perspective." *Journal of Forecasting*, *39*(8):1253-1276.

Marfatia, H. A., Q. Ji, and J. Luo. 2022. "Forecasting the volatility of agricultural commodity futures: The role of co-volatility and oil volatility." *Journal of Forecasting*, *41*(2):383-404.

Martin, I. 2017. "What is the Expected Return on the Market?." *The Quarterly Journal of Economics*, *132*(1): 367-433.

Martin, I. W. and C. Wagner. 2019. "What is the Expected Return on a Stock?." *The Journal of Finance*, *74*(4):1887-1929.

Pan, Z., Y. Wang, L. Liu, and Q. Wang. 2019. "Improving volatility prediction and option valuation using VIX information: A volatility spillover GARCH model." *Journal of Futures Markets*, *39*(6):744-776.

Triantafyllou, A., G. Dotsis, and A. H. Sarris. 2015. "Volatility forecasting and time-varying variance risk premiums in grains commodity markets." *Journal of Agricultural Economics*, *66*(2): 329-357.

Triantafyllou, A., G. Dotsis, and A. Sarris. 2020. "Assessing the vulnerability to price spikes in agricultural commodity markets." *Journal of Agricultural Economics*, *71*(3):631-651.

Trujillo-Barrera, A., P. Garcia, and M. L. Mallory. 2018. "Short-term price density forecasts in the lean hog futures market." *European Review of Agricultural Economics*, *45*(1):121-142.

Wu, F., R. J. Myers, Z. Guan, and Z. Wang. 2015. "Risk-adjusted implied volatility and its performance in forecasting realized volatility in corn futures prices." *Journal of Empirical Finance*, *34*: 260-274.

Table 1: Summary Statistics of the variables used in the analysis.

Variables	No. of Obs.	Mean	Std. dev.	Min	Max
Corn					
Realized volatility	4,307	25.76	10.13	6.48	67.38
VIX	4,322	25.84	6.88	10.37	57.27
SVIX	4,322	25.88	6.87	10.40	57.29
(VIX-SVIX)	4,322	-0.04	0.09	-0.64	1.00
|VIX-SVIX|	4,322	0.07	0.06	0.00005	1.00
Soybean					
Realized volatility	4,307	21.04	8.32	7.73	62.97
VIX	4,322	22.20	6.34	9.86	54.58
SVIX	4,322	22.24	6.34	9.84	54.40
(VIX-SVIX)	4,322	-0.04	0.08	-0.34	0.45
|VIX-SVIX|	4,322	0.07	0.05	0.000005	0.45
Wheat					
Realized volatility	4,307	30.27	11.00	8.90	91.31
VIX	4,322	28.02	6.77	15.70	58.78
SVIX	4,322	28.08	6.75	15.80	59.40
(VIX-SVIX)	4,322	-0.06	0.08	-1.55	0.38
|VIX-SVIX|	4,322	0.08	0.06	0.00005	1.55

Note: |VIX-SVIX| denotes the absolute difference between VIX and SVIX measures.

Table 2: Regression results for Corn futures options.

Variables	(1) *RV*	(2) *RV*	(3) *RV*	(4) *RV*	(5) *RV*	(6) *RV*	(7) *RV*	(8) *RV*
RV_{t-30}	0.188***	0.189***	0.611***	0.609***	0.189***	0.191***	0.189***	0.193***
	(0.0209)	(0.0210)	(0.0131)	(0.0129)	(0.0206)	(0.0207)	(0.0206)	(0.0208)
VIX	0.802***				0.802***	0.791***		
	(0.0266)				(0.0267)	(0.0266)		
SVIX		0.802***					0.802***	0.791***
		(0.0267)					(0.0267)	(0.0268)
(VIX-SVIX)			0.718		-0.591		0.211	
			(1.462)		(1.354)		(1.351)	
|VIX-SVIX|				14.46***		11.14***		10.58***
				(1.837)		(1.701)		(1.687)
Constant	0.181	0.101	10.04***	9.021***	0.121	-0.427	0.121	-0.455
	(0.399)	(0.401)	(0.339)	(0.343)	(0.418)	(0.409)	(0.418)	(0.409)
Observations	4,285	4,285	4,285	4,285	4,285	4,285	4,285	4,285
R-squared	0.490	0.490	0.374	0.383	0.490	0.495	0.490	0.495

