Properties and the Predictive Power of Implied Volatility in Dairy Market

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Abstract

We examine the statistical properties and predictive power of an Implied Volatility Index derived from New Zealand Exchange (NZX) options on Whole Milk Powder futures. To construct the implied volatility index for the Dairy market (termed the DVIX) we follow an approach similar to the CBOE VXO methodology. The DVIX reveals an annual seasonality with a decrease in the DVIX in the months of April, May and June. We further document an inverse return-volatility relationship which is asymmetric, implying that increases in WMP futures prices are associated with larger absolute changes in the DVIX than decreases. In-sample, the results strongly suggest that the DVIX has a high information content regarding conditional variance and that the inclusion of historical information further improves the predictive power. Out-of-sample, we find that the DVIX provides substantial information about the future realized volatility. We also document that a combination of historical volatility and the DVIX provides the best out-of-sample forecasts.

Keywords: Agricultural commodities; implied volatility; milk powder; variance forecasting

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1 Introduction

New Zealand is the world's largest exporter of dairy commodities, representing approximately one third of international dairy trade each year. Almost half of global Whole Milk Powder (WMP) exports are sourced from NZ, making the dairy products one of the most important agricultural commodity for NZ. As of June 2017, New Zealand's top four dairy export products are: whole milk powder (44%), butter (11%), cheese (11%) and skim milk powder (9%).[5] Panel A of Figure 1 shows that the price of NZ milk powder exhibits a significant fluctuation over time, suggesting high volatility. This high volatility can have a significant impact on the ability of NZ dairy farmers to manage cash flow and service debt, and can have serious consequences for the health of NZ's most influential agricultural sector. In this paper, we estimate the implied volatility of WMP and study its predictive ability for future realized volatility.

Milk powder is one of the most volatile commodities globally.[6] Though it is well-accepted that historical volatility is a good proxy of future volatility, in this study we aim to improve this forecast. Ample evidence suggests that volatility forecasts based on option implied volatility outperform those that use historical information (see Jorion (1995), Szakmary, Ors, Kim and Davidson (2003), Fleming (1998), Blair, Poon and Taylor (2001), Triantafyllou, Dotsis and Sarris (2015) among others). Implied volatility is obtained by inverting an option pricing formula and is often interpreted as the expected volatility over the life of the option. Implied volatility is generally considered to be a superior predictor of future volatility due to the ability of the market participants to effectively incorporate all publicly available information as well as any additional information that is relevant for predicting volatility into security prices. By construction, implied volatility is a forward-looking measure, as opposed to the historical volatility which relies on historical data. Over the last three decades, extensive research for financial and non-financial markets has examined the information content of implied volatility (for an overview, see Poon and Granger (2003) and Gonzalez-Perez (2015)). It has been shown empirically that implied volatility produces superior forecasts of future volatility across different asset classes. For example, Giot (2003) finds that past squared returns (i.e., GARCH effects) provide no significant volatility information in addition to the lagged implied volatility for the cocoa and sugar futures contracts. Triantafyllou, Dotsis and Sarris (2015) compute the implied

[5] http://www.stats.govt.nz/browse_for_stats/industry_sectors/imports_and_exports/overseas-merchandise-trade/HS10-by-country.aspx

[6] Figure 2 depicts volatility of different commodities and S&P 500. For the period between December 2011 and January 2018 annualized standard deviation of weekly returns for WMP Futures equals to 37.1%, while for S&P 500, CRB Crude Oil, Gold, Cocoa and Sugar Indices it is equal to 12%, 34.5%, 23.9%, 31.3% and 33.6%, respectively.

variance for US wheat, corn and soybean futures. They find that for corn and wheat option-implied variance outperforms the historical information, while for soybeans both historical and implied variance are significant determinants of future realized variance.

This paper provides a comprehensive analysis of the information contained in the NZ dairy option market in predicting subsequent realized volatility and our contribution is threefold. First, we construct the dairy volatility index (DVIX) and analyze its statistical properties. The DVIX is a 22-trading day at-the-money implied volatility index constructed from four call and four put options. We observe that the DVIX exhibits month-of-the-year effect with the lower values during April, May and June. We also find an inverse relationship between one-day lagged returns and the changes in the DVIX. Second, we assess the in-sample forecasting performance of the DVIX in a GARCH-type setting. The results strongly suggest that the DVIX has a high information content regarding conditional variance and that the historical information only marginally improves the information content provided by the DVIX. Third, we evaluate implied volatility as a forecast for future realized volatility out-of-sample. Information content is measured in terms of the ability of the DVIX to forecast 1, 5, 10 and 22 day ahead volatility. The predictive performance of implied volatility is assessed against four alternative time-series forecasts: historical volatility realized during the past 30 trading days and GARCH-type forecasts. We find that the DVIX provides substantial information about future realized volatility, while being a biased estimate of the future realized volatility. We also document that a combination of historical volatility and the DVIX provides the best forecast accuracy for all forecast horizons.

To our knowledge, we are the first to construct and examine the predictive power of implied volatility for the dairy NZ market. The construction of the DVIX allows us to visualize the volatility in the dairy sector and emphasizes the necessity of using risk management techniques for farmers and manufacturers. The results of our paper are particularly important for decision makers in the financial and agricultural sectors who require a volatility estimate as an input for pricing and risk management.

The rest of the paper is structured as follows. Section 2 provides an overview on the measures of volatility and highlights an importance of implied volatility as a predictor of future volatility. Section 3 presents the data and the methodology of the DVIX construction. Section 4 explores the statistical properties of the DVIX and conducts in-sample and out-of-sample forecasting tests. Section 5 summarizes the main results of the paper.

2 Literature Review

2.1 Historical Versus Forward-Looking Volatility

There are two main types of volatility which are used to describe fluctuations of an asset's price. The first one is historical, or backward-looking volatility, and the second one is implied or forward-looking volatility.

The simplest measure of historical volatility is computed as the standard deviation of a set of past observations. A more sophisticated type of time-series models is presented by ARCH (Autoregressive Conditional Heteroscedasticity) and GARCH (Generalized ARCH) models introduced by Engle (1982) and Bollerslev (1986), respectively. GARCH models have been developed to account for 'stylized facts' documented in financial return series, such as volatility clustering (absolute or squared returns display a positive autocorrelation over several days), excess kurtosis (the distribution of returns displays a heavy tail) and leverage effect (negative stock market returns are associated with changes in volatility that are much larger than those associated with positive returns of similar size). In these models, the variance of residuals is not constant and the next period variance is conditional on information this period.

The implied volatility of an asset can be obtained from the market prices of options written on that asset. Option implied volatility is interpreted as a market's expectation about the volatility of an asset over the life of the option. The first volatility index (VIX) was introduced by the CBOE in 1993 and was computed using the implied volatilities from eight near-the-money options written on the S&P 100. In 2013, the CBOE, together with Goldman Sachs, revised their methodology. They incorporated out-of-the-money put and call options over a wide range of strike prices and replaced the S&P 100 options with S&P 500 options. The VIX gained market acceptance and later the CBOE expanded its range of volatility indexes for different stock indexes, interest rates, currency futures, ETFs and single stocks.[7] VIX-type indexes on commodity assets that trade as ETFs include crude oil, gold, silver and energy. In the context of our paper, the most interesting is the existence of the volatility indexes on agricultural commodities. In June 2011, the CBOE began disseminating volatility benchmarks based on CME Group corn and soybean option prices. In July 2012, the CBOE started disseminating volatility benchmark based on CME Group wheat options. The corn, soybean and wheat VIXes are based on the same updated methodology developed by the CBOE for the CBOE VIX.

Shortly after introduction the VIX became a benchmark of expected short-term market volatility and is known as the "investor fear gauge" due to its property to spike during

[7]The full list of all volatility indexes available at http://www.cboe.com/products/vix-index-volatility/volatility-indexes.

periods of market turmoil (Whaley (2009)). Another empirical observation is that the return-VIX relation is asymmetric, meaning that negative stock market moves are associated with much larger moves in the VIX than those associated with positive stock market moves of similar size (Fleming, Ostdiek and Whaley (1995), Whaley (2009)).[8] Padungsaksawasdi and Daigler (2014) examine the return-VIX relation between the commodity ETF (the euro, gold and oil) price changes and their associated VIXes and document several interesting results. First, they find that co-movement between the price changes of commodity ETFs and their respective VIX changes are much weaker than documented for stock indexes. Second, they find a positive contemporaneous return-VIX relation for gold. Third, they do not find asymmetric return-VIX relation for commodity market. The results highlight differences of the return-VIX relation among different asset classes.

2.2 Forecasting of Volatility

The widely used approaches to forecast volatility is to use time-series models (historical volatility, GARCH) and to use implied volatilities from options. For an overview of models used in volatility forecasting see Poon and Granger (2003). While some empirical studies find that GARCH models produce good forecast of future volatility over short periods (Andersen and Bollerslev (1998)), there is little evidence suggesting that GARCH models outperform option-implied estimates of future volatility. It has been found empirically that implied volatility produces superior forecasts of future volatility across different asset classes. For example, Jorion (1995) examines currency markets and shows that moving average and GARCH models are outperformed by option-implied forecasts. Fleming (1998) uses the S&P 100 options to extract implied volatility estimation and shows that the predictive power of implied volatility is superior to the GARCH(1,1) and historical volatility.[9] Blair, Poon and Taylor (2001) follow Fleming, Ostdiek and Whaley (1995) and use the VIX as a more accurate measurement of implied market volatility from S&P 100 options. They compare the out-of-sample accuracy of four different volatility forecasts

[8]Traditionally, there are two hypothesis which explain negative and asymmetric return-volatility relation. Black (1976) and Christie (1982) develop the leverage hypothesis, according to which when the stock price of a firm declines, the firm's debt-to-equity ratio increases, which makes the firm riskier and increases the volatility of its equity as a result. Campbell and Hentschel (1992) and French, Schwert and Stambaugh (1987) postulate volatility feedback hypothesis. If volatility is priced, an anticipated increase in volatility would raise the required rate of return, which leads to current stock price decline. Contrary to fundamental approach, Hibbert, Daigler and Dupoyet (2008) propose a behavioral approach, which relies on concepts of representativeness, affect, and extrapolation bias.

[9]The call (put) implied volatility is estimated from all call (put) option transactions within a 10-min window centered around the stock market close via averaging technique. Fleming (1998) chooses Fleming and Whaley (1994) modified binomial model as an option pricing model.

for 1, 5, 10 and 20 days ahead. The four models are the historic volatility, the daily-frequency ARCH forecast, the intraday volatility calculated from 5-min and overnight returns and the implied volatility index VIX. Results show that the VIX contains all the relevant forecasting information for the forecast horizons of 1, 5, 10 and 20 days ahead.

