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 analysis of seasonalities in 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 exhibits asymmetry, implying that positive moves in the WMP futures prices are associated with larger absolute changes in the DVIX than negative moves in the WMP Futures prices. In the in-sample forecasting exercise, we combine the GARCH model with implied volatility. 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. In the out-of-sample forecasting exercise, we formulate and test several hypotheses related to the information content of implied volatility relative to several alternatives (such as historical volatility or a forecast from GARCH-type models). While we find that the DVIX is not an unbiased estimate, it 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

1 Introduction

New Zealand is the world's largest exporter of dairy commodities, representing approximately 1/3 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%).[1] 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 affects the ability of NZ dairy farmers to manage cash flow and service debt, and hampers the health of the most influential agricultural sector of NZ.

Milk powder is one of the most volatile commodities globally. 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 outperforms those that use historical information. This forecast is obtained from the observed prices by inverting a theoretical pricing formula and is called implied volatility and is often interpreted as the expected volatility over the life of the option. In an efficient options market, implied volatility is generally considered to be a superior predictor of future volatility due to the ability of investors to effectively incorporate all publicly available information into security prices. By construction implied volatility is a forward-looking estimate which is opposed to the historical volatility which relies on the historical data. Over the last three decades, extensive research has been produced for financial and non-financial markets which examines the information content of implied volatility (for an overview, see Poon and Granger (2003) and Gonzalez-Perez (2015)). It has been found empirically that implied volatility produces a superior forecast 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 futures contracts and for the sugar futures contracts. Triantafyllou, Dotsis and Sarris (2015) compute model-free implied variance for US wheat, corn and soybean futures markets. They find that for maize 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

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

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 constructed from four call and four put NZX WMP 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 performance of the DVIX by considering the historical information form WMP futures returns and the DVIX in the 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 implied volatility to forecast 1, 5, 10 and 22 trading day volatility. The predictive performance of implied volatility is assessed against two alternative time-series forecasts: historical volatility realized during the 30 trading day time period and GARCH-type forecasts. 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 construction of the DVIX allows to visualize the volatility in the dairy sectors 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 financial and agricultural sector who requires the estimate of volatility for pricing and risk management purposes.

The rest of the paper is structured as follows. Section 2 provides a literature review. Section 3 presents the data and the methodology of the DVIX construction. Section 4 explores the statistical properties of the DVIX, conducts in-sample and out-of-sample analysis. 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 volatility, or backward-looking volatility, and the second one is implied volatility which is also referred to as forward-looking volatility.

The simplest measure of historical volatility is computed as 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. In these models variance of residuals is not constant and the next period volatility is conditional on information this period.

Implied volatility of an asset results from the market prices of options written on that asset. Implied volatility can be considered as an indicator of the magnitude the underlying asset can move over the life of an option. To make things clear, we will consider the process of implied volatility estimation based on Black and Scholes (1973) European option pricing formula. According to the theoretical formula, option price at time t is a function of the price of the underlying asset S_t, the strike price X, the risk-free interest rate r, time to option maturity T and volatility σ of the underlying asset over the period from t to T. Once the market price of an option is known, entering four other inputs into the Black-Sholes formula and solving for the value of the volatility which equate the market price with the theoretical price results in a volatility estimate which is called option implied volatility. Since the reference period is from time t to T, option implied volatility is interpreted as a market's expectation of volatility over the life of the option, i.e. the period from t to T.

The first volatility index (VIX) was introduced by the CBOE in 1993. The original construction of an index uses the prices from eight near-the-money options written on the S&P100. In 2013, the CBOE together with Goldman Sachs revised their methodology and replaced the S&P 100 options with S&P 500 options as well as incorporated out-of-the-money put and call options over the wide range of strike prices. 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.[2] For example, 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 and CME Group entered into a license agreement and 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 VIX are based on the same 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 "investor fear gauge" due to its property to spike during periods of market turmoil (Whaley (2009)). Another interesting empirical fact is that

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

the stock market return-volatility 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)). Padungsaksawasdi and Daigler (2014) examine the return-volatility relation between the commodity ETF price changes, namely the euro, gold and oil, and their associated VIXs. They document several interesting results. First, they find that co-movements 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-volatility relation for gold. Third, they do not find asymmetric return-volatility relation for commodity market. The results highlight differences of the return-volatility relation among different asset classes.

2.2 Forecasting of Volatility

The widely used approaches to forecast volatility is to use time-series models and to use implied volatilities from options. For an excellent survey 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 a superior forecast of future volatility across different asset classes. For example, Jorion (1995) examines currency market and shows that a moving average and a GARCH models are outperformed by option-implied forecasts.

Fleming (1998) uses the S&P 100 options and shows that a predictive power of implied volatility is superior to the GARCH(1,1) volatility and historical volatility extracted from daily index returns. 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 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 not-financial assets. Giot (2003) considers the similar topic but for agricultural commodities (cocoa, coffee, and sugar futures contracts). The in-sample analysis shows that at the 1% level the null hypothesis that past squared returns (i.e., GARCH effects) provide no significant volatility information in addition to the lagged implied volatility is not

rejected for the cocoa futures contracts and for the sugar 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 the historical 2-month realized variance, model-free implied variance, model-free implied skewness to explain the 2-month ahead realized variance. They find that for maize 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 historic volatility or GARCH framework), the implied volatility outperforms the historical volatility in predicting future realized volatility.

When testing a forecast power of option implied volatility we need to take into account that this test is a joint test of option market efficiency and a correct option pricing model. Thus, it is reasonable to expect that a forecast power of implied volatility might differ among different asset classes.