Note: RV is (30 days ahead) realized volatility. (VIX-SVIX) denotes difference between VIX and SVIX measures. |VIX-SVIX| indicates the absolute difference between VIX and SVIX measures. Robust standard errors in parentheses. Asterisks ***, **, * denote significance level at 1%, 5%, and 10% level respectively.

Table 3: Regression results for Soybean futures options.

Variables	(1) *RV*	(2) *RV*	(3) *RV*	(4) *RV*	(5) *RV*	(6) *RV*	(7) *RV*	(8) *RV*
RV_{t-30}	0.154***	0.156***	0.649***	0.632***	0.156***	0.156***	0.156***	0.158***
	(0.0196)	(0.0196)	(0.0148)	(0.0151)	(0.0199)	(0.0197)	(0.0199)	(0.0197)
VIX	0.812***				0.810***	0.803***		
	(0.0266)				(0.0270)	(0.0276)		
SVIX		0.810***					0.810***	0.802***
		(0.0266)					(0.0270)	(0.0277)
(VIX-SVIX)			-5.006***		-1.036		-0.227	
			(1.468)		(1.296)		(1.302)	
|VIX-SVIX|				14.67***		3.332*		2.680
				(2.038)		(1.958)		(1.971)
Constant	-0.241	-0.264	7.176***	6.756***	-0.269	-0.304	-0.269	-0.311
	(0.347)	(0.347)	(0.292)	(0.293)	(0.345)	(0.344)	(0.345)	(0.344)
Observations	4,285	4,285	4,285	4,285	4,285	4,285	4,285	4,285
R-squared	0.557	0.557	0.419	0.426	0.557	0.558	0.557	0.557

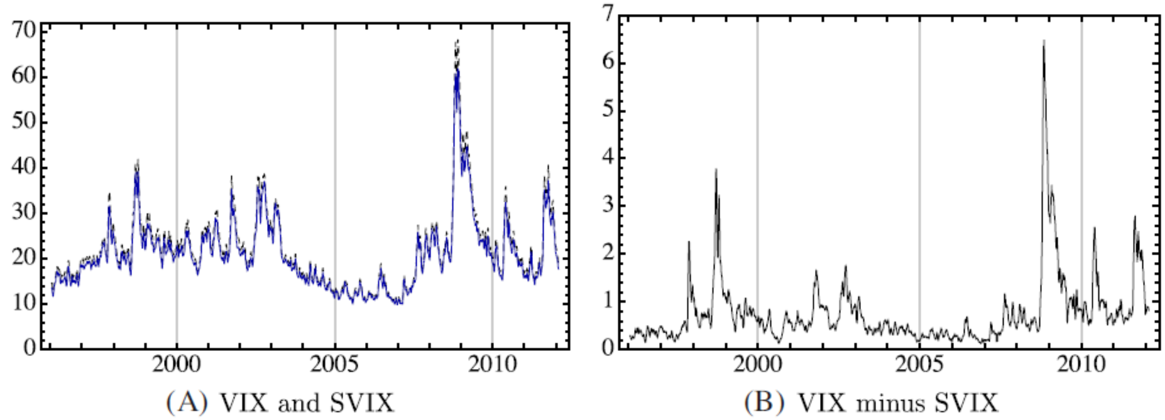
Note: RV is (30 days ahead) realized volatility. (VIX-SVIX) denotes difference between VIX and SVIX measures. |VIX-SVIX| indicates the absolute difference between VIX and SVIX measures. Robust standard errors in parentheses. Asterisks ***, **, * denote significance level at 1%, 5%, and 10% level respectively.

Table 4: Regression results for wheat futures options.