Another strand of research considers implied volatilities from options written on non-financial assets. Giot (2003) focuses on implied volatilities for agricultural commodities (cocoa, coffee, and sugar futures contracts). In-sample analysis shows that past squared returns (i.e., GARCH effects) provide no volatility information in addition to the lagged implied volatility for the cocoa futures contracts. Triantafyllou, Dotsis and Sarris (2015) compute model-free implied variance for US wheat, corn and soybean futures markets. Along with macroeconomic data they use historical 2-month realized variance, model-free implied variance, model-free implied skewness to explain 2-month ahead realized variance. They find that for corn and wheat past realized variance is an insignificant predictor of future realized variance, while for soybeans both historical and implied variance are significant determinants of future variance. Szakmary, Ors, Kim and Davidson (2003) examine a wide variety of asset classes, such as futures options on equity index, currencies and crude oil, short-term and long-term interest rates, agricultural commodities, livestock, metals, refined pertroleum products, and natural gas. They find that regardless of how the historical measures of volatility are modeled (simple 30-day moving average or GARCH), implied volatility outperforms historical volatility in predicting future realized volatility. Manfredo and Sanders (2004) examine the performance of implied volatility derived from live cattle options to forecast one-week volatility of live cattle futures prices. They find that implied volatility outperforms alternative forecasters and that it has improved its forecasting quality over time.

3 Data and Volatility Calculation

In this section we describe the NZX dairy derivatives market, as well as the data used to construct the DVIX. After discussing the methodology used to construct the DVIX, we present some summary statistics.

3.1 Background

In 2010 exchanges worldwide launched dairy derivatives to help the industry to hedge against dairy price volatility. In May 2010, the Chicago Mercantile Exchange was the first to launch International Skimmed Milk Powder futures and options contracts with physical delivery points located around the world. In the same month, the Frankfurt-based Eurex launched trading in-cash settled futures on Skimmed Milk Powder and Butter. The NZX launched its first derivative in the agricultural asset class, a Whole Milk Powder (WMP) Futures contract, in October 2010. It was followed by Skim Milk Powder (SMP) and Anhydrous Milk Fat (AMF) Futures contracts in February 2011. In November 2011 NZX launched WMP Options contracts and in December 2014 added Butter (BTR) Futures to its derivative product offering. Two most recent dairy derivatives are Milk Price (MKP) Futures and MKP Options, launched in May 2016 and June 2016, respectively. The futures contracts are quoted in US dollars, with one contract representing one tonne of product. NZX Dairy futures contracts are cash-settled rather than physically delivered. One WMP options contract represents the right to buy or sell one WMP futures contract and is also quoted in US dollars. Table 1 summarizes contracts specifications of all seven currently available dairy derivatives.

Amongst all NZX Dairy Derivatives WMP Futures make up the majority of volume traded. Figure 3 depicts aggregated trading volume for each month for all available dairy derivatives traded at the NZX. It confirms that the most actively traded dairy derivative is the WMP Futures, and the least traded is recently launched MKP Options. Figure 4, which depicts average open interest for each month for all available dairy derivatives traded at the NZX, confirms our conclusion. Across all seven dairy derivatives, the NZX recorded a trading volume of nearly 30,000 lots as of June 2017 and the average open interest of just over 48,500 lots. Figure 5 plots separately the trading volume for WMP options and futures. It shows that WMP Futures experience a growth in the trading volume and in June 2017 it amounted to about 15,000 lots. WMP options are less actively traded. The first trade occurred in June 2014, which is nearly two and a half years after their launch, and in June 2017 the trading volume amounted to about 5,600 lots.

3.2 Data

We use data on the NZX WMP Futures and Options contracts which we retrieve from NZX Research Centre with daily frequency. The database contains information about four sets of data: the trading levels and trading prices on the NZX Futures and Options; Global Dairy Trade auction prices; NZ milk production statistics; pastoral growth index for regions in NZ and on a national level. We collect option and futures daily settlement prices which we use to construct the dairy volatility index. The sample period starts on 30 November 2011 - the issue date for WMP Options and ends 8 January 2018. As a proxy for the risk-free rate we collect USD Overnight Index Swap (OIS) rates for various maturities available from DataStream. The estimation period of in-sample and out-of-sample analysis includes period from 5 January 2015 to 8 January 2018.[10]

3.3 Dairy Implied Volatility Computation

We compute the DVIX closely following the methodology applied to the early version of the CBOE VIX.[11] To construct the DVIX we need three types of information: 1) an option valuation model; 2) the values of the model's determinants (except for volatility); 3) an observed option price. For a given option price, inverting the pricing model yields the implied volatility of that option. We construct the DVIX from eight options, four calls and four puts, written on the WMP futures. The DVIX is constructed in a way that it is at-the-money and has a constant 30 calendar days (22 trading days) to expiration. To achieve the at-the-money implied volatility we combine in- and just-out-of the money options, and to achieve a constant time to expiry we combine the first and second nearby options. As option prices can be very volatile when approaching the expiration date, we use options which have at least eight trading days prior to expiration. To address the early exercise feature of American-style options we use quadratic approximation of American option values proposed by Barone-Adesi and Whaley (1987). A detailed explanation of the construction of the DVIX is provided in Appendix A2.

Figure 6 plots the DVIX over time. Particularly interesting is a noticeable drop in the DVIX value between 17 August 2016 and 23 August 2016 - a trading week from Wednesday to Tuesday (5 trading days). The value plummeted from nearly 0.40 to 0.145 and reached its minimum 0.075 on Tuesday. This rapid drop in the DVIX is likely to be caused by the positive news on the price of the WMP, which jumped 18.9% in the Global Dairy Trade[12] auction.[13] Average dairy prices increased by 12.7%. The highest value of 0.780 and 0.789 is achieved on 7 and 8 September 2015. Though for these two days we cannot identify any relevant news in NZ, during that time in mainland Europe farmers protested against falling dairy and meat prices.[14]

From Figure 6 one can observe that the DVIX has little variation in the beginning of

[10] As subsequent analysis will show, the DVIX values are nearly constant during years 2011-2014, thus we perform the in-sample and out-of-sample evaluation starting with year 2015.

[11] The new VIX formula requires the availability of options across a full range of strikes. In practice, only moderately in- or out-of-the-money WMP options are actively quoted and traded. Thus we choose to follow the CBOE VXO methodology which relies on eight near-the-money options at the two nearest maturities.

[12] Global Daily Trade auction was established in 2008 to provide a reliable, transparent, price discovery platform for globally traded dairy commodities. The auctions occur twice a month.

[13] http://www.nzherald.co.nz/business/news/article.cfm?c_id=3&objectid=11694758

[14] http://money.cnn.com/2015/09/07/news/economy/europe-milk-prices-protest/index.html https://www.theguardian.com/environment/2015/sep/07/farmers-clash-police-brussels-milk-meat-prices-protest

the sample, which is due to the low activity in WMP options, and fluctuates around the value of 0.49. Thus, we exclude the period from 30 of November 2011 till 30 of June 2014 for further analysis. For subsequent analysis it is important to check the stationarity of the DVIX. The daily DVIX level shows a high persistence with a first-order autocorrelation of 0.819. For example, the US Equity VIX shows a first-order autocorrelation of 0.866 during the same time period, indicating similarity between two volatility indices. The Augmented Dickey-Fuller test rejects the null hypothesis on non-stationarity at 1% level. This finding supports the stylized fact that volatility in the dairy market is a persistent but mean-reverting process.

We calculate summary statistics for daily DVIX changes over the period 1 July 2014 to 14 July 2017 and for three sub-periods. The choice of the sub-periods is dictated by the observation on the WMP options volume from Figure 5. One can notice a drop in the WMP options volume during the period December 2015 till November 2016. Table 2 presents the results. The mean daily change and the standard deviation remains relatively stable for the three sub-periods. The daily change in the DVIX exhibits positive excess kurtosis, meaning that distribution has fatter tails than a normal distribution. Skewness varies from negative to positive values, showing that the DVIX has a tendency to both abrupt decreases and increases. The first-order autocorrelation ranges quite significantly from -0.0931 to -0.2049. We can conclude, that statistical properties of the DVIX exhibit some variation, however not significant, and we can consider the whole period, starting at 1 July 2014, for the subsequent analysis.

4 The Information Content of Implied Volatility

In this section we test for the presence of seasonal patterns, examine the intertemporal relationship between WMP futures returns and the DVIX. We also investigate whether the DVIX contains information for future WMP futures volatility in-sample and out-of-sample.

4.1 Statistical Properties of the DVIX

Next, we want to check for some seasonalities in the DVIX. The day-of-the-week effect in the US stock market was first documented by Cross (1973), according to which the mean return between close of Friday and close of Monday is negative. As for the volatility index, Fleming, Ostdiek and Whaley (1995) investigate patterns in the VIX and find that the VIX declines throughout the week. To test the day-of-the-week effect in the DVIX, we estimate the following regression model:

$$VIX_t = \alpha + \beta_1 D_{1,t} + \beta_2 D_{2,t} + \beta_4 D_{3,t} + \beta_5 D_{5,t} + \epsilon_t, \tag{1}$$

where $D_{i,t}$ is a dummy variable for each day of the week. To avoid multicollinearity, we exclude the dummy variable for Wednesday. In Table 3 we report the results for the regression as well as Newey-West adjusted t-statistics in parentheses. We do not find any day-of-the-week effects, as all the coefficients on dummy variables are insignificant at any conventional significance level.

The second interesting pattern to investigate is a month-of-the-year seasonality. Shadbolt and Apparao (2016) notice that milk production in New Zealand is driven by the availability of pasture, which is in turn determined by rainfall. Milking season starts in August and ends in May. The milk production curve is the lowest during June and July ("winter milk"), and the end of the season, April and May. As a response to such variation the processing plants make long-life products, such as powders, cheeses and whey products at peak of the production curve. Since the supply of milk may affect the DVIX, we investigate monthly patterns in the DVIX. Figure 7 shows monthly behavior of the DVIX.[15] From the graph, one can see that the DVIX experiences its lowest volatility during April - July, potentially reflecting the fact, that during those month the availability of the WMP is not uncertain, as the uncertainty originates with the start of the season. For the more rigorous analysis of the month-of-the-year effect we consider the following regression:

$$VIX_t = \alpha + \sum_{i=2}^{12} \beta_i D_{i,t} + \epsilon_t, \tag{2}$$

where $D_{i,t}$ is a dummy variable for each month of the year. To avoid multicollinearity, we exclude the dummy variable for January. Results are presented in Table 3, and support our earlier observation on a lower DVIX level during April, May and June, but not July.