3 Data and Volatility Calculation

3.1 Data

In 2010, due to increased fluctuations in milk prices, 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 Exchange 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 2 depicts aggregated trading volume for each month for all available dairy derivatives traded at the NZX. It confirms that the most popular dairy derivative is WMP Futures, and the least popular is recently launched MKP Options. Figure 3, 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 2016 and the average open interest of just over 48,500 lots. Figure 4 plots separately the trading volume for WMP options and futures. It shows that WMP Futures experience participation growth and in June 2017 the trading volume amounted to about 15,000 lots. WMP options demonstrate less popularity, as since the launch of the product the first trade occurred in June 2014 and in June 2017 the trading volume amounted to about 5,600 lots.

We use data on the NZ WMP Futures and Options contracts which we retrieve from NZX Research Centre with daily frequency. The sample period starts on 30 Novermber 2011 - the issue date for WMP Options and ends 14 July 2017. As a proxy for the risk-free rate we collect USD Overnight Index Swap (OIS) rates available from DataStream. Maturities include 1-week, (1W), 2W, 1M, 2M, 3M.

3.2 Dairy Implied Volatility Computation

In practice, implied volatility depends on the time to maturity and strike of an option, thus a decision needs to be made on which options to use to derive a market volatility forecast. The common strategy is to use implied volatility derived from ATM options and to use a weighting scheme which relies on the CBOE VXO (old VIX) calculation.[3]

We compute the Dairy VIX closely following the methodology applied to the early version of the CBOE VIX.[4] To construct the Dairy VIX 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 an implied volatility. We construct the dairy VIX from eight options, four calls and four puts, written on the WMP futures. It is constructed in a way that it is at-the-money and has a constant 30 calendar days (22 trading days) to expiration. To

[3]See Poon and Granger (2003) for a justification.

[4]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.

achieve the at-the-money implied volatility we combine just in- and just-out-of the money options, and to achieve a constant time to expiry we combine the first and second nearby options. To address the early exercise option of American style options we use quadratic approximation of American option values proposed by Barone-Adesi and Whaley (1987). Detailed construction of the DVIX is provided in Appendix A.

When estimating option implied volatility one needs to be careful about market microstructure and measurement errors. The possible estimation problems are that the underlying asset price and the option price are not recorded at the same time, the use of stale prices, the poor trading volume.

Figure 5 demonstrates the calculated DVIX. 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 GDT auction. Average dairy prices increased by 12.7%. The highest value of 0.780 and 0.789 is achieved on 7 and 8 September 2015. For these two days we cannot identify any relevant news.

The DVIX is the 22 trading days implied volatility of the WMP futures, which is expressed as an annual number. When the DVIX is quoted at 0.5, this can be interpreted as an expected annualized move, up or down, of 50% in the WMP futures over the next 22 trading days. The DVIX also can be used to determine the expected 22 trading day market-price fluctuations. To do so, the DVIX needs to be divided by the square root of 12. If the DVIX is quoted at 0.5, the expected price movement is about 14.43% over the next 22 days.

From Figure 5 one can observe that the DVIX has a little variation in the beginning of 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 common wisdom that volatility in the dairy market is a stationary process.

We calculate summary statistics for daily DVIX changes over the period 1 July 2014 till 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 4. 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 entire period for the subsequent analysis.

4 The Information Content of Implied Volatility

4.1 Statistical Properties of the DVIX

Next, we want to check for some calendar anomalies in the DVIX. The day-of-the-week effect was first documented by Cross (1973), according to which the mean return between close of Friday and close of Monday is negative. The presence of such effect undermines the Efficient Market Hypothesis since investors could profit from the non-random movements in stock prices. Kohers, Kohers, Pandey and Kohers (2004) reports that the day-of-the week anomaly appears to diminish in the developed economies, indicating an improvement in market efficiency. Figure 6 shows the intraweek behavior or the DVIX. The average DVIX level starts hight on Monday and approaches Friday with the lowest value. At first sight, the pattern suggest a presence of inefficiency in the NZ dairy futures market. To test the day-of-the-week effect in a more rigorous way, 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 a multicollinearity problem, we exclude a 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 the month-of-the-year anomaly. 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 during 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 have influence on the volatility index, we investigate intramonth patterns in the DVIX. Figure 6 shows intramonth behavior of the DVIX.[5] From the graph one can see that the DVIX exhibits 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 a multicollinearity problem, we exclude a 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 one more efficiency test for the DVIX. In this test we want to asses whether the past historical information is informative for the future DVIX. We run a regression of the following form, where we control for the persistence of the DVIX:

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

where $HISTV$ is a the sample standard deviation of nearby futures returns over the previous 30 days. We report the results in Table 4. The results show that the DVIX is a persistent process with a one day lagged DVIX being positively associated with the next day DVIX. We find no evidence that the previous day historical volatility affects the current value of the DVIX, confirming the forward-looking nature of the DVIX.

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) and Padungsaksawasdi and Daigler (2014) we run 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

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

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 intertemporal relationship between return and implied volatility and incorporates 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 -0.3933, where as when the return is negative the impact is equal to $\alpha_2 - \beta_4$, or -0.0467. 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 Model

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 returns 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. The estimation period starts from 1 July 2014 to 14 July 2017. 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 (M1) 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 (M2) 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 (M3) is defined by Equation 7 and ignores historical information and uses only information from option market:

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

We estimate the parameters of the models M1, M2 and M3 by maximizing the log of the likelihood functions, with the constraints $\omega \geq 0$, $\alpha_1 \geq 0, \alpha_2 \geq 0, \beta_1 \geq 0$, which ensures the non-negativity of the conditional variance process. We present the results in Table 6. In the M1 the coefficient α_2 is close to 1, which is consistent with the documented clustering of volatility. Including the lagged DVIX in the variance equation (model M2) leads to the decrease in the value of α_2 as the lagged DVIX takes into account a part of the GARCH effect. To test for the added value of the implied volatility we use the likelihood ratio (LR) test. We first compare models M1 and M2. The LR test statistic is calculated as twice the difference between the log-likelihood of M2 and M1 and is equal to 29.84. Results suggest that we can reject the null hypothesis of $\beta_1 = 0$ at 1% significance level, supporting the GARCH model with the DVIX over the standard GARCH(1, 1). Next, we compare models M2 and M3, the test statistic is equal to 5.42, the null hypothesis that the past information does not add significant variance information is rejected at the 10% level only (critical value for the $\chi(2)$ with 2 degrees of freedom equals to 4.60 at the 10%), while we fail to reject the null at the 5% level (critical value for the $\chi(2)$ with 2 degrees of freedom equals to 5.99 at the 5% level). This means that the difference in log likelihoods between models M2 and M3 is quite small, allowing us to conclude that the DVIX subsumes nearly all information relevant for predicting future variance.