Variables	(1) RV	(2) RV	(3) RV	(4) RV	(5) RV	(6) RV	(7) RV	(8) RV
RV_{t-30}	0.0956***	0.0980***	0.530***	0.539***	0.0880***	0.0980***	0.0880***	0.100***
	(0.0213)	(0.0214)	(0.0170)	(0.0160)	(0.0212)	(0.0212)	(0.0212)	(0.0212)
VIX	0.898***				0.896***	0.893***		
	(0.0345)				(0.0346)	(0.0343)		
SVIX		0.896***					0.896***	0.892***
		(0.0346)					(0.0346)	(0.0343)
(VIX-SVIX)			5.775**		5.169***		6.065***	
			(2.664)		(2.004)		(2.000)	
|VIX-SVIX|				7.973***		3.811*		3.020
				(2.410)		(2.020)		(2.019)
Constant	2.238***	2.167***	14.61***	13.33***	2.819***	1.985***	2.819***	1.975***
	(0.584)	(0.588)	(0.565)	(0.488)	(0.646)	(0.604)	(0.646)	(0.605)
Observations	4,285	4,285	4,285	4,285	4,285	4,285	4,285	4,285
R-squared	0.400	0.399	0.292	0.292	0.401	0.400	0.401	0.400

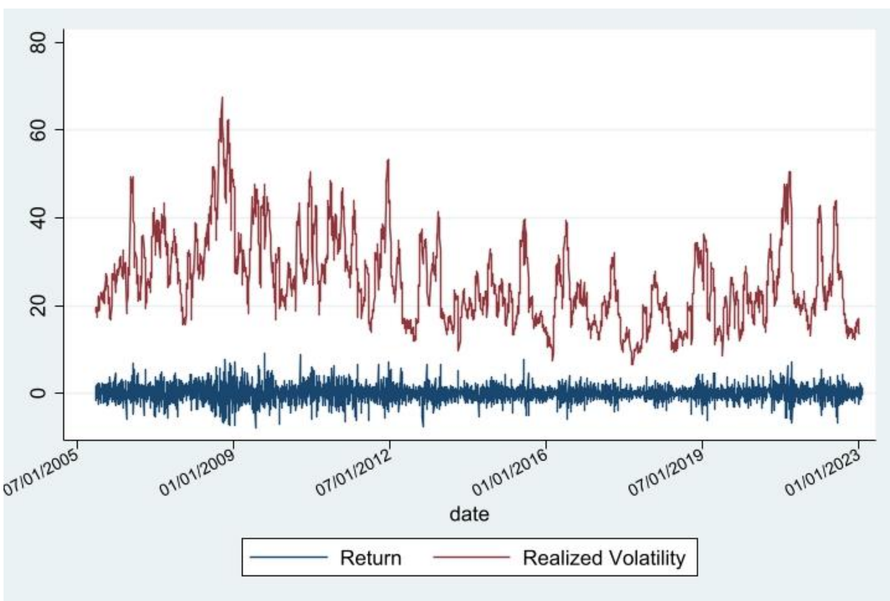
Note: RV is (30 days ahead) realized volatility. (VIX-SVIX) denotes difference between VIX and SVIX measures. |VIX-SVIX| indicates the absolute difference between VIX and SVIX measures. Robust standard errors in parentheses. Asterisks ***, **, * denote significance level at 1%, 5%, and 10% level respectively.