Next, we want to run a predictive regression for the DVIX. In this test we want to asses whether the past historical information is informative for the future DVIX. We run several regressions with the most general specification of the following form:

$$\begin{aligned} DVIX_t = \alpha_0 + \alpha_1 DVIX_{t-1} + \alpha_2 DVIX_{t-2} + \alpha_3 DVIX_{t-3} + \\ \alpha_4 DVIX_{t-4} + \alpha_5 DVIX_{t-5} + \beta_1 HISTV_{t-1} + \epsilon_t, \end{aligned} \tag{3}$$

where $HISTV$ is the sample standard deviation of nearby futures returns over the previous 30 days. In first model we only use the historical volatility as a predictor of the DVIX (α_1,...,$\alpha_5 = 0$). Next, we include only the lagged DVIXs to explain current value of the DVIX ($\beta_1 = 0$). Lastly, we include both the historical volatility and the lagged

[15] We delete the outliers during Septemper 2015 and August 2016.

values of the DVIX. We report the results in Table 4. When we only use lagged historical volatility to predict the next day DVIX, we find that historical volatility is a significant determinant with R^2 equal to 8.4%. Second models reveals that the DVIX is a persistent process with one-day lagged DVIX being positively associated with the next day DVIX, with explanatory power being 80.5%. When we include both historical volatility and the lagged DVIX, the significance of historical volatility drops out, and R^2 remains unchanged at 80.5%. Thus we find no evidence that the previous day historical volatility affects the current value of the DVIX, when we control for the lagged values of the DVIX, meaning that the DVIX subsumes information contained in historical volatility.

Lastly, we analyse co-movements of the DVIX with WMP futures returns. Padungsaksawasdi and Daigler (2014) examine the return-volatility relation for the commodity returns, namely the euro, gold and oil. They find that commodity markets behave differently from the stock market, which has the negative and asymmetric return-volatility relation. Following Fleming, Ostdiek and Whaley (1995), Frijns, Tallau and Tourani-Rad (2010) and Padungsaksawasdi and Daigler (2014) we estimate the following specification:

$$\begin{aligned} \Delta DVIX_t = \alpha_0 + \alpha_1 R_{t-2} + \alpha_2 R_{t-1} + \alpha_3 R_t + \alpha_4 R_{t+1} + \alpha_5 R_{t+2} + \\ \beta_1 |R_{t-2}| + \beta_2 |R_{t-1}| + \beta_3 |R_t| + \beta_4 |R_{t+1}| + \beta_5 |R_{t+2}| + \epsilon_t, \end{aligned} \tag{4}$$

where $\Delta DVIX_t$ is the change in the DVIX from day $t-1$ to t, R_{t-2}, R_{t-1} are two- and one-day lagged returns, R_{t+1}, R_{t+2} are one- and two-day lead returns and R_t is a contemporaneous return. Return is based on the price of the nearby futures contract, F, and daily return is defined as $R_t \equiv ln(F_t) - ln(F_{t-1})$. The model aims to capture the intertemporal relationship between return and implied volatility and incorporates the possible asymmetric reaction of volatility to upside and downside moves in the WMP market. The sum of $\alpha_i + \beta_i$ measures the asymmetry of the return-volatility relationship. Table 5 reports the results. The results show that there is no contemporaneous relationship between return and volatility, but there is significant negative coefficient for the one-day lagged return and volatility. The absolute return variable on a one-day lagged return also turns out to be significant and negative, indicating the asymmetric effect in the return-volatility relation. The impact on the change in DVIX when the return is positive is equal to $\alpha_2 + \beta_4$, or -0.3934, where as when the return is negative the impact is equal to $\alpha_2 - \beta_4$, or -0.0476. This means that if today the price of the WMP futures goes up, next day the DVIX exhibits decrease in value, while a drop in the WMP futures price is associated with an increase in the next-day option's implied volatility by a much smaller value. This finding supports the asymmetric effect between the return-volatility relation for the dairy market.

4.2 In-sample Volatility Forecasts

Empirical evidence suggests, that for several financial and non-financial assets, option implied volatility contains all relevant (including historical) information about future volatility. In this section we evaluate three models which aim to asses whether the DVIX contains information about future volatility of the WMP futures.

Our in-sample models are similar to the models by Kroner, Kneafsey and Claessens (1995) and Giot (2003), Blair, Poon and Taylor (2001). To compare the in-sample performance of several models which use historical information from futures and implied volatilities, we employ GARCH-type models. We estimate each model using daily log returns of the nearby futures, which has at least eight trading days prior to expiration. We compute daily futures returns always using two consecutive prices of the same contract, to avoid any effect which might result from rollover. We first specify the dynamics of the returns:

$$r_t = \mu + \epsilon_t,$$
$$\epsilon_t | \mathcal{F}_{t-1} \sim N(0, h_t),$$

where μ is an average return, $\mathcal{F}_{t-1}$ is the information set at time $t-1$ and ϵ_t is the error term at time t, which has a conditional Normal distribution with zero mean and variance h_t. We consider three specifications to model the variance equation. The first specification is a standard GARCH(1, 1) model and is defined by the following equation:

$$h_t = \omega + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 h_{t-1}. \tag{5}$$

In Equation 5 the conditional variance ia a function of a constant term, the squared error term from the last period and the last period conditional variance.

The second specification is a GARCH(1, 1)-DVIX model. It is defined by Equation 6 and uses both historical information and forward-looking information from option market:

$$h_t = \omega + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 h_{t-1} + \beta_1 DVIX_{t-1}^2, \tag{6}$$

where $DVIX_{t-1}$ is the daily implied volatility computed from the DVIX as $DVIX/\sqrt{252}$.

The third model ignores historical information and uses only information from option market. It is called a GARCH(0, 0) - DVIX model and is defined by Equation 7:

$$h_t = \omega + \beta_1 DVIX_{t-1}^2. \tag{7}$$

We estimate the parameters of the models by maximizing the log-likelihood functions, with the constraints $\omega \geq 0$, $\alpha_1 \geq 0, \alpha_2 \geq 0, \beta_1 \geq 0$, which ensure the non-negativity of the conditional variance process. We present the results in Table 6. In the GARCH(1,

1) specification the coefficient α_2 is close to 1, which is consistent with the documented clustering of volatility. Including the $DVIX_{t-1}$ in the variance equation leads to the decrease in the value of α_2, as the $DVIX_{t-1}$ takes into account a part of the GARCH effect. The GARCH(1, 1)-DVIX model has the highest log-likelihood of 1920.97, then follows the GARCH(0, 0)-DVIX with the log-likelihood of 1891.8 and the log-likelihood of GARCH(1, 1) is 1885.76. To test for the added value of the implied volatility we use the likelihood ratio (LR) test, calculated as twice the difference between the log-likelihoods. For the GARCH(1, 1) versus the GARCH(1, 1)-DVIX, results suggest that we can reject the null hypothesis of $\beta_1 = 0$ at the 1% level (the LR statistics is 35.21), suggesting that the augmented GARCH(1, 1)-DVIX model outperforms the GARCH(1, 1). Next, we compare the models GARCH(1, 1)-DVIX and GARCH(0, 0)-DVIX, the test statistic is equal to 29.17, thus we reject the null hypothesis that the past information does not add significant variance information at the 1% level. The estimation results show that the augmented GARCH(1, 1)-DVIX model performs significantly better than the standard GARCH(1, 1), but the DVIX alone does not subsumes all information relevant for predicting future variance.

4.3 Out-of-sample Volatility Forecasts

After assessing the in-sample forecast performance of several models, we move to the most important part - evaluation of the out-of-sample forecasting power. The predictive performance of the DVIX is evaluated against four alternative predictors of volatility, the GARCH, EGARCH, GJR-GARCH (later referred to as GARCH-type models) and historical volatility. To obtain GARCH-type volatility forecast over the T-period horizon we simply find the average of T individual forecasts at horizons $1, 2, ..., T$, annualize it and then take a square root (see Kroner, Kneafsey and Claessens (1995), Jorion (1995)):

$$GARCHV_{t,t+T} = \sqrt{\frac{252}{T} \sum_{j=1}^{T} \widehat{h}_j}. \tag{8}$$

Another alternative of a time-series model for the volatility is a simple historical average, estimated for example over a 30-day window, for each day t (see Szakmary, Ors, Kim and Davidson (2003)):

$$HISTV_t = \sqrt{\frac{252}{30} \sum_{j=1}^{30} R^2_{t-j+1}}. \tag{9}$$

Volatility is an unobservable variable and should be estimated. To proxy for actual ex-post volatility at each date t during the next T trading days, we use a set of daily squared returns according to the following equation:

$$RV_{t,t+T} = \sqrt{\frac{252}{T}\sum_{j=1}^{T} R_{t+j}^2}. \tag{10}$$

The realized volatility during the interval T is expressed in annual terms.

GARCH-type specifications are estimated for daily futures returns from 1 December 2011 to 2 July 2015 and the forecasts for the conditional variance are made for the next $T = 22$ days, 10 days, 5 days and 1 day, using estimated parameters. The data are then rolled forward one day, keeping the estimation window of the same size by discarding the last observation from the previous estimation. The 22-steps-ahead forecasts provide prediction for 3 July 2015 to 14 June 2017 inclusive, totaling 485 observations. The 10-steps-ahead forecasts provide prediction for 3 July 2015 to 30 June 2017 inclusive, totaling 497 observations. The 5-steps-ahead forecasts provide prediction for 3 July 2015 to 7 July 2017 inclusive, totaling 502 observations. The 1-step-ahead forecasts provide prediction for 3 July 2015 to 13 July 2017 inclusive, totaling 506 observations.

Following the existing literature (Szakmary, Ors, Kim and Davidson (2003), Egelkraut and Garcia (2006), Brittain, Garcia and Irwin (2011)) we address three different questions related to the bias and information content of the different volatility forecasts. First, we want to investigate whether any of the forecasts defined previously is an unbiased forecast of future realized volatility. To answer this question we estimate a univariate regression of the form:

$$RV_{t,t+T} = \alpha + \beta X_t + \epsilon_{t,t+T}, \tag{11}$$

where X_t is either a time-series forecast of volatility, such as $HISTV_t$ or a more sophisticated GARCH-type volatility, or the $DVIX_t$ volatility forecast. If X_t is an unbiased estimate of future realized volatility, then in Equation 11 the intercept should be zero and the slope coefficients should be one. We use a Wald test to test the joint hypothesis $H_0 : \alpha = 0 \text{ and } \beta = 1$.

Panel A of Table 7 reports the results for unbiasedness tests. For each five models, reported in first five columns, we present the regression coefficients along with t-statistics, where the standard errors of the estimates are adjusted for serial correlation and heteroscedasticity using the Newey-West (1987) procedure. We discuss unbiasedness of the forecasters only for the forecast horizon of $T = 22$, as the DVIX is the 22 trading days implied volatility of the WMP futures expressed as an annual number. We find that all slope coefficients are smaller than one, ranging from 0.425 for EGARCHV to 0.817 for GARCHV. The intercept is significantly different from zero for HISTV and EGARCHV. A χ^2 test statistics with p-values in brackets strongly rejects the joint hypothesis $\alpha = 0$ and $\beta = 1$ for all the models except for the estimate which is produced by the standard GARCH model. The results suggest that HISTV, EGARCHV, GJR-GARCHV and DVIX are biased estimates of the future realize volatility.