4.3 Out-of-sample Model

After assessing the in-sample 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. They are 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 (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 (Szakmary, Ors, Kim and Davidson (2003)):

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

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.

Following the existing literature (Szakmary, Ors, Kim and Davidson (2003), Egelkraut and Garcia (2006), Brittain, Garcia and Irwin (2011)) we formulate and test several hypothesis related to the information content of the HISTV, GARCHV and DVIX.

H1: Implied volatility is an unbiased forecast of future realized volatility.

To test our first hypothesis we consider a univariate regression of the form:

$$RV_{t,t+T} = \alpha + \beta_2 DVIX_t + \epsilon_{t,t+T}. \tag{11}$$

If an implied volatility forecast 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 hypothesis $H_0 : \alpha = 0$ and $\beta = 1$. We also run a similar test for unbiasedness for historical volatility and GARCH-type forecasts.

H2: Implied volatility has more predictive power than alternative time-series forecasts of future realized volatility.

To test this hypothesis we first need to estimate the following regressions:

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

where TSV_t is a time-series estimate of volatility, such as $HISTV_t$ or a more sophisticated $GARCHV_t$. If the DVIX forecasts the future realized volatility better than time-series forecasts, then the R^2 from the regression described by Equation 11 exceed that from the regressions described by Equation 12.

H3: Implied volatility efficiently impounds all information about future realized volatility, including that represented by time-series forecasts.

To test our third hypothesis we need to consider the results from the encompassing regressions involving the DVIX and either the HISTV or GARCHV:

$$RV_{t,t+T} = \alpha + \beta_1 TSV_t + \beta_2 DVIX_t + \epsilon_{t,t+T}. \tag{13}$$

The hypothesis that the DVIX is the informationally efficient estimate of the subsequent realized volatility and that the time-series forecasts contain to information beyond what is already included in the DVIX implies that $\beta_1 = 0$ in Equation 13. Thus, our third testable hypothesis means that the time-series forecasts have no explanatory power beyond that already contained in the DVIX.

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.

In total we have 9 models (M1 - M9), which are used to examine hypothesis H1-H3.

Here we list their specifications:

$$RV_{t,t+T} = \alpha + \beta_1 HISTV_t + \epsilon_{t,t+T}, \tag{M1}$$

$$RV_{t,t+T} = \alpha + \beta_1 GARCHV_t + \epsilon_{t,t+T}, \tag{M2}$$

$$RV_{t,t+T} = \alpha + \beta_1 EGARCHV_t + \epsilon_{t,t+T}, \tag{M3}$$

$$RV_{t,t+T} = \alpha + \beta_1 GJR\text{-}GARCHV_t + \epsilon_{t,t+T}, \tag{M4}$$

$$RV_{t,t+T} = \alpha + \beta_2 DVIX_t + \epsilon_{t,t+T}, \tag{M5}$$

$$RV_{t,t+T} = \alpha + \beta_1 HISTV_t + \beta_2 DVIX_t + \epsilon_{t,t+T} \tag{M6}$$

$$RV_{t,t+T} = \alpha + \beta_1 GARCHV_t + \beta_2 DVIX_t + \epsilon_{t,t+T} \tag{M7}$$

$$RV_{t,t+T} = \alpha + \beta_1 EGARCHV_t + \beta_2 DVIX_t + \epsilon_{t,t+T} \tag{M8}$$

$$RV_{t,t+T} = \alpha + \beta_1 GJR\text{-}GARCHV_t + \beta_2 DVIX_t + \epsilon_{t,t+T} \tag{M9}$$

The estimation results for four different forecasting horizons and 9 models are reported in Table 7, where the p-values of the estimates are adjusted for serial correlation and heteroscedasticity using the Newey-West (1987) procedure. We first discuss estimation results for the forecast horizon $T = 22$, as only in this case the hypothesis of unbiasedness can be tested. Estimation results for models M1 - M5 imply that all five different volatility measures contain important information about future volatility, as all slope coefficients are positive and significant. Our first testable hypothesis H1 investigates whether the considered volatility measures are unbiased forecasts for future actual volatility. 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 of our first testable hypothesis suggest that the implied volatility estimate is a biased estimate of the future realize volatility. The results of the next two testable hypotheses H2 and H3 will show whether the DVIX contains some useful information in predicting future realized volatility on different horizons.

If the second hypothesis H2 is correct, then R^2 for the model M5 should be higher than for models M1-M4. In fact we see that HISTV produces higher explanatory power and outperforms all alternative forecasts. R^2 coefficient is equal to 0.227 for the model which includes HISTV as a forecast for future realized volatility in comparison to 0.141 for the model with the DVIX, allowing us to reject H2 for the forecast horizon of 22 trading days.

