The Impact of USDA Reports on Dairy Futures Volatility

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(ABSTRACT)

This paper applies an event study approach to measure the impact of United States Department of Agriculture reports on dairy futures price volatility over January 2011 to December 2023. Dairy futures are a relatively understudied commodity market with a unique pricing structure and settlement procedure. An E-GARCH model is used to estimate price volatility with exogenous dummy variables of lagged volume, NDPSR, WASDE, Cold Storage, Dairy Products, and Milk Production. Milk Production had the strongest impact, significantly increasing price volatility in all markets but Class III. NDPSR was found to significantly decrease volatility in all markets except Class III. The other reports studied had mixed impacts on the dairy markets.

The Impact of USDA Reports on Dairy Futures Volatility

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(GENERAL AUDIENCE ABSTRACT)

This paper attempts to measure the impact of United States Department of Agriculture reports on dairy futures price volatility from January 2011 to December 2023. Dairy futures are a relatively understudied commodity market with a unique pricing structure and settlement procedure. A volatility estimation model is used to estimate price volatility with exogenous variables of lagged volume, NDPSR, WASDE, Cold Storage, Dairy Products, and Milk Production. Milk Production is the most impactful of USDA reports, positively impacting all markets but Class III. NDPSR was found to have a negative impact on all markets except Class III. The other reports studied had mixed impacts on markets.

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Chapter 1

Introduction

The U.S. dairy market is a significant component of the world's agricultural sector and is essential to people's nutrition worldwide. Dairy, along with eggs, is one of two naturally occurring foods that contain all the necessary nutrients to sustain complex organisms (Prentice, 2014). However, fluid milk is not easily stored without significant changes to its structure. This has led to a surplus of milk being processed into other products, such as cheese, butter, and milk powders, which are more easily stored. According to the U.S. Dairy Export Council, the industry generates 3.3 million jobs and has a significant economic impact of $753 billion (Dykes, 2018). Nevertheless, the increasing costs of production and unprecedented price volatility have made profitability in the dairy industry challenging, especially for smaller farms (MacDonald, 2020).

Despite their importance, the dairy markets and their dynamics have not received as much research attention as other agricultural commodities. This is partly due to the complexity and relatively immature nature of dairy markets (Staugaitis, 2019). Volatility inherent in futures markets means that market participants face a certain level of risk when entering a position. When volatility increases, certainty about the future product price decreases. According to a study by Nguyen and Prokopczuk (2019), butter and milk have experienced the most significant price jump over the last four decades among 29 different commodities from the agriculture, energy, and metals sectors.

To help address this volatility, the U.S. government provides various resources to dairy market participants in the form of pricing structure and reporting, price and revenue insurance products, as well as supply and demand information and outlook reports. The unique pricing structure for dairy products is implemented by the USDA under the Federal Milk Marketing Orders (FMMO) and released in the National Dairy Product Sales Reports (NDPSR) on a weekly basis. Fan et al. (2023) assessed the impact of the FMMO pricing system and NDPSR on futures volatility across all dairy commodities and found that dairy futures markets showed increased trading activity in response to USDA's NDPSR information. Additionally, information released in the NDPSR reduced total volatility as contract expiration approached. However, the COVID-19 pandemic increased volatility in dairy commodities and reduced the impact of information uncertainty on volatility, indicating the effectiveness of the NDPSR as a price discovery tool.

The USDA also aims to bring information to the uncertain dairy markets by releasing reports that provide valuable insights into various market aspects. USDA reports have been shown to have a significant impact on various commodity markets in previous studies. These studies typically follow an event-study format to examine the impacts of USDA report releases on cash and futures price volatility and other market dynamics, as well as the impacts of report releases on options implied volatility and impacts of unanticipated information in USDA reports (Massa et al., 2023). For example, a study by Isengildina et al. (2006) investigated the influence of USDA reports on the livestock markets and found that most USDA reports, with the exception of Cold Storage, had a statistically significant impact on live/lean hog and live cattle futures returns. Xie et al. (2016) utilized an Integrated Generalized Auto-Regressive Conditional Heteroskedasticity (IGARCH) model to analyze the impact of public and semi-public reports on cotton futures. The study identified Prospective Plantings and the WASDE as the two most significant USDA reports affecting cotton futures.