Although unbiasedness is a desired property, a bias of a known form does not affect a predictive power of a forecaster. In our next question, we want to compare the predictive power of the various forecasters for different horizons. For that, we again estimate regressions of the realized volatility against the various forecasters, described by Equation 11, and compare the R^2. For example, if the DVIX forecasts the future realized volatility better than time-series forecasts, then the R^2 from the corresponding regression needs to be the highest. First five columns of Table 7 present estimation results for all the models and for the different forecast horizons. Results imply that all five different volatility measures contain important information about future volatility, as all slope coefficients are positive and significant. Comparing the explanatory power for the different forecast horizons reveals an interesting pattern. The degree of predictability offered by different volatility measures decreases as we decrease the forecast horizon from 22 to 1 trading day (from the highest of 22.7% to 0.8%). We attribute it to the fact that the realized volatility expressed by Equation 10 for short horizons might be a noisy proxy for the true volatility, as the prices of futures contracts which we use to calculate daily returns often remain unchanged for the two consecutive days, thus yielding zero returns. We find that the historical volatility HISTV outperforms all alternative forecasters for all the forecast horizons, supported by the highest R^2 value. The DVIX shows the second best result in forecasting the subsequent realized volatility. At the 22-day horizon, the R^2 coefficient is equal to 22.7% for the model which includes HISTV as a forecast for future realized volatility in comparison to 14.1% for the model with the DVIX. At the 10-day horizon, the difference in R^2 diminishes to 11.2% vs. 11.1%. At the 5-day horizon, the R^2 is 6.9% vs. 5.8% and at the 1-day horizon 1.9% vs. 1.6%. GARCH-type forecasters do not produce better forecast than HIST or DVIX at any of the horizons.

In the third question we want to assess whether the DVIX efficiently impounds all information about future realized volatility, including what represented by time-series forecasts. To answer this question, we need to consider the results from the encompassing regressions involving the DVIX and either the HISTV or GARCH-type forecasts:

$$RV_{t,t+T} = \alpha + \beta_1 TSV_t + \beta_2 DVIX_t + \epsilon_{t,t+T}. \tag{12}$$

If the DVIX is the informationally efficient predictor of the subsequent realized volatility and the time-series forecasts contain no information beyond what is already included in the DVIX, then we should expect $\beta_1 = 0$ in Equation 12. If both β_1 and β_2 are significant, then the time-series forecast complements the DVIX. The estimation results for four different forecast horizons and four models are reported in columns six through nine of Table

7. At the 22-day horizon we find that the DVIX efficiently impounds all information when the alternative volatility forecast is modeled with GJR-GARCHV estimate, indicated by the insignificant β_1 coefficient. However, when the alternative volatility forecast is modeled with HISTV, GARCHV or EGARCHV, we find that both approaches complement each other. When we look at the shorter-term horizons, we find that the DVIX efficiently impounds all information when the alternative volatility forecast is modeled with the GARCH-type models. However, HISTV offers some additional information which is not captured by the DVIX alone. We also notice that the model which includes both HISTV forecast and the DVIX produces the highest R^2, representing the best combination of the time-series and implied volatility estimates for predicting subsequent realized volatility. For the 22-day horizon, movements in HISTV alone can explain 22.7% of the variability in subsequent realized volatility, while the combination of the DVIX and HISTV can explain 26.9%, suggesting that the HISTV forecast offers some additional information which is not captured by the DVIX.

Previous results show that the combination of two volatility forecasts (a time-series forecast with the DVIX) has a better predictive power, measured by the R^2, than a time-series forecast alone. Following Rapach, Strauss and Zhou (2010) we compare the mean squared prediction error (MSPE) for the predictive regression with one forecaster against a combination of two volatility forecasters. We construct the out-of-sample R^2 statistic, R^2_{OS}, which measures the reduction in MSPE for a long model relative to a parsimonious model. R^2_{OS} is defined as follows:

$$R^2_{OS} = 1 - \frac{\sum_{i=1}^{q}(\sigma_i - \hat{\sigma}_i^{large})^2}{\sum_{i=1}^{q}(\sigma_i - \hat{\sigma}_i^{parsimonious})^2}, \qquad (13)$$

where σ is realized volatility and $\hat{\sigma}^{parsimonious}$ ($\hat{\sigma}^{large}$) is a forecast of σ constructed by using a time-series forecast (a time-series forecast and the DVIX), q is a number of data points in out-of-sample forecast. As in Clark and West (2007) we generate out-of-sample forecasts of the realized volatility using an expanding estimation window. More specifically, we divide the total sample from 3 July 2015 to 8 January 2018 into two equal sub-samples, an in-sample portion of the first m observations and an out-of-sample portion of the last q observations. We construct a forecast using only the data available up to the time at which the forecast is made. To form initial out-of-sample forecast, we use regression coefficients from Equations 11 and 12, estimated on the evaluation period of m observations, the next out-of-sample forecast uses regression estimates based on m+1 observations. The last out-of-sample forecast is based on $m + q - 1$ observations. When $R^2_{OS} > 0$, a long model forecast outperforms a parsimonious forecast. We conduct Clark and West (2007) test to find out whether a long model has a significantly lower MSPE than the parsimonious model. Statistic of Clark and West (2007) is an adjusted version of Diebold and Mariano (1995) and West (1996) statistic, and can be used for comparing forecasts from nested models. The null hypothesis of the test is that there is no difference in the accuracy of two forecasts (equal MSPE). Under the alternative, MSPE from a larger model is less than that of a parsimonious model. Table 8 shows the results for 4 different forecasting horizons. Almost each entry of Table 8 is positive and statistically significant, which means that combining the DVIX with a time-series forecaster improves an accuracy of realized volatility forecasting. We also notice that the statistical significance of the R^2_{OS} statistic falls as we shorten the forecasting horizon. This finding is intuitive, as the DVIX is 22-trading days estimate of future volatility, and its forecasting performance deteriorates on lower forecasting horizons.

5 Conclusions

In this paper we evaluate the ability of options implied volatility to forecast future realized volatility in New Zealand's largest goods export sector - the dairy sector. To conduct both in-sample and out-of-sample analysis we use data for the most actively traded NZX Dairy Derivatives - WMP futures and options contracts. We compare two basic approaches in volatility forecasting exercise - time-series models and the market-based forecast recovered from the option market. The time-series predictors include the historical volatility and GARCH-type forecasts. To construct the dairy implied volatility index, we closely follow the CBOE VXO methodology. Before investigating the forecasting performance of the DVIX we asses its time-series properties, seasonalities and the relationship between the DVIX and WMP futures returns.

The analysis of the intraweek pattern does not reveal any day-of-the-week effect in the DVIX. While the investigation of seasonalities at the monthly level reveals a decrease in the DVIX during April, May and June - coinciding with months of the lowest production of milk in NZ. We also find that an increase in the implied volatility at time t is associated with a decline in the WMP futures returns at time $t-1$, suggesting an inverse one day lagged return-volatility relationship. Further investigation shows that this relationship is asymmetric. Positive moves in the WMP Futures prices are associated with larger absolute changes in the DVIX than negative moves in the WMP Futures prices.

Next, we compare the in-sample performance of three different models designed for predicting conditional future variance: a standard GARCH model which only uses historical information, a GARCH model which uses both historical information and implied volatility, a model which uses the information of the DVIX only. The results strongly suggest that the DVIX has a high information content regarding conditional variance and that the inclusion of historical information further improves the model's fit.

Finally, we perform the out-of-sample forecast of the future realized volatility using the DVIX and the other alternative volatility forecasts. The forecast horizons range from 22 trading days to 1 day. While we find that the DVIX is not unbiased estimate of the future realized volatility, it provides substantial information about future realized volatility. We also document that the combination of historical information and the DVIX provides the best forecast accuracy for all forecast horizons.

To our knowledge, we are the first who construct and examine the predictive power of implied volatility for the dairy NZ sector. The results of our paper are particularly important for decision makers in financial and agricultural sector who requires the estimate of volatility for pricing and risk management purposes. By constructing the implied volatility index we have created a measure of volatility in the dairy sector. The DVIX quantifies volatility and by comparing its current level with some historical values one can gauge the behavior of the NZ dairy market.

A1 Approximation of American Option Values by Barone-Adesi and Whaley and Its Inversion

Let F denote the current futures price, T is the time to expiration of the futures contract, σ is volatility and X is the strike price of an American option on futures. Let c denote the value of a European call option (Black and Scholes (1973)). According to Barone-Adesi and Whaley (1987), the value C of an American futures call option is approximated by Equations A.1 - A.7

$$C = \begin{cases} c(F,T,X) + A_2\left[\frac{F}{F^*}\right]^{q_2}, & F < F^* \\ F - X, & F \geqslant F^* \end{cases} \tag{A.1}$$

$$c(F,T,X) = Fe^{-rT}N(d_1) - Xe^{-rT}N(d_2) \tag{A.2}$$

$$d_1 = \frac{ln(\frac{F}{X}) + 0.5\sigma^2 T}{\sigma\sqrt{T}} \tag{A.3}$$

$$d_2 = d_1 - \sigma\sqrt{T} \tag{A.4}$$

$$A_2 = [\frac{F^*}{q_2}]\{1 - e^{-rT}N[d_1(F^*)]\} \tag{A.5}$$

$$q_2 = \frac{1}{2}[1 + \sqrt{1 + \frac{8r}{\sigma^2(1 - e^{-rT})}}]. \tag{A.6}$$

The critical value F^* is defined as a solution of

$$F^* - X = c(F^*) + A_2(F^*). \tag{A.7}$$

The approximation formulas for an American futures put option are similar and are described by the following set of Equations A.8 - A.14:

$$P = \begin{cases} p(F,T,X) + A_1\left[\frac{F}{F^{**}}\right]^{q_1}, & F > F^* \\ X - F, & F \leq F^* \end{cases} \tag{A.8}$$

$$p(F,T,X) = Xe^{-rT}N(-d_2) - Fe^{-rT}N(-d_1) \tag{A.9}$$

$$d_1 = \frac{ln(\frac{F}{X}) + 0.5\sigma^2 T}{\sigma\sqrt{T}} \tag{A.10}$$

$$d_2 = d_1 - \sigma\sqrt{T} \tag{A.11}$$

$$A_1 = -[\frac{F^{**}}{q_1}]\{1 - e^{-rT}N[-d_1(F^{**})]\} \tag{A.12}$$

$$q_1 = \frac{1}{2}[1 - \sqrt{1 + \frac{8r}{\sigma^2(1 - e^{-rT})}}]. \tag{A.13}$$

The critical value F^{**} is determined by solving

$$X - F^{**} = p(F^{**}) + A_1(F^{**}). \tag{A.14}$$

In our paper we are interested in extracting implied volatility and for that we use numerical methods, as there is no closed-form inverse solution of Barone-Adesi and Whaley (1987) formula. Each iterative step initiated to find implied volatility involves other iterative procedure, which solves Equation A.7 for the critical price F^*. Thus we have two nested iterative procedure.