Figure 1: Gap between VIX and SVIX measure for S&P500 index



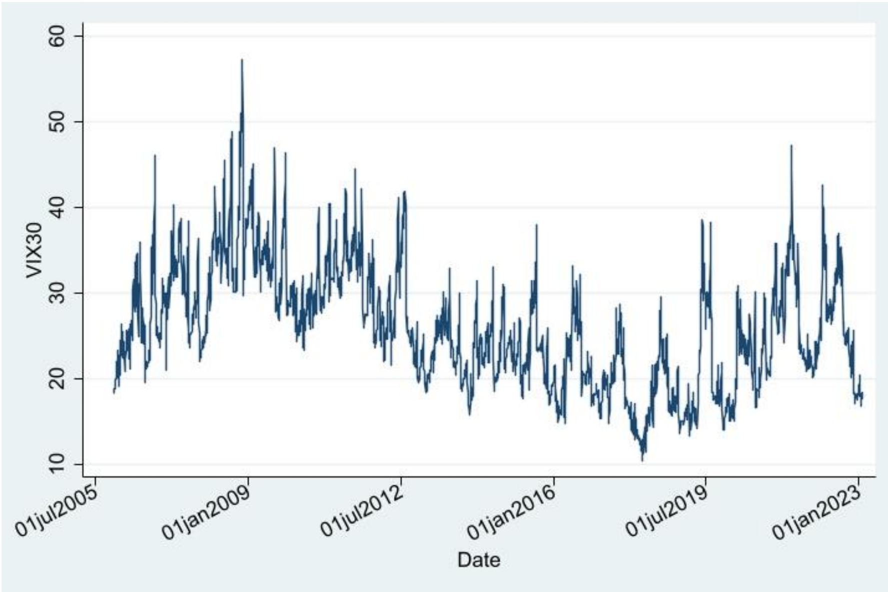
Source: Martin (2017)

Figure 2: Return and realized volatility for (next-month) Corn futures.



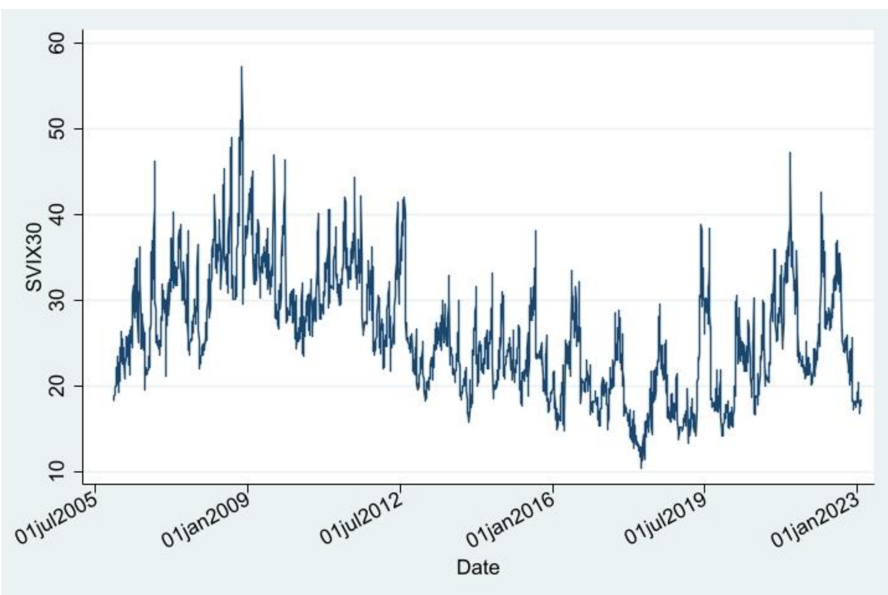
Source: Author's calculation

Figure 3: VIX for Corn.