In the third hypothesis, we analyze informational efficiency of the DVIX relative to the alternative forecasts. We find that DVIX efficiently impounds all information when the alternative volatility forecast is modeled with GJR-GARCHV estimate, as the slope

coefficients for the model M9 is insignificant. However the hypothesis H3 does not hold when the alternative volatility forecast is modeled with the historical volatility forecast HISTV, GARCHV or EGARCHV. The results of Model M6 provide evidence that the HISTV forecasts offer some additional information which is not captured by the DVIX. For the horizon T = 22 trading days, movements in historical volatility can explain 22.7% of the variability in subsequent realized volatility, while the combination of the DVIX and historical volatility can explain 26.9%. We also notice that the model which includes both the historical volatility 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.

We now discuss the hypotheses H2 and H3 for horizons $T = 10, 5, 1$ trading days. When we consider univariate regressions we again find that the historical volatility has the highest explanatory power of the subsequent realized volatility, supported by the highest R^2 value. As for H3 we find that the DVIX efficiently impounds all information when the alternative volatility forecast is modeled with GARCH-type models. However, the historical volatility offer some additional information which is not captured by the DVIX alone. Thus for the horizons $T = 10, 5, 1$ we cannot provide an evidence of informational efficiency of the DVIX. We also find that the combination of the DVIX and the HISTV provides the highest R^2, indicating that not all information is incorporated in the DVIX and the HISTV appears to provide additional information about future realized volatility.

We want to notice that 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.

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 (DVIX), we closely follow the CBOE VXO (old VIX) methodology. Before investigating the forecast-

ing 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 historical information only marginally improves the information content provided by the DVIX.

Finally, we perform the out-of-sample forecast of the future realized volatility using the DVIX and the other alternative volatility forecasts. We formulate three testable hypothesis which help us to compare time-series models and the implied volatility. 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.

A 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:

$$\sigma_t = \sigma_c\Big(\frac{\sqrt{N_c}}{\sqrt{N_t}}\Big), \tag{A.1}$$

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:

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

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). Next, we apply the trading-day adjustment using Equations A.1 and A.2. 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:

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

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

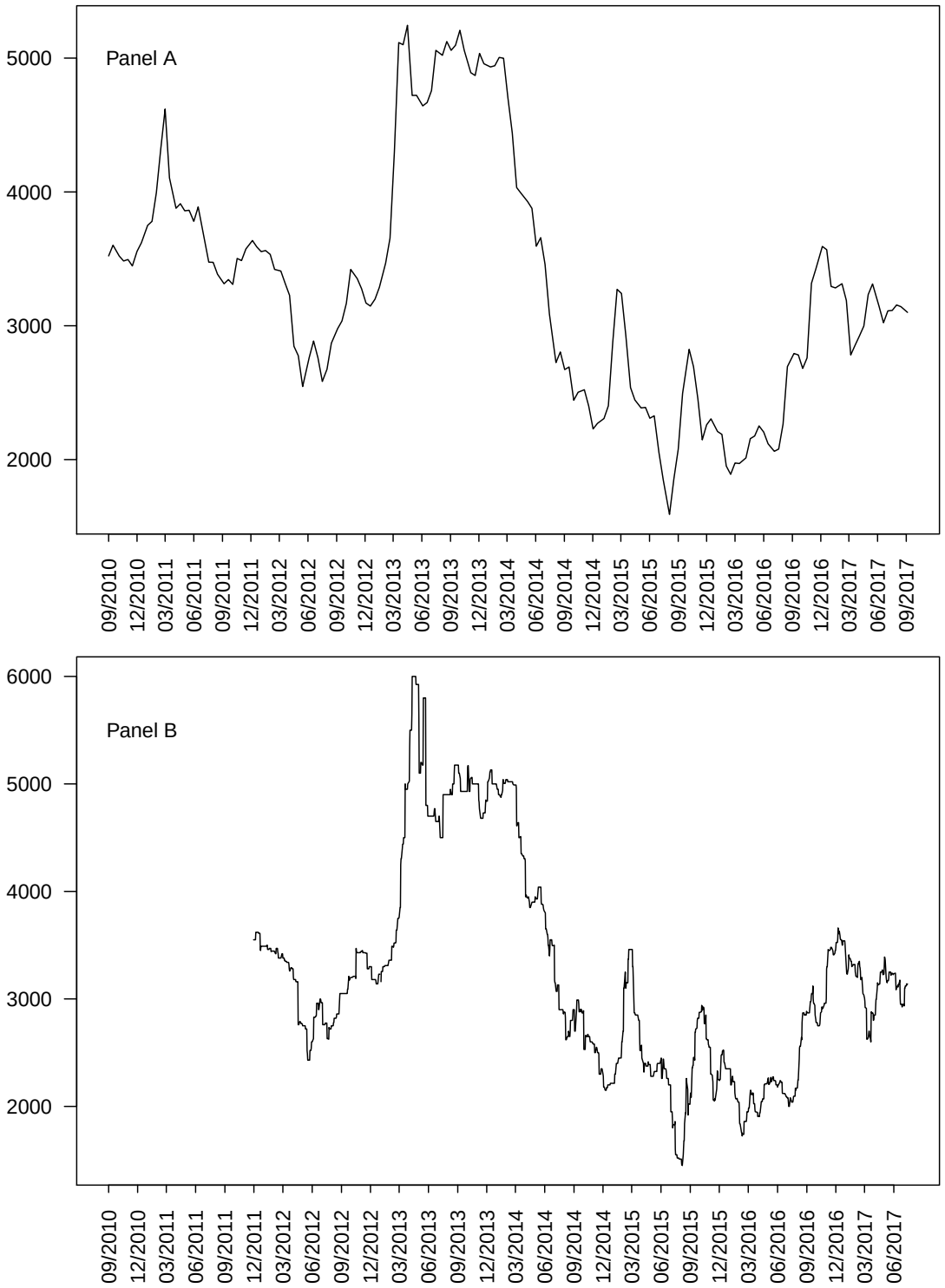
$$\sigma_1 = \sigma^{X_d^1}\Big(\frac{X_u^1 - F_1}{X_u^1 - X_d^1}\Big) + \sigma^{X_u^1}\Big(\frac{F_1 - X_d^1}{X_u^1 - X_d^1}\Big)$$
$$\sigma_2 = \sigma^{X_d^2}\Big(\frac{X_u^2 - F_2}{X_u^2 - X_d^2}\Big) + \sigma^{X_u^2}\Big(\frac{F_2 - X_d^1}{X_u^2 - X_d^2}\Big)$$