A2 Calculation of the Dairy VIX

The Chicago Board of Options Exchange (CBOE) introduced the CBOE Volatility Index (VIX) in 1993, which later was renamed the VXO. The VXO is constructed from the Black and Scholes (1973) option implied volatilities of the eight near-the-money, nearby, and second nearby options on the S&P 100 index. The VXO is based on trading days, meaning that instead of directly using the calendar implied volatility, the implied volatility is transformed to a trading-day basis in the following manner:

$$\sigma_t = \sigma_c\Big(\frac{\sqrt{N_c}}{\sqrt{N_t}}\Big), \tag{A.15}$$

where σ_t (σ_c) is the trading-day (calendar-day) implied volatility rate and N_t (N_c) is the number of trading (calendar) days to option expiration, computed as:

$$N_t = N_c - 2 \times \text{int}(N_c/7). \tag{A.16}$$

In constructing the DVIX we closely follow the methodology described in Whaley (1993). Because options on WMP futures are American style, to extract implied volatilities we use the option pricing approximation of Barone-Adesi and Whaley (1987), which is detailed in Appendix A1. Next, we apply the trading-day adjustment using Equations A.15 and A.16. The construction of the Dairy VIX is based on the eight near-the-money, nearby, and second nearby options on WMP futures contracts. We denote the option strike price just below the current underlying futures price, F_i, as X_d^i, and the strike price just above the current settlement futures price as X_u^i, where i corresponds to maturity $i \in 1, 2$. We can arrange the implied volatilities of the nearby and second nearby options in the following array:

	Nearby Conrtact			Second Nearby Conrtact	
	Call	Put		Call	Put
X_d^1 $(< F_1)$	$\sigma_c^{X_d^1}$	$\sigma_p^{X_d^1}$	X_d^2 $(< F_2)$	$\sigma_c^{X_d^2}$	$\sigma_p^{X_d^2}$
X_u^1 $(\geq F_1)$	$\sigma_c^{X_u^1}$	$\sigma_p^{X_u^1}$	X_u^2 $(\geq F_2)$	$\sigma_c^{X_u^2}$	$\sigma_p^{X_u^2}$

The next step is to average the put and call implied volatilities in each of the four categories of options (at each of the four strike prices), that is:

$$\sigma^{X_d^1} = (\sigma_c^{X_d^1} + \sigma_p^{X_d^1})/2$$
$$\sigma^{X_u^1} = (\sigma_c^{X_u^1} + \sigma_p^{X_u^1})/2$$
$$\sigma^{X_d^2} = (\sigma_c^{X_d^2} + \sigma_p^{X_d^2})/2$$
$$\sigma^{X_u^2} = (\sigma_c^{X_u^2} + \sigma_p^{X_u^2})/2$$

Next, interpolate between the two near-the-money average implied volatilities to obtain at-the-money implied volatilities. More specifically:

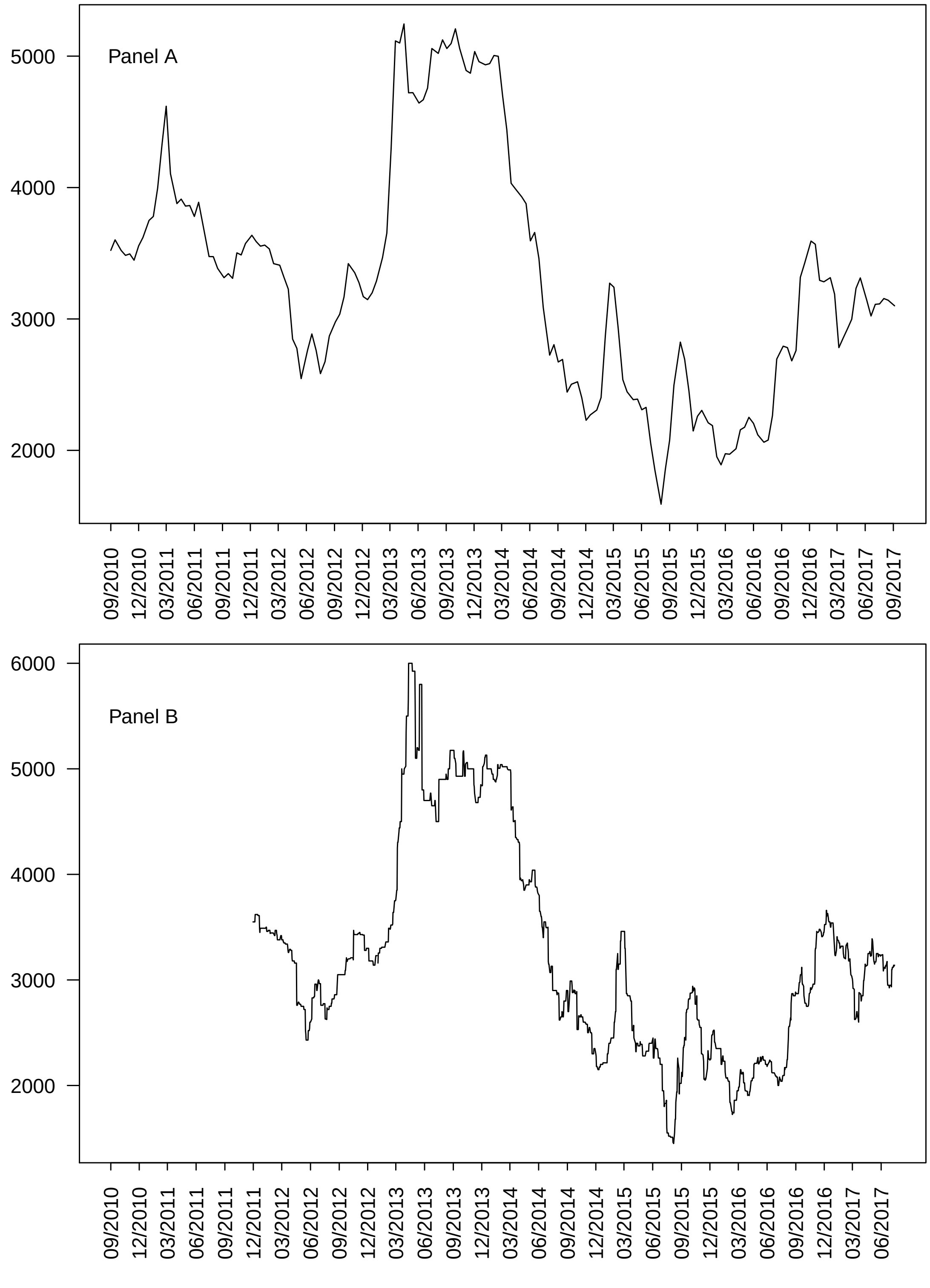
$$\sigma_1 = \sigma^{X_d^1}\Big(\frac{X_u^1 - F_1}{X_u^1 - X_d^1}\Big) + \sigma^{X_u^1}\Big(\frac{F_1 - X_d^1}{X_u^1 - X_d^1}\Big)$$
$$\sigma_2 = \sigma^{X_d^2}\Big(\frac{X_u^2 - F_2}{X_u^2 - X_d^2}\Big) + \sigma^{X_u^2}\Big(\frac{F_2 - X_d^1}{X_u^2 - X_d^2}\Big)$$

Lastly, interpolate between the nearby and second nearby implied volatilities to create a 22 trading days implied volatility as follows:

$$DVIX = \sigma_1\Big(\frac{N_{t_2} - 22}{N_{t_2} - N_{t_1}}\Big) + \sigma_2\Big(\frac{22 - N_{t_1}}{N_{t_2} - N_{t_1}}\Big),$$

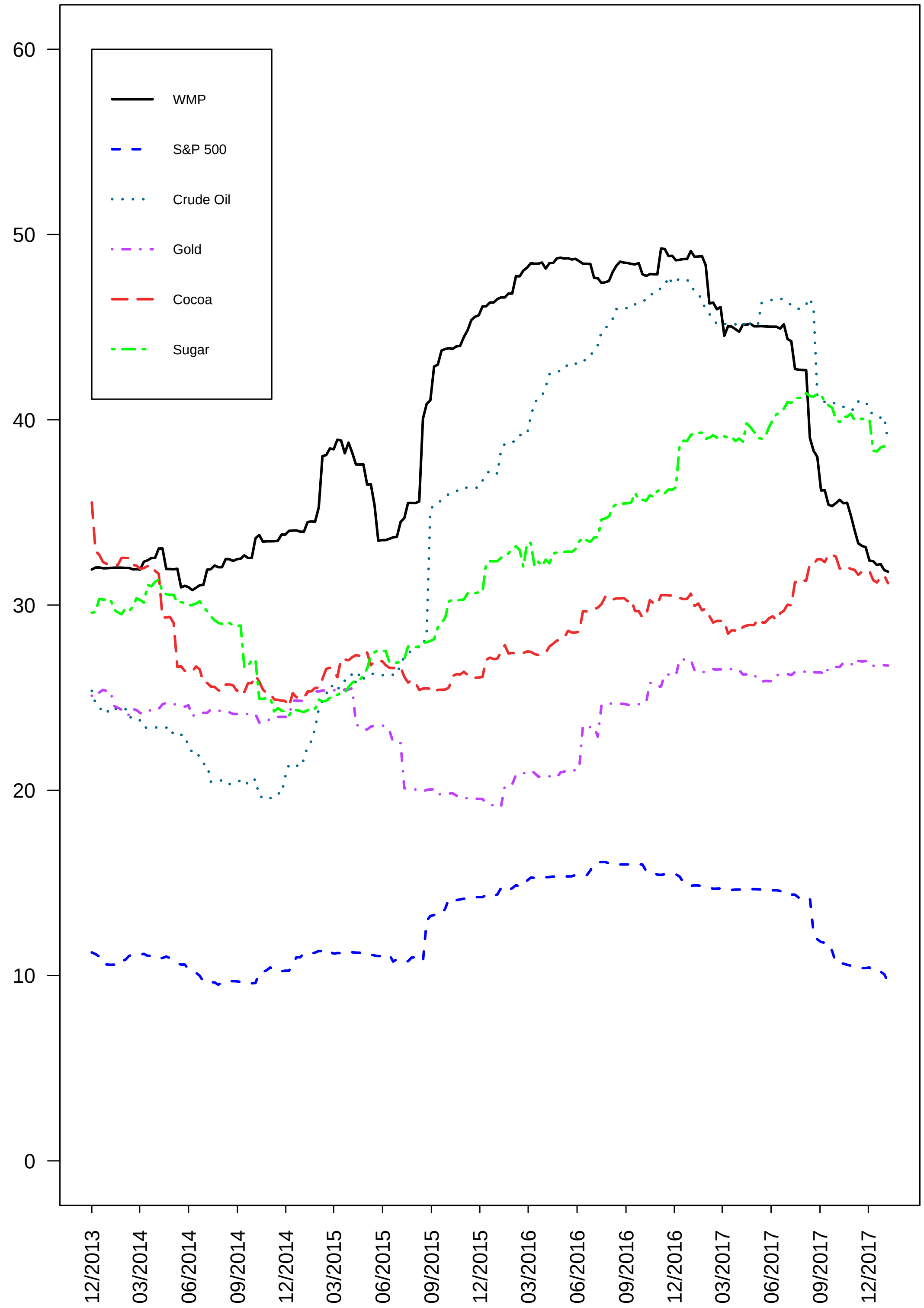
where N_{t_1} and N_{t_2} are the number of trading days to expiration of the nearby and second nearby contract, respectively.