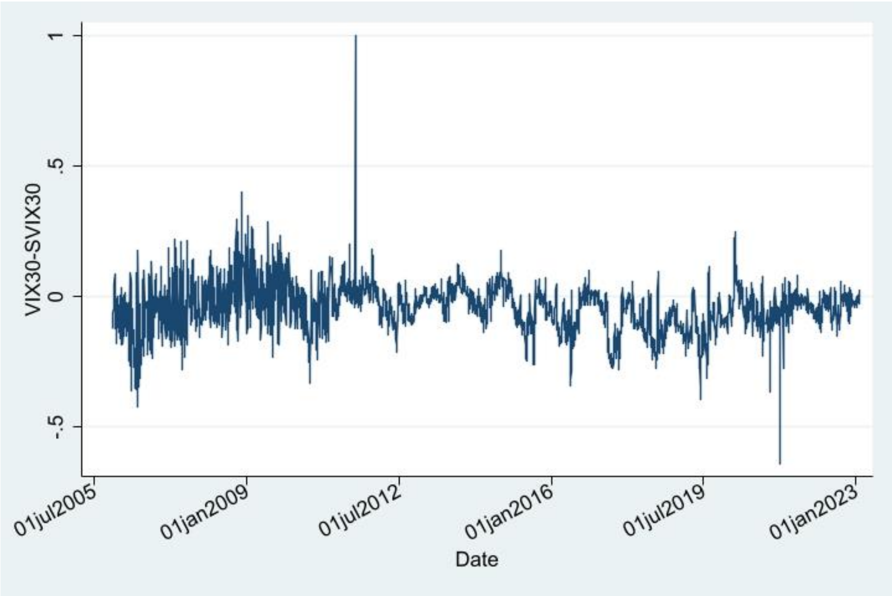
Source: Author's calculation

Figure 4: SVIX for Corn.



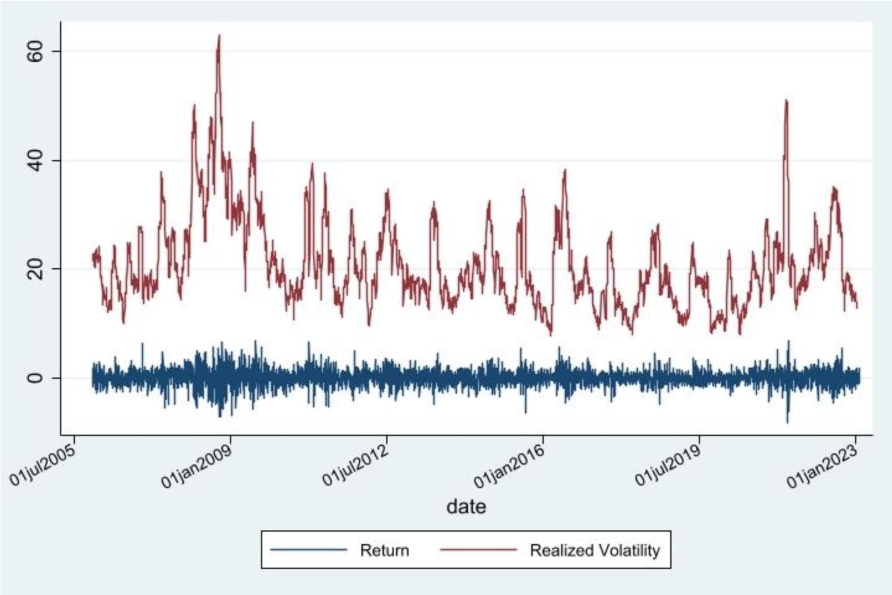
Source: Author's calculation

Figure 5: VIX minus SVIX for Corn.



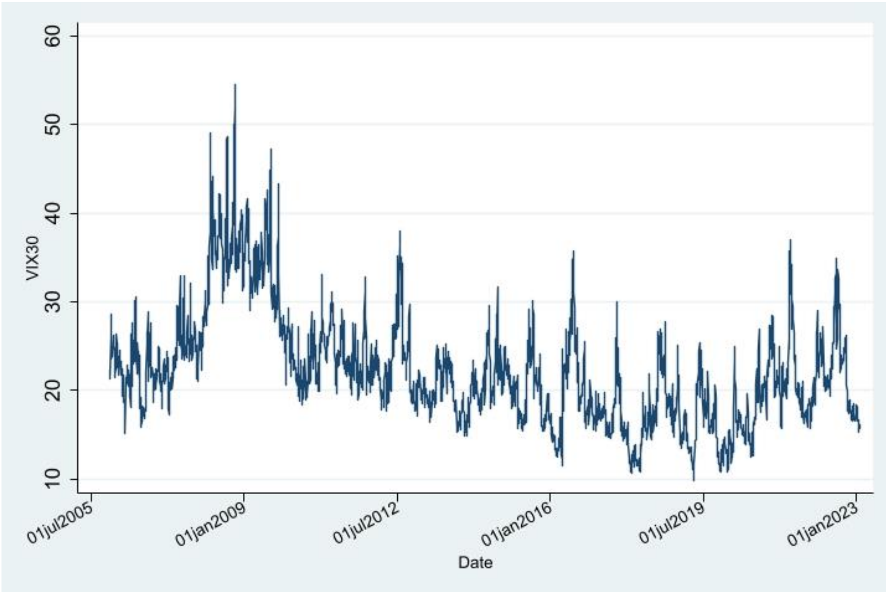
Source: Author's calculation.