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

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

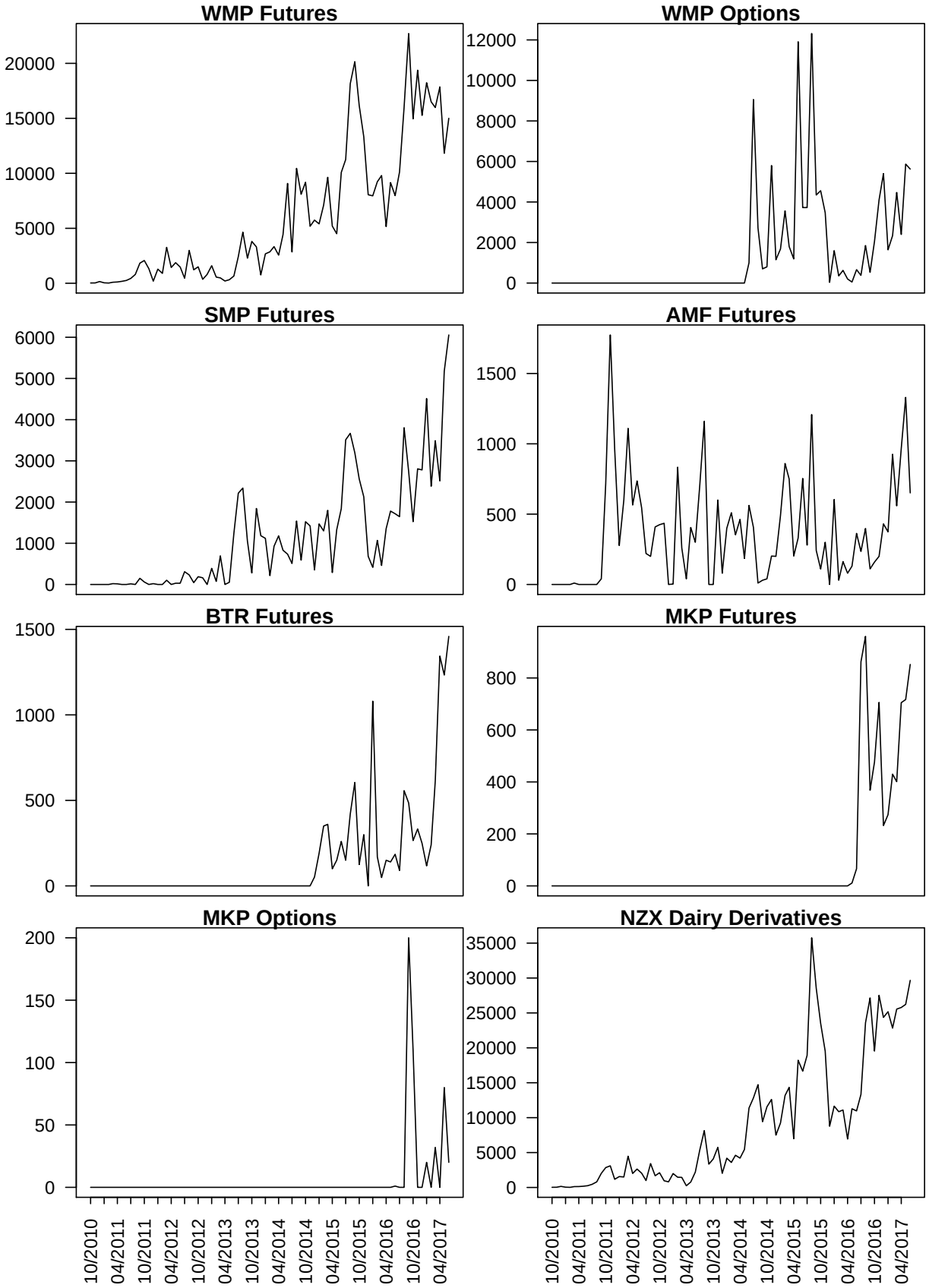
where N_{t_1} and N_{t_2} are the number of trading days to expiration of the nearby and second nearby contract, respectively.