Figure 1: WMP GDT Auction and Futures Prices



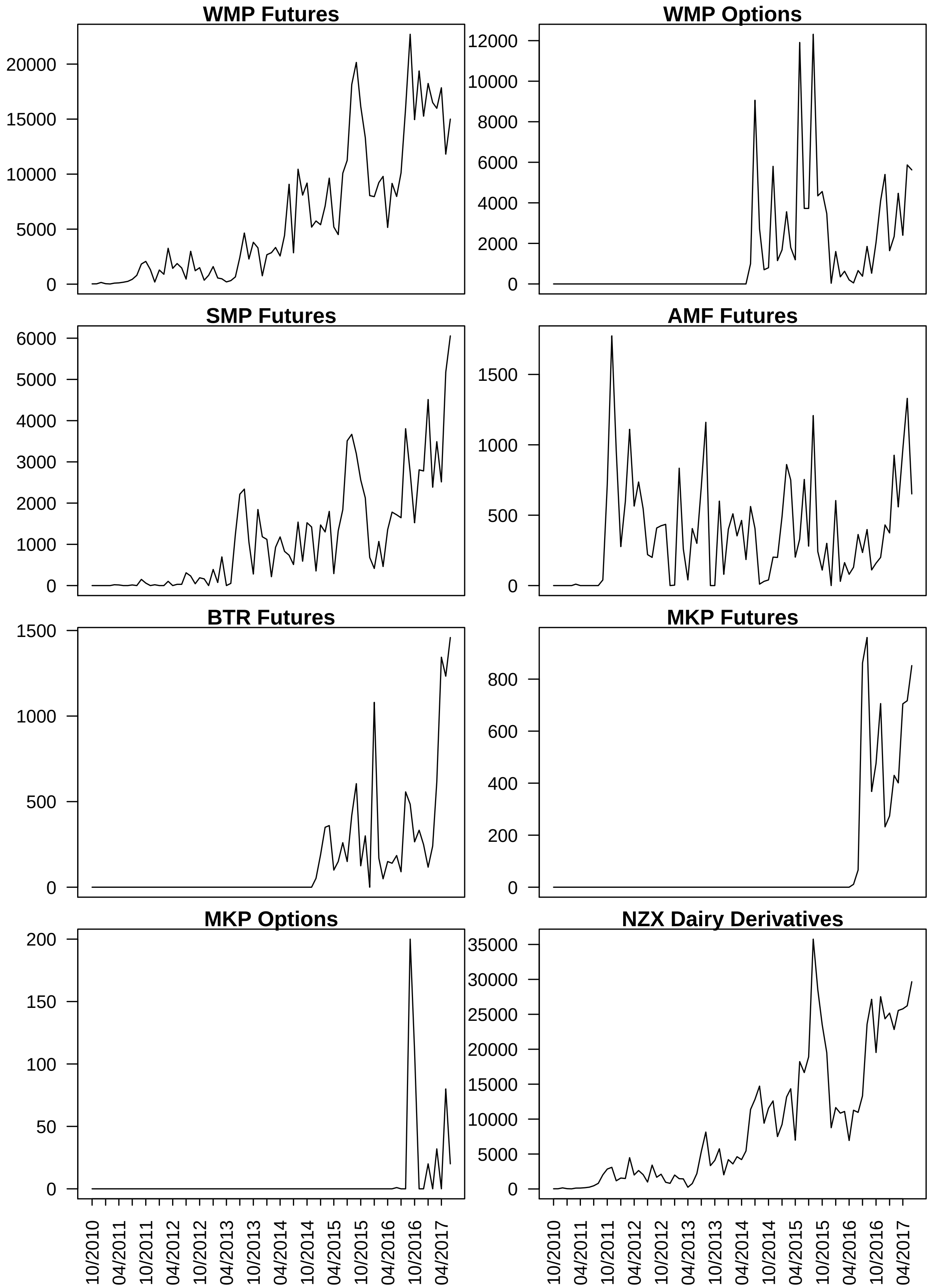
Note: This figure shows GDT auction weighted average price for all contracts of the WMP for the period between September 1, 2011 and September 5, 2017 (Panel A). The price is in USD per metric tonne. Panel B depicts the settlement price of the nearby WMP futures contracts.

Figure 2: Volatility in Commodity and Other Asset Prices (in a percentage)



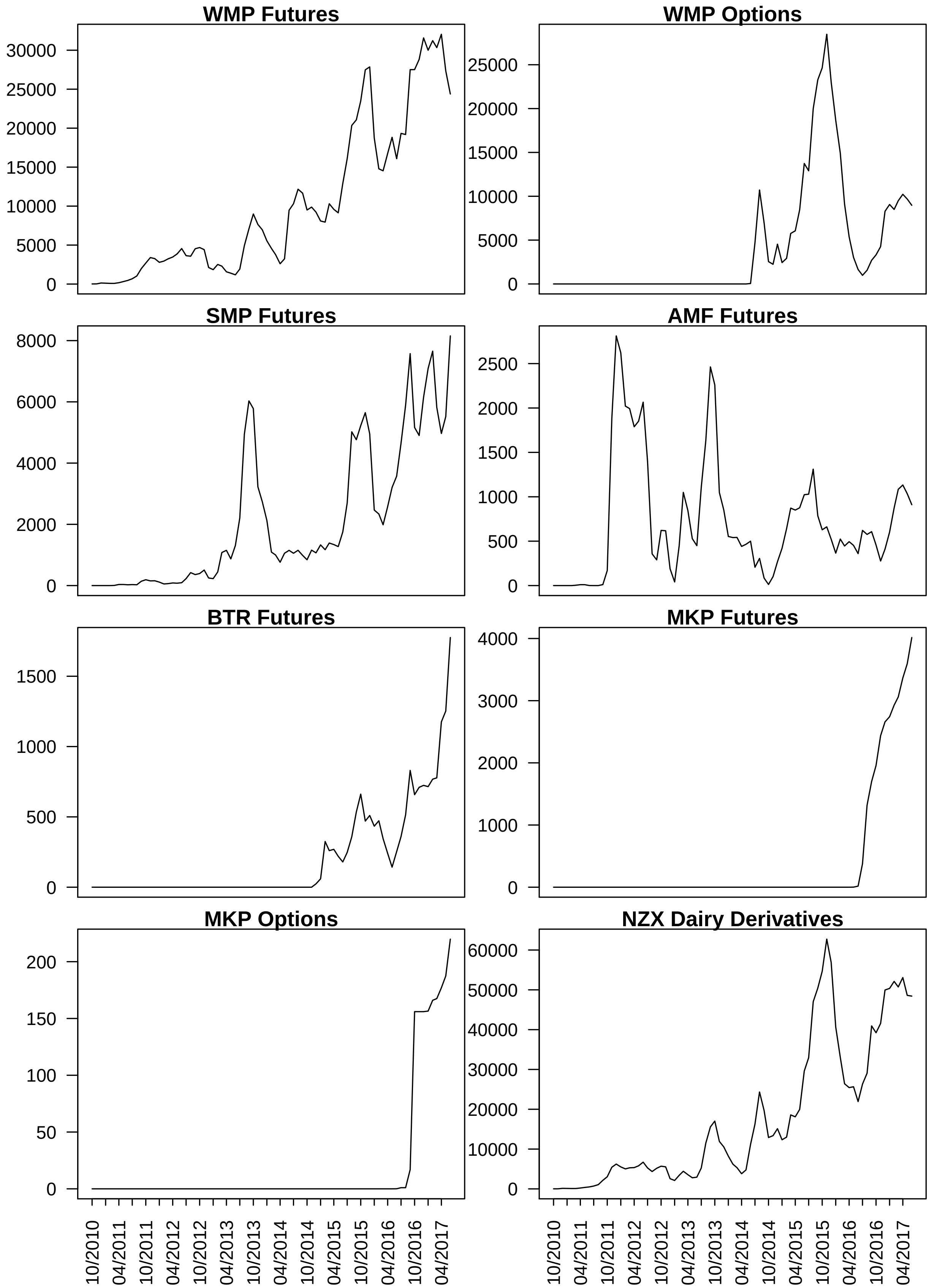
Note: This figure shows annualized volatility of WMP Futures, S&P 500, CRB Crude Oil, Gold, Cocoa and Sugar Indices for the period between December 5, 2011 and January 8, 2018. Volatility is measured as the standard deviation of weekly returns over preceding 2 years.

Figure 3: NZX Dairy Derivatives Volume



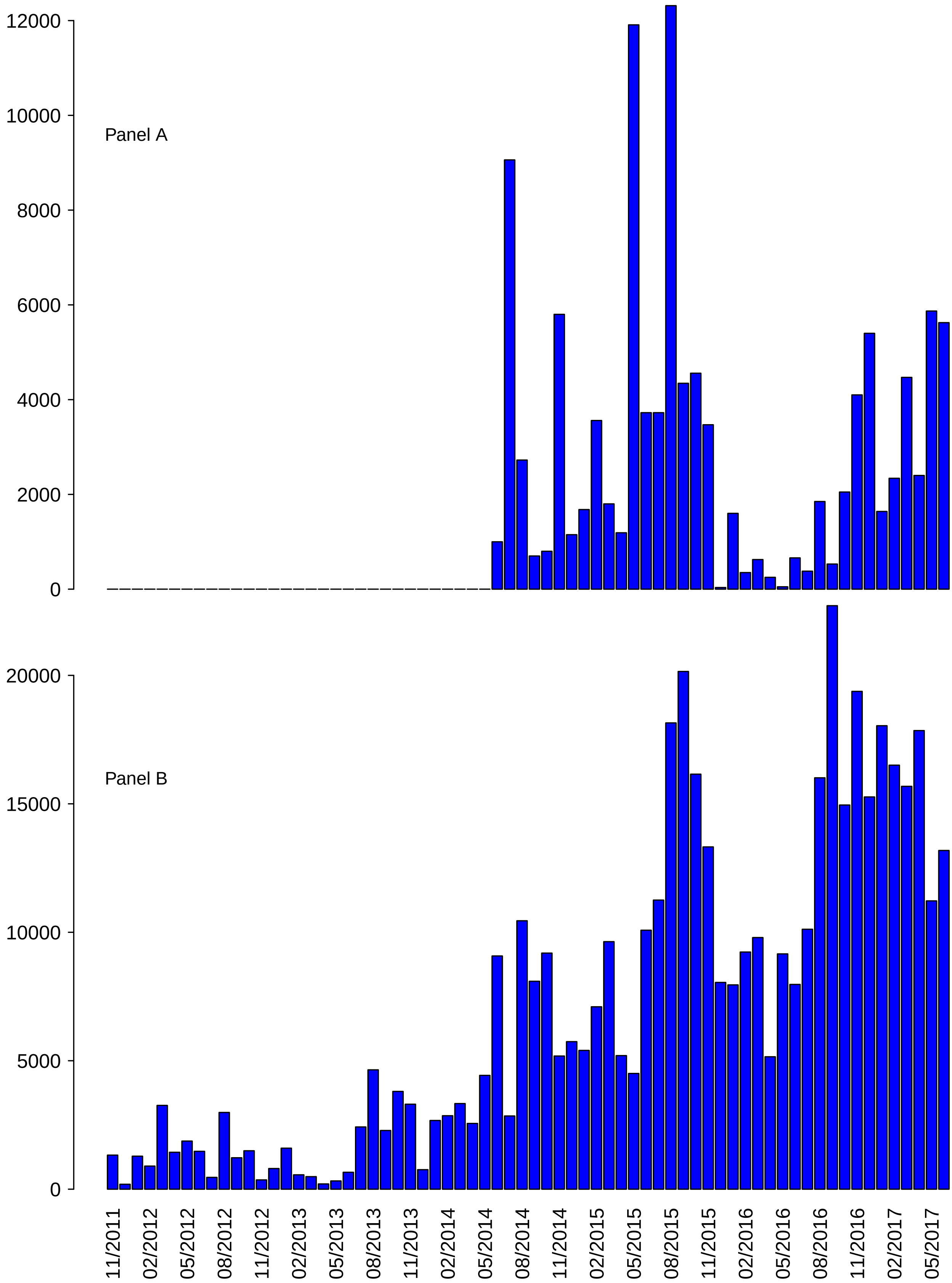
Note: This figure shows the monthly trading volume for all NZX Dairy Derivatives for the period between October 8, 2010 and June 30, 2017.