Figure 6: Return and realized volatility for (next-month) Soybean futures.



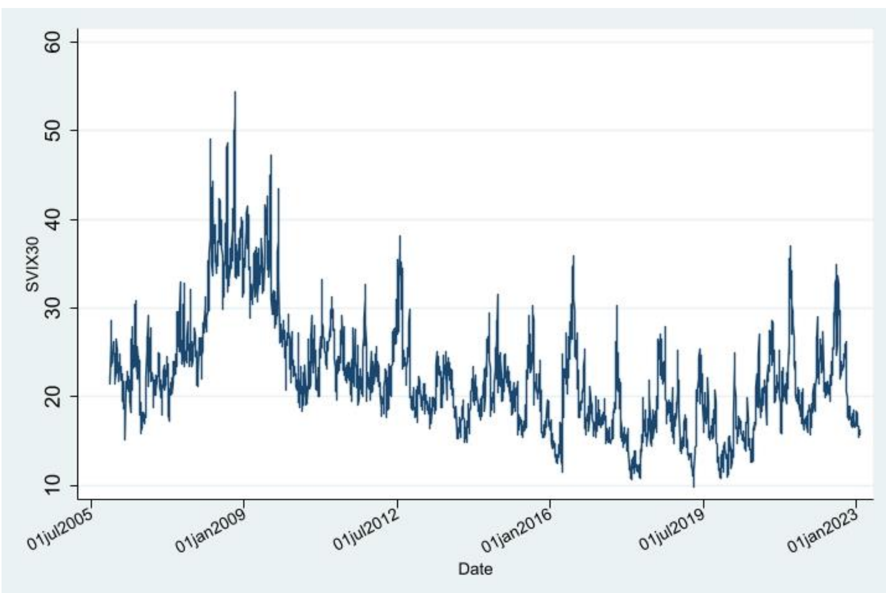
Source: Author's calculation.

Figure 7: VIX for Soybean.



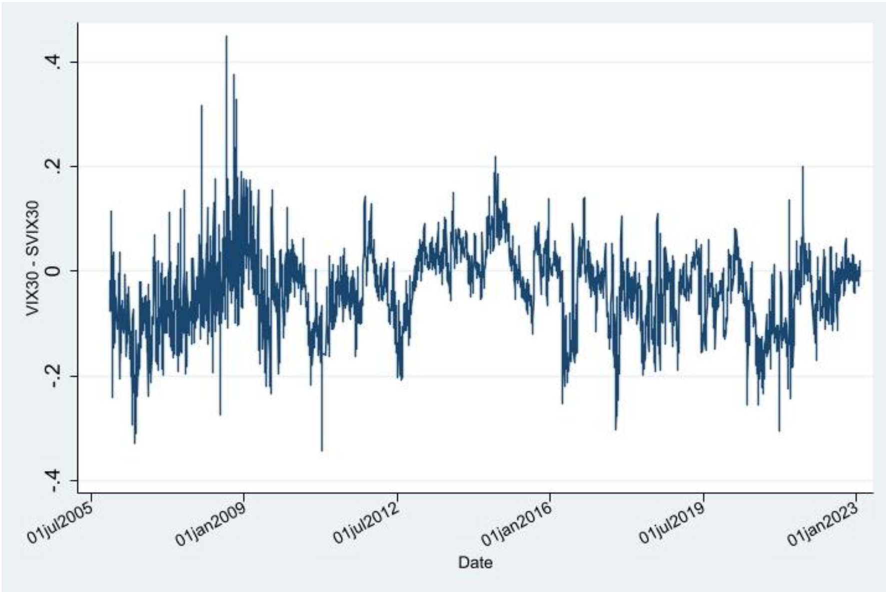
Source: Author's calculation.