Figure 1: WMP GDT Auction and Futures Prices



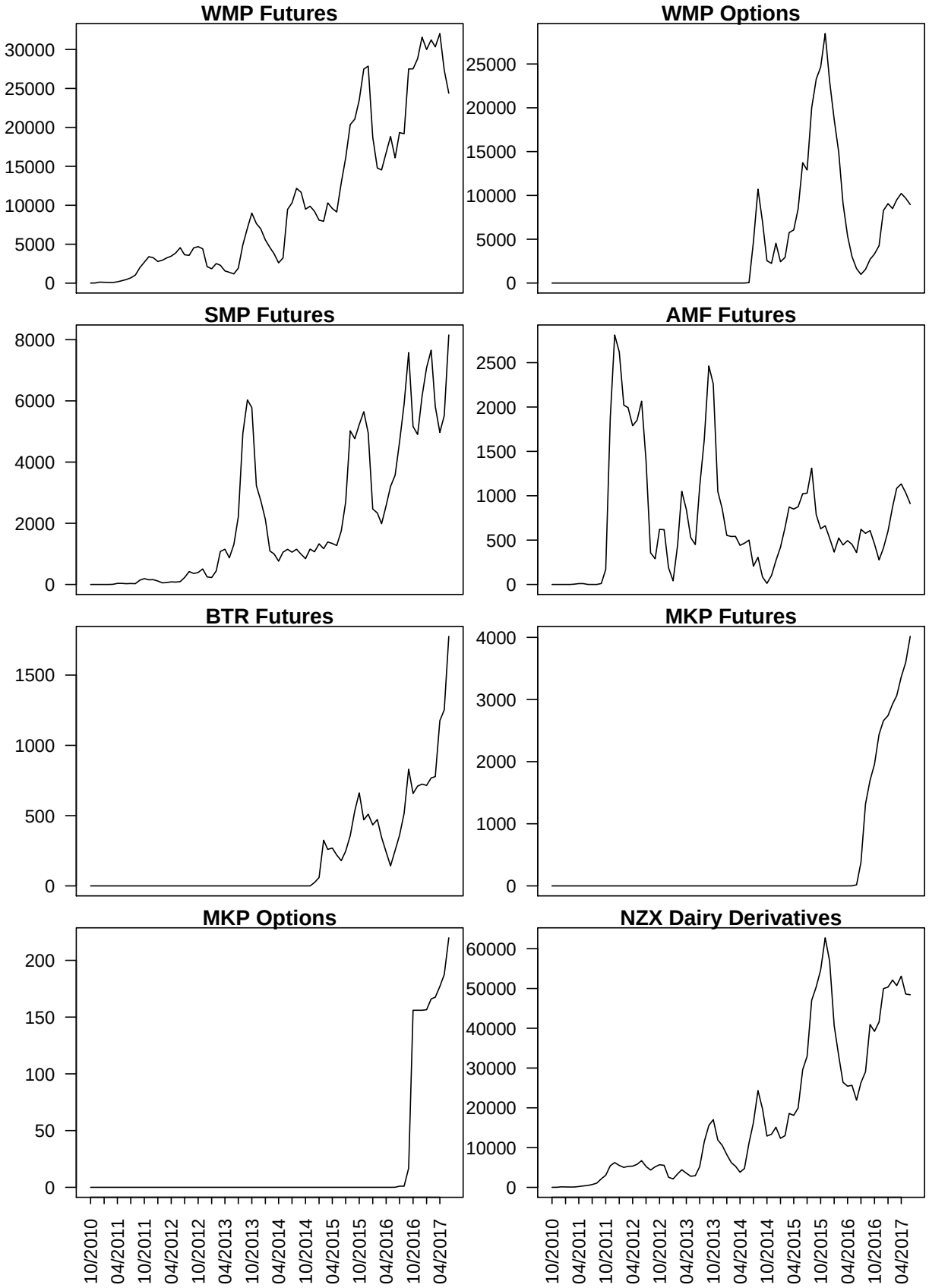
Note: This figure shows GDT auction weighted average price for all contracts of the WMP for the period between September 1, 2011 and September 5, 2017 (Panel A). The price is in USD per metric tonne. Panel B depicts the settlement price of the nearby WMP futures contracts.

Figure 2: NZX Dairy Derivatives Volume



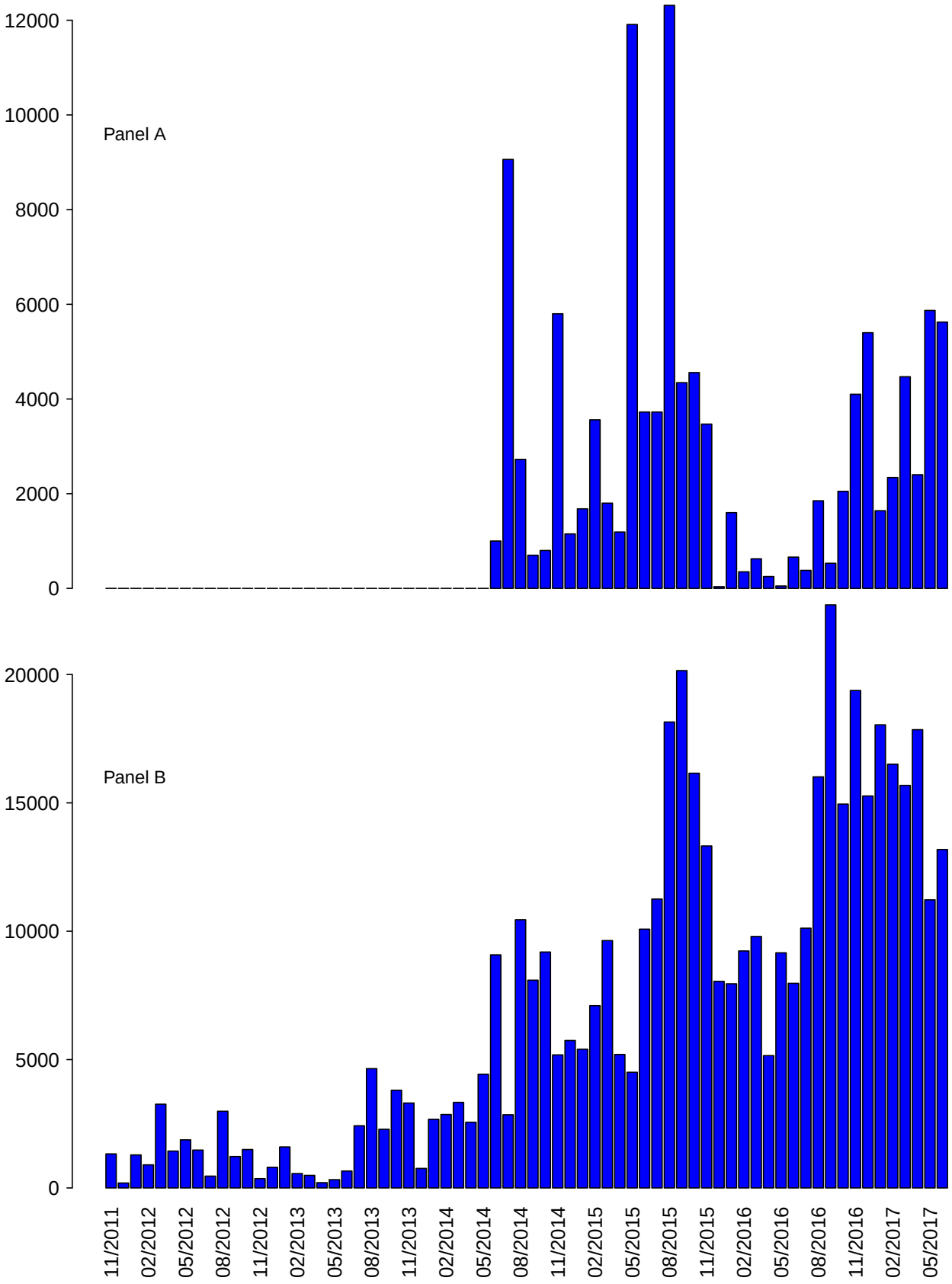
Note: This figure shows the monthly trading volume for all NZX Dairy Derivatives for the period between October 8, 2010 and June 30, 2017.