Figure 4: NZX Dairy Derivatives Open Interest



Note: This figure shows the monthly average open interest for all NZX Dairy Derivatives for the period between October 8, 2010 and June 30, 2017.

Figure 5: WMP Futures and Options Volume



Note: This figure shows the monthly trading volume for the WMP Options (Panel A) and WMP Futures (Panel B) for the period between November 1, 2011 and June 30, 2017.

Figure 6: Dairy VIX

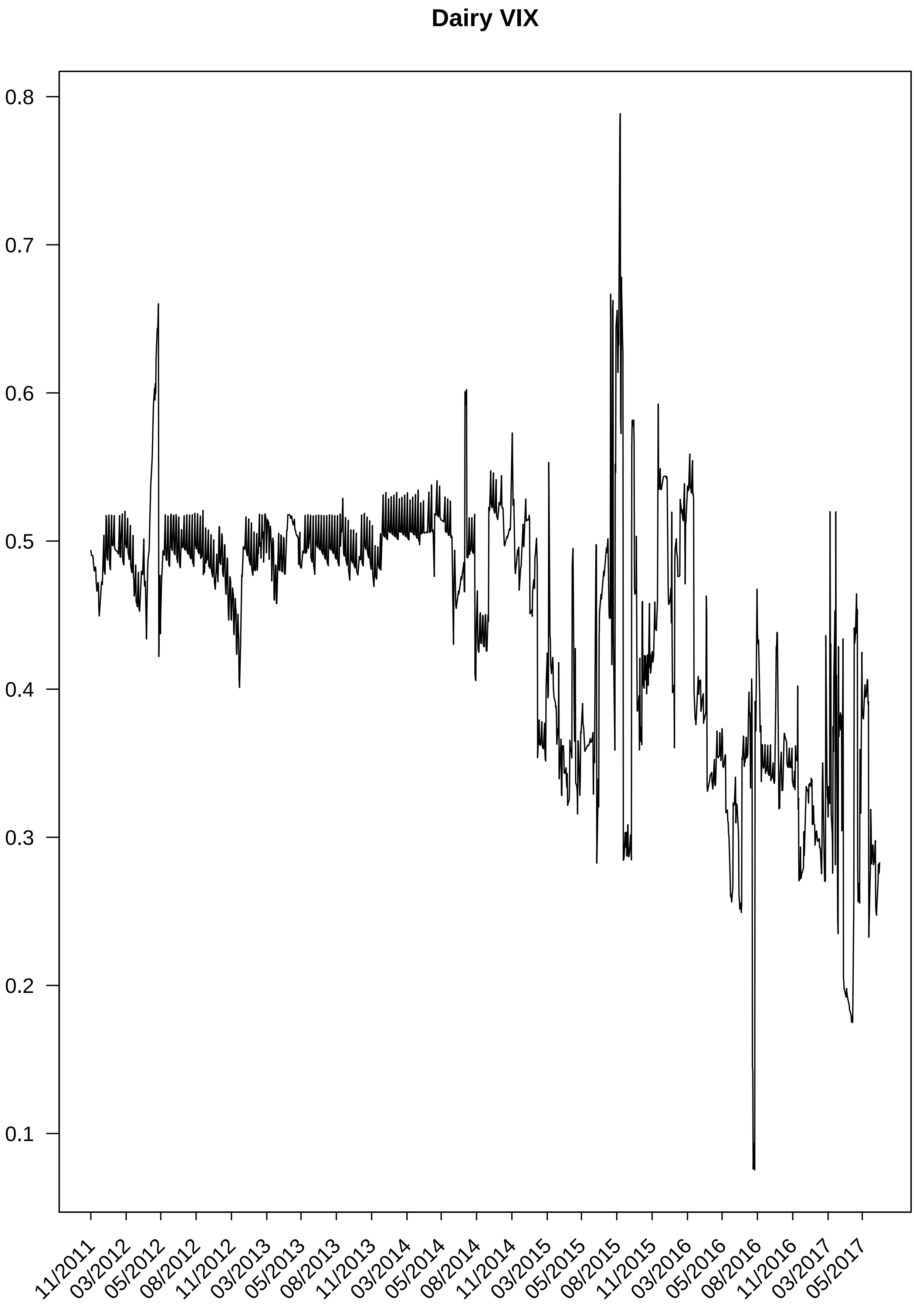
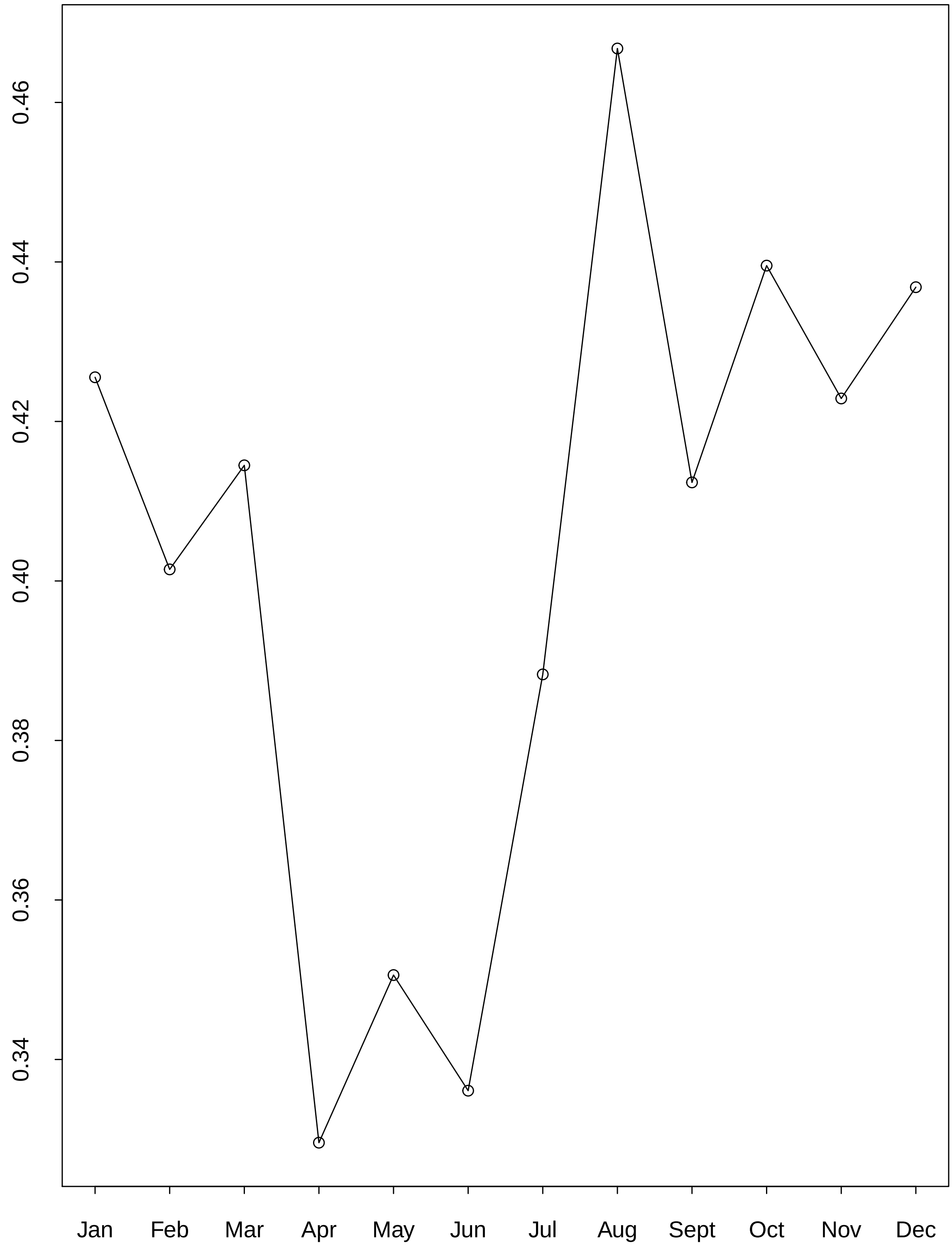


Figure 7: Average Intraweek and Intramonth DVIX



Note: This figure shows the average monthly dairy volatility levels. The averages computed for the period between November 1, 2014 and July 14, 2017 (excluding 07/09/2015 - 08/09/2015 and 17/08/2016 - 23/08/2016).

Table 1: NZX Dairy Derivatives Products

Contract/ Commodity	Cotract Size	Terminal Price/ Settlement Method	First Traded	Contract Month
Whole Milk Powder (WMP) Futures*	1 metric tonne	Cash settled against Global-DairyTrade WMP prices	October 8, 2010 *November 30, 2011	18 months are available for trading *12 months are available for trading
Skim Milk Powder (SMP) Futures	1 metric tonne	Cash settled against Global-DairyTrade SMP prices	February 18, 2011	18 months are available for trading
Anhydrous Milk Fat (AMF) Futures	1 metric tonne	Cash settled against Global-DairyTrade AMF prices	February 18, 2011	18 months are available for trading
Butter (BTR) Futures	1 metric tonne	Cash settled against Global-DairyTrade Butter prices	December 12, 2014	18 months are available for trading
Milk Price (MKP) Futures*	6,000 kilograms of milk solids	Cash settled against Fonterra's Farmgate Milk Price	May 26, 2016 *June 28, 2016	Every September such that up to 5 calendar years are available for trading

Note: This table summarizes all currently available dairy derivatives at the NZX. *denotes options are also available, and their specifications.