Figure 8: SVIX for Soybean.



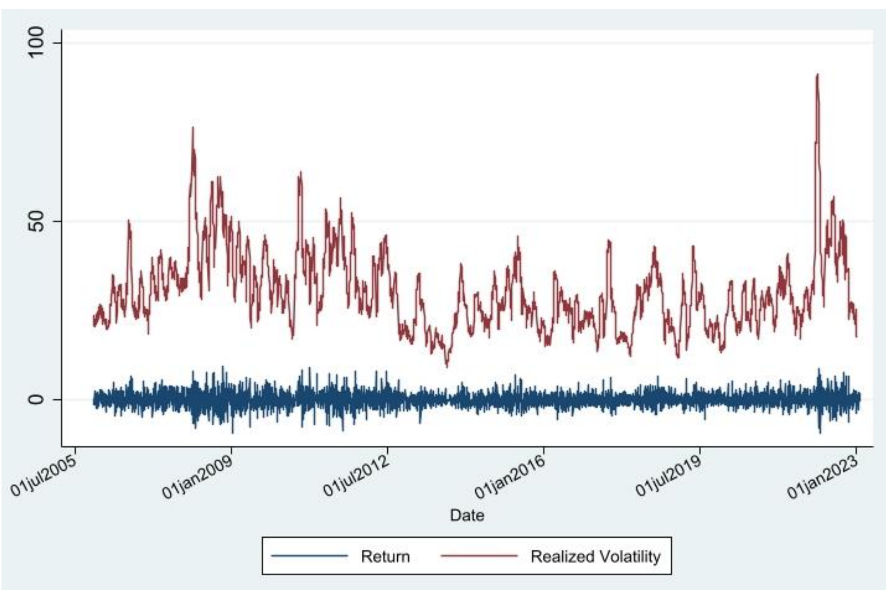
Source: Author's calculation.

Figure 9: VIX minus SVIX for Soybean.



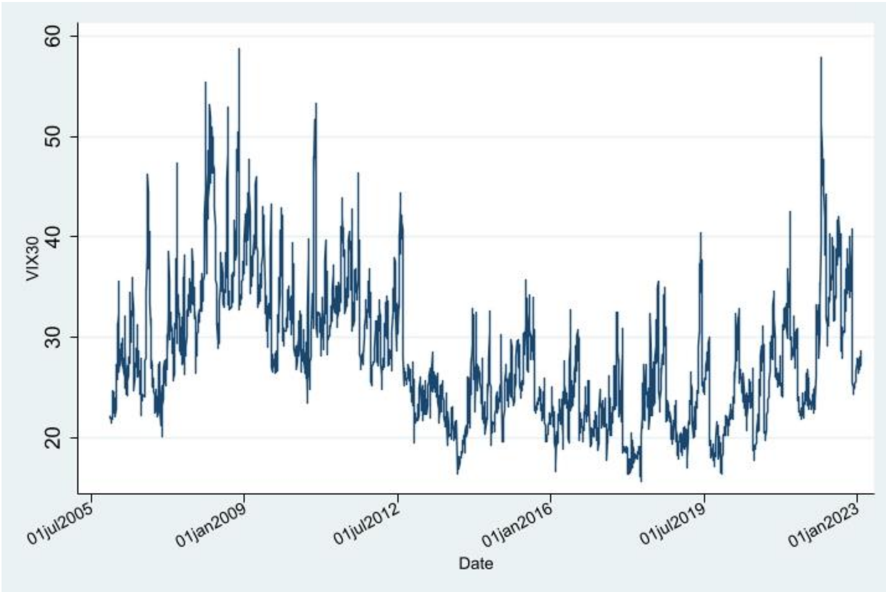
Source: Author's calculation.