Figure 3: 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 4: 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 5: Dairy VIX

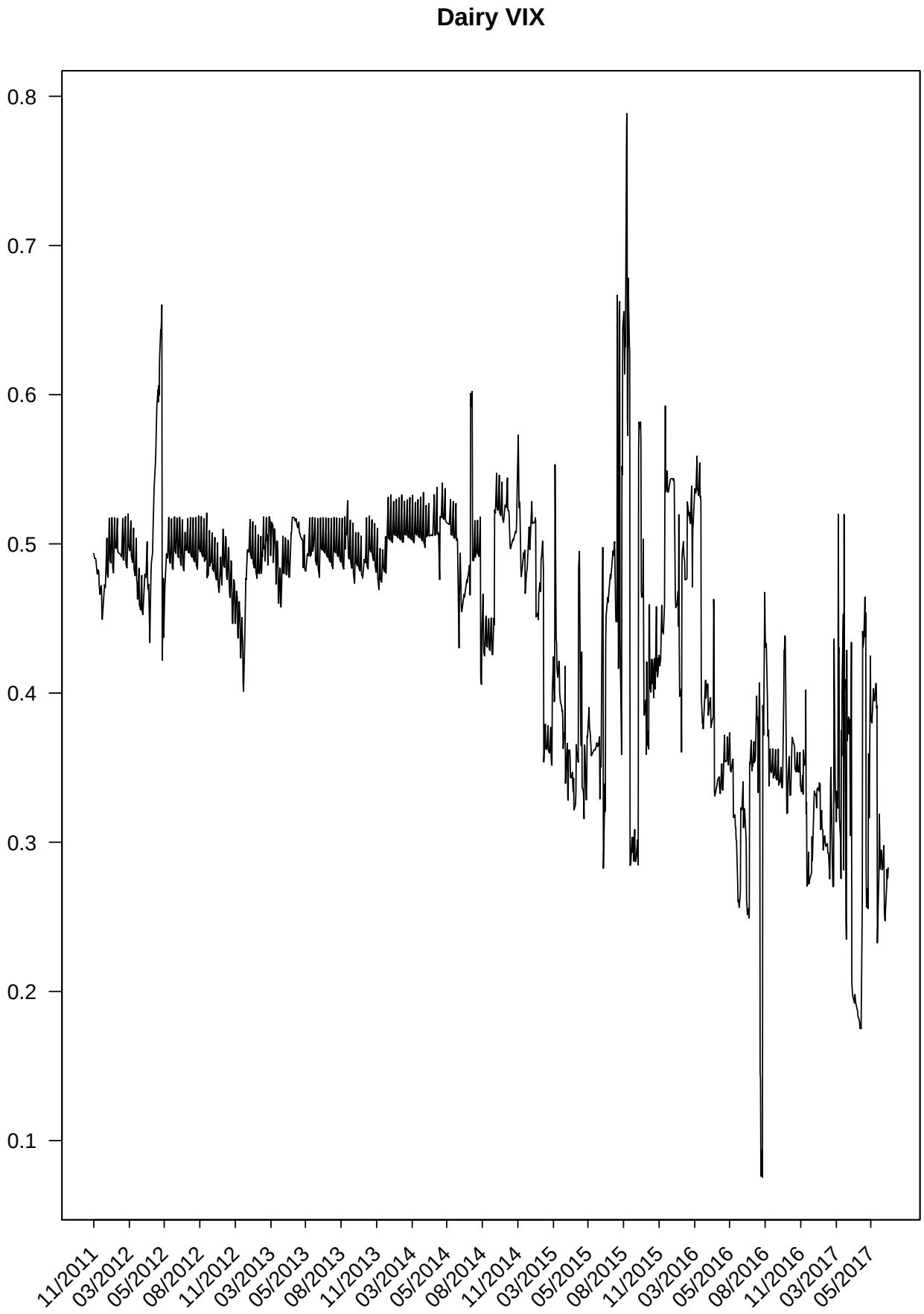
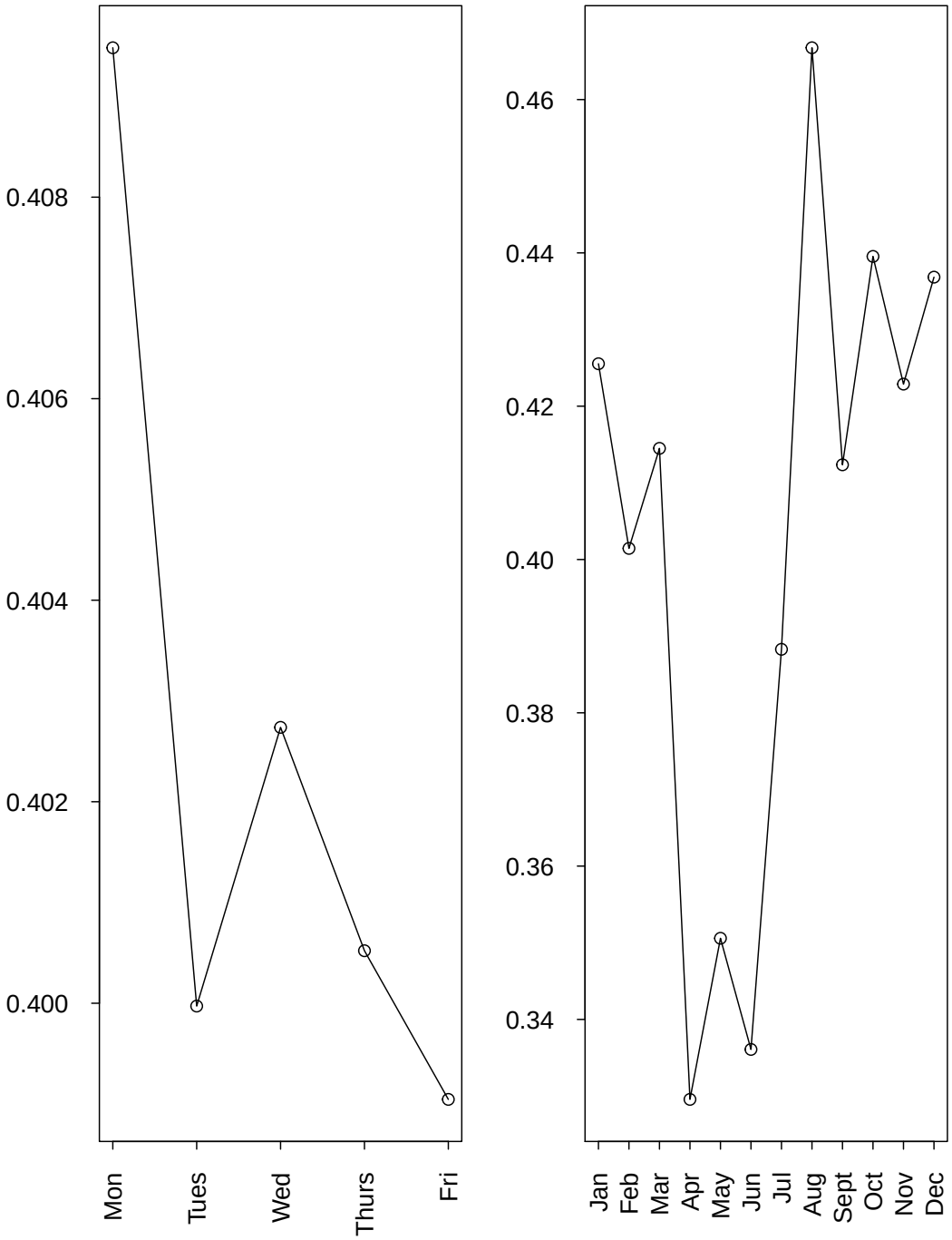