Table 2: Descriptive Statistics

	2014/07/01 2017/07/14	2014/07/01 2015/11/30	2015/12/03 2016/10/03	2016/10/10 2017/07/14
Mean	-0.0002	0.0000	-0.0004	-0.0004
Median	-0.0003	0.0000	-0.0002	-0.0009
Max	0.3162	0.2786	0.3162	0.1734
Min	-0.3378	-0.3378	-0.2502	-0.2296
St. Dev.	0.0454	0.0488	0.0396	0.0450
Skewness	-0.2334	-0.5522	1.3150	-0.5696
Kurtosis	16.1666	15.7062	27.4446	7.7313
$\rho(1)$	-0.1313**	-0.1112**	-0.0931	-0.2049**
$\rho(2)$	-0.0911**	-0.1643**	-0.0064	-0.0002
$\rho(3)$	-0.0661	-0.1252**	0.0602	-0.0399
No. of Obs.	756	358	202	194

Note: This table reports descriptive statistics on the daily DVIX level changes at one day frequency for the full sample and for three sub-samples. ** indicates significance at 5% level.

Table 3: Calendar Anomalies in the Dairy VIX

Day-of-the-Week Effects			Month-of-the-Year Effects		
const	0.4027***	(30.653)	*const*	0.426***	(11.977)
Monday	0.0067	(1.326)	*Feb*	-0.024	(-0.462)
Tuesday	-0.0028	(-0.673)	*Mar*	-0.011	(-0.276)
Thursday	-0.0022	(-0.694)	*Apr*	-0.096**	(-2.185)
Friday	-0.0037	(-0.823)	*May*	-0.075*	(-1.749)
R^2	-0.0043		*Jun*	-0.089**	(-2.276)
			Jul	-0.037	(-0.740)
			Aug	0.041	(1.022)
			Sept	-0.013	(-0.235)
			Oct	0.014	(0.267)
			Nov	-0.003	(-0.062)
			Dec	0.011	(0.196)
			R^2	0.183	

Note: This table presents parameter estimates for the regression of the DVIX on day-of-the-week and month-of-the-year dummy variables. ***, **, * is used to indicate significance at the 1%, 5% and 10% levels.

Table 4: DVIX Predictive Regression

α_0	α_1	α_2	α_3	α_4	α_5	β_1	R^2
0.337***						0.200***	0.084
(10.914)						(2.255)	
0.029***	0.786***	0.045	-0.013	0.048	0.059		0.805
(3.210)	(13.637)	(0.605)	(-0.144)	(0.746)	(1.102)		
0.029***	0.786***	0.045	-0.013	0.048	0.058	0.006	0.805
(2.972)	(13.654)	(0.604)	(-0.147)	(0.735)	(1.105)	(0.380)	

Note: This table reports regressions results of the following equation:

$$DVIX_t = \alpha_0 + \alpha_1 DVIX_{t-1} + \alpha_2 DVIX_{t-2} + \alpha_3 DVIX_{t-3} +$$
$$\alpha_4 DVIX_{t-4} + \alpha_5 DVIX_{t-5} + \beta_1 HISTV_{t-1} + \epsilon_t.$$

Table 5: Intertemporal Rlationship between Daily DVIX Changes and WMP Futures Returns

$Intercept$	0.0005	(0.2454)
R_{t-2}	0.0134	(0.1380)
R_{t-1}	-0.2205**	(-2.1973)
R_t	0.1478	(1.0160)
R_{t+1}	-0.1404	(-1.3128)
R_{t+2}	0.0151	(0.1693)
$\|R_{t-2}\|$	0.0123	(0.1247)
$\|R_{t-1}\|$	-0.1729*	(-1.8278)
$\|R_t\|$	0.0825	(0.5558)
$\|R_{t+1}\|$	0.0952	(0.8226)
$\|R_{t+2}\|$	-0.0825	(-0.7777)
$Adj - R^2$	0.0258	

Note: This table reports the estimation results for the regressions described by Equation 5. ***, **, * is used to indicate significance at the 1%, 5% and 10% levels. Specifically, the model is defined by the equation:

$$\Delta DVIX_t = \alpha_0 + \alpha_1 R_{t-2} + \alpha_2 R_{t-1} + \alpha_3 R_t + \alpha_4 R_{t+1} + \alpha_5 R_{t+2} + \beta_1|R_{t-2}| + \beta_2|R_{t-1}| + \beta_3|R_t| + \beta_4|R_{t+1}| + \beta_5|R_{t+2}| + \epsilon_t$$

Table 6: In-sample Estimation of GARCH and DVIX Specifications

	GARCH(1, 1)		GARCH(1, 1) - DVIX		DVIX	
	coeff	t-stat	coeff	t-stat	coeff	t-stat
ω ($\times 10^5$)	0.206	(0.747)	-1.963***	(-3.897)	7.116	(1.333)
α_1	0.014	(1.545)	-0.013	(-1.506)		
α_2	0.980***	(81.243)	0.591***	(7.249)		
β_1			0.346***	(5.245)	0.617***	(4.286)
LL	1885.76		1920.97		1891.8	
$LR-stat$	35.21***				29.17***	

Note: This table reports the estimation results for the in-sample analysis for the period from 5 January 2015 to 8 January 2018. t-statistics are robust following White (1982) and presented in parentheses. *** is used to indicate significance at the 1% level. In addition we report the log-likelihood of each model and the likelihood ratio test statistic. Three specifications look as follows:

$$
\begin{aligned}
r_t &= \mu + \epsilon_t, \\
\epsilon_t|\mathcal{F}_{t-1} &\sim N(0, h_t), \\
h_t &= \omega + \alpha_1\epsilon^2_{t-1} + \alpha_2 h_{t-1}, \\
h_t &= \omega + \alpha_1\epsilon^2_{t-1} + \alpha_2 h_{t-1} + \beta_1 DVIX^2_{t-1}, \\
h_t &= \omega + \beta_1 DVIX^2_{t-1},
\end{aligned}
$$

Table 7: Out-of-Sample Estimation of Forecasting Regressions

Parameter	Model								
	HISTV	GARCHV	EGARCHV	GJR-GARCH	DVIX	HISTV+DVIX	GARCHV+DVIX	EGARCHV+DVIX	GJR-GARCH + DVIX
Panel A: Forecast for T = 22									
const	0.147***	0.024	0.138**	0.105	0.093	0.052	-0.023	0.037	0.044
	(3.109)	(0.280)	(2.503)	(1.614)	(1.579)	(0.768)	(-0.249)	(0.516)	(0.572)
TSV	0.472***	0.817***	0.425***	0.556***		0.385**	0.535**	0.252*	0.329
	(2.885)	(3.137)	(2.750)	(2.711)		(2.454)	(2.198)	(1.748)	(1.738)
$DVIX$					0.537***	0.319**	0.367**	0.433***	0.365**
					(3.189)	(2.356)	(2.301)	(2.630)	(2.436)
R^2	0.227	0.135	0.092	0.128	0.141	0.269	0.185	0.168	0.172
χ^2	10.513***	3.099	19.402***	6.699**	16.506***				
	(0.005)	(0.212)	(0.000)	(0.035)	(0.000)				
Panel B: Forecast for T = 10									
const	0.134***	0.020	0.116*	0.065	0.042	0.015	-0.034	0.003	-0.002
	(2.838)	(0.222)	(1.744)	(1.023)	(0.808)	(0.263)	(-0.392)	(0.038)	(-0.025)
TSV	0.393**	0.710***	0.381**	0.557***		0.281*	0.356	0.180	0.298
	(2.406)	(2.563)	(2.106)	(2.838)		(1.797)	(1.326)	(1.101)	(1.534)
$DVIX$					0.567***	0.404***	0.454***	0.493***	0.411***
					(3.750)	(3.207)	(3.022)	(3.462)	(2.791)
R^2	0.112	0.071	0.051	0.089	0.111	0.159	0.125	0.121	0.129
Panel C: Forecast for T = 5									
const	0.127**	0.008	0.077	0.050	0.039	0.014	-0.037	-0.007	-0.002
	(2.439)	(0.098)	(1.102)	(0.872)	(0.707)	(0.234)	(-0.417)	(-0.086)	(-0.030)
TSV	0.405**	0.620**	0.397*	0.480***		0.256*	0.370	0.227	0.284
	(2.184)	(2.293)	(1.884)	(2.704)		(1.662)	(1.462)	(1.239)	(1.507)
$DVIX$					0.465***	0.316**	0.339**	0.377***	0.314*
					(2.985)	(2.164)	(2.335)	(2.851)	(1.831)
R^2	0.069	0.048	0.036	0.053	0.058	0.088	0.071	0.068	0.070
Panel D: Forecast for T = 1									
const	0.073**	0.009	0.066	0.057	0.024	0.003	-0.029	-0.004	0.007
	(2.051)	(0.124)	(1.158)	(1.226)	(0.508)	(0.059)	(-0.402)	(-0.066)	(0.132)
TSV	0.285**	0.460**	0.283*	0.308**		0.216*	0.259	0.141	0.118
	(2.292)	(2.083)	(1.652)	(2.160)		(1.681)	(1.017)	(0.783)	(0.702)
$DVIX$					0.365***	0.240*	0.275*	0.312**	0.302*
					(2.729)	(1.743)	(1.773)	(2.220)	(1.907)
R^2	0.019	0.012	0.008	0.009	0.016	0.025	0.018	0.017	0.016

Note: This table presents the out-of-sample estimation results of Equations 11 and 12 for the period from July 2015 to July 2017. GARCH-type models are estimated using daily returns from December 2011 to July 2015 and then rolling forward by one observation. We use the Newey and West (1987) correction to adjust the coefficient standard errors to account for the the heteroscedastic and autocorrelated error structure. ***, **, * is used to indicate significance at the 1%, 5%, 10% levels respectively.

Table 8: R^2_{OS} statistics

Parsimonious vs Long Model	Forecast Horizon			
	T = 22	T = 10	T = 5	T = 1
HISTV vs. HISTV+DVIX	0.197***	0.113***	0.058***	0.007*
	(2.902)	(2.490)	(2.693)	(1.482)
GARCHV vs. GARCHV+DVIX	0.216***	0.182***	0.100***	0.021***
	(3.094)	(3.684)	(3.842)	(2.581)
EGARCHV vs. EGARCHV+DVIX	0.223***	0.191***	0.102***	0.021***
	(2.687)	(2.917)	(3.302)	(2.645)
GJR-GARCH vs. GJR-GARCH + DVIX	0.164***	0.154***	0.068**	-0.080
	(2.593)	(2.436)	(1.906)	(-2.170)

Note: This table reports R^2_{OS} statistic. Clark and West (2007) test statics is presented in parentheses. We use the Newey and West (1987) standard error estimate to control for autocorrelation. ***, **, * is used to indicate significance at the 1%, 5% and 10% levels.

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