Figure 10: Return and realized volatility for (next-month) Wheat futures.



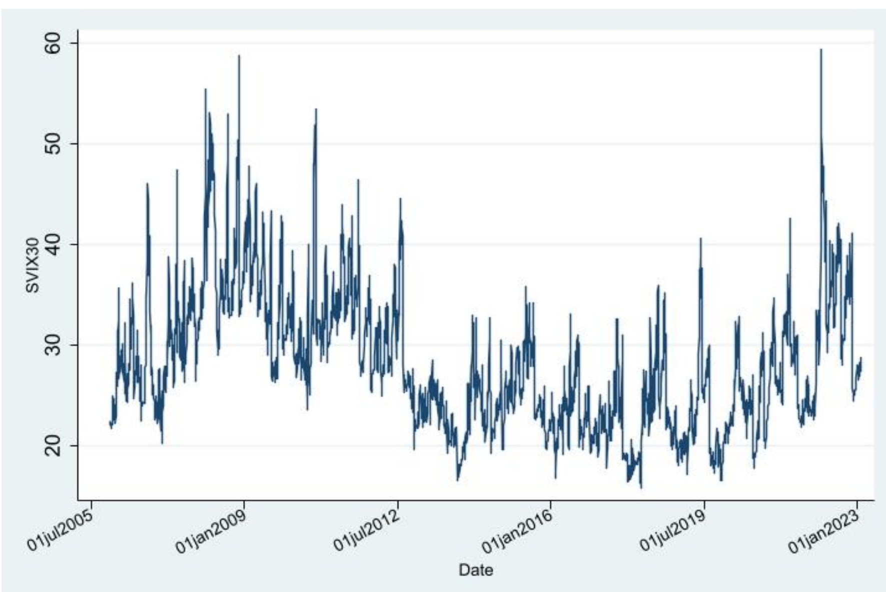
Source: Author's calculation.

Figure 11: VIX for Wheat.



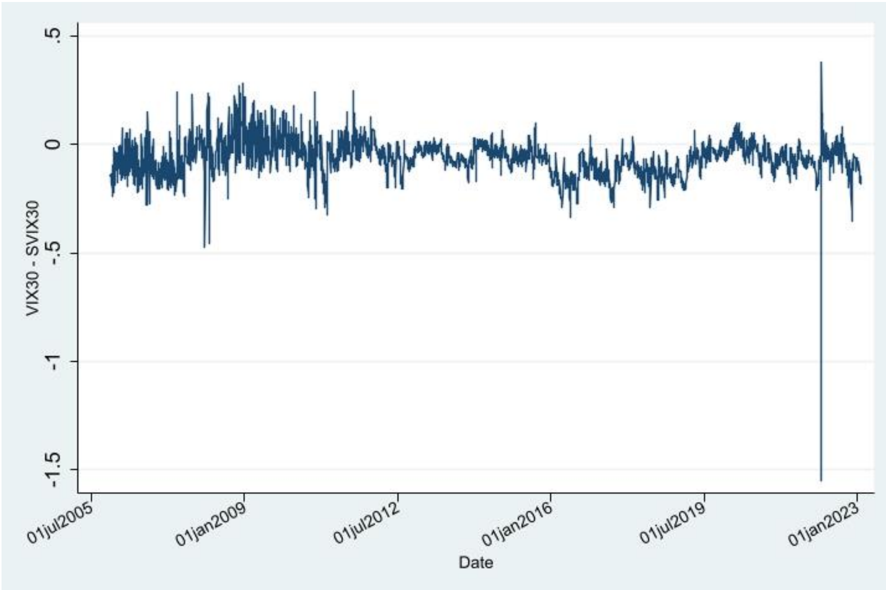
Source: Author's calculation.

Figure 12: SVIX for Wheat.



Source: Author's calculation.

Figure 13: VIX minus SVIX for Wheat.



Source: Author’s calculation.