Figure 6: Average Intraweek and Intramonth DVIX



Note: This figure shows the average intraweek (left panel) and intramonth (right panel) 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

	2014/10/01 2017/07/14	2014/10/01 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
0.029***	0.786***	0.045	-0.013	0.048	0.057	0.006	0.771
(2.951)	(13.661)	(0.608)	(-0.149)	(0.733)	(1.094)	(0.399)	

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}	0.0133	(0.1380)
R_{t-1}	-0.2200**	(-2.1973)
R_t	0.1470	(1.0160)
R_{t+1}	-0.1399	(-1.3128)
R_{t+2}	0.0164	(0.1693)
$\|R_{t-2}\|$	0.0122	(0.1247)
$\|R_{t-1}\|$	-0.1733*	(-1.8278)
$\|R_t\|$	0.0819	(0.5558)
$\|R_{t+1}\|$	0.0951	(0.8226)
$\|R_{t+2}\|$	-0.0809	(-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 GARCH Estimation

	M1		M2		M3	
	coeff	t-stat	coeff	t-stat	coeff	t-stat
μ	-0.001	(-1.470)	-0.001	(-1.220)	-0.001	(-1.090)
ω	0.000***	(2.187)	0.000	(0.286)	0.000	(1.608)
α_1	0.009***	(3.524)	0.000	(0.000)		
α_2	0.980***	(164.971)	0.341**	(1.784)		
β_1			0.476***	(4.872)	0.641***	(7.793)
LL	1829.47		1844.39		1841.68	
$LR-stat$	29.84***				5.42*	

Note: This table reports the estimation results for the in-sample analysis for the period from 1 July 2014 to 14 July 2017. ***, **, * is used to indicate signi
cance at the 1%, 5% and 10% levels. Three specifications look as follows:

$$
\begin{aligned}
r_t &= \mu + \epsilon_t, \\
\epsilon_t|\mathcal{F}_{t-1} &\sim N(0, h_t), \\
h_t &= \omega + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 h_{t-1}, && \text{(M1)} \\
h_t &= \omega + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 h_{t-1} + \beta_1 DVIX_{t-1}^2, && \text{(M2)} \\
h_t &= \omega + \beta_1 DVIX_{t-1}^2, && \text{(M3)}
\end{aligned}
$$

Table 7: Estimation Results, GARCH Type models are estimated using daily returns from December 2011 to July 2015 and then rolling forward by one observation. Out-of-Sample estimation from July 2015 to July 2017.

Parameter	Model								
	M1	M2	M3	M4	M5	M6	M7	M8	M9
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 estimation results of Equations 11, 12, 13. 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. Models M1 - M9 access information content in the DVIX and time-series estimates in predicting future actual return volatility and expressed by Equations M1 - M9.

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