To the best of our knowledge, no previous study evaluated the impact of USDA reports (other than NDPSR) on dairy markets. This paper aims to address this gap by comprehensively analyzing the impact of the World Agricultural Supply and Demand Estimates (WASDE), Cold Storage, Milk Production, and Dairy Products report on dairy futures market volatility. Specifically, our objective is to estimate the direct impact of USDA reports on overall dairy price volatility.

Dairy markets present a particularly interesting case for this investigation for the following reasons. First, they are relatively new and complex, with multiple closely related commodities traded and contracts maturing every month. For instance, Tejeda et al. (2021) examined the relationship between Class III and cheese contracts, and recommended eliminating one of the two futures contracts to increase liquidity and price stability in the other, as they appear to serve the same purpose. Second, in the presence of the federal pricing and reporting system, reports may have different impacts, with some increasing volatility as markets try to find an equilibrium in response to new information, with others decreasing volatility as they report the price to which futures contracts will be settled, as explained in section 2 of this manuscript. Third, these markets are thin, with low liquidity compared to other agricultural futures such as corn, soybeans, and even livestock. Thus, Du and Dong (2016) found that the so-called "settlement effect" is present in Class III milk futures markets, where price volatility decreases with increased market information via weekly USDA published information. A positive link between price volatility and trade volume was also discovered, as expected in many financial markets.

We utilize an Exponential Generalized Auto-Regressive Conditional Heteroskedasticity (EGARCH) model to accommodate for asymmetric responses of daily price returns to USDA report releases. By employing this methodology, we aim to provide a more comprehensive understanding of the factors influencing dairy futures markets and contribute valuable insights to both market participants and the USDA. This paper is organized as follows. The next chapter provides an overview of the pricing structure of dairy markets and its unique characteristics relative to other agricultural commodity markets. Chapter 3 describes the data collection process and the USDA reports included in this study. Chapter 4 explains the methodology used to perform estimation. Chapter 5 provides a comprehensive discussion of findings that assess the impact of USDA events on dairy price volatility and Chapter 6 presents the conclusions from this study. Despite the atypical market structure, our results indicate that many of the reports studied significantly affect dairy price volatility. There are also connections between futures markets within the dairy complex, indicating a possible oversaturation of dairy futures that may cause liquidity issues within these markets.

Chapter 2

Dairy Markets Background

According to the United States Department of Agriculture (USDA), milk is categorized into four classes under the Federal Milk Marketing Orders (FMMO). Class I refers to fluid milk for consumption, while Class II is used for soft products such as ice creams and yogurts. Class III is designated for cheese and dry whey, and Class IV is for butter and milk powders. It is worth noting that base Class I skim milk is priced as the average of Class III and Class IV skim milk plus 74 cents, while Class II skim milk is priced as the Class IV skim milk price plus 70 cents. The Chicago Mercantile Exchange (CME) currently offers contracts for Class III and Class IV milk, as well as cheese, dry whey, butter, and nonfat dry milk (powder), as shown in Table 2.1. These contracts are cash-settled and do not allow for physical delivery. They rely on the USDA price calculations, which connect dairy product and milk class prices.[1] For example, prices of cheese, butter, and dry whey are components of Class III prices and commonly referred to as Class III crush. While butter and nonfat dry milk impact Class IV prices (Class IV crush). The fact that these dairy futures only allow cash settlement lies in stark contrast to traditional agricultural commodity futures that allow for physical delivery at contract expiration. These dairy futures have contracts for every calendar month extending 24 months before expiration. Additionally, the CME provides spot dairy markets for butter, dry whey, nonfat dry milk, and cheese (measured in blocks and barrels). All four spot markets are open for 10 minutes daily and allow companies

[1] https://www.ams.usda.gov/sites/default/files/media/PriceFormula2019.pdf

with physical dairy exposure to manage their inventory effectively.[2]

Table 2.1: Dairy Commodity Futures Specifications

Commodity	Contract Initiation	Contract Size (lbs)	Limits ($)	Expanded Limits ($)	Avgerage Volume
Class III	January 1996	200,000	0.75	1.50	331.90
Cheese	June 2011	20,000	0.075	0.150	60.49
Dry Whey	November 1998	44,000	0.04	0.08	8.01
Class IV	July 2000	200,000	0.75	1.50	6.93
Butter	September 1996	20,000	0.075	0.150	21.59
Nonfat Dry Milk	November 1998	44,000	0.04	0.08	25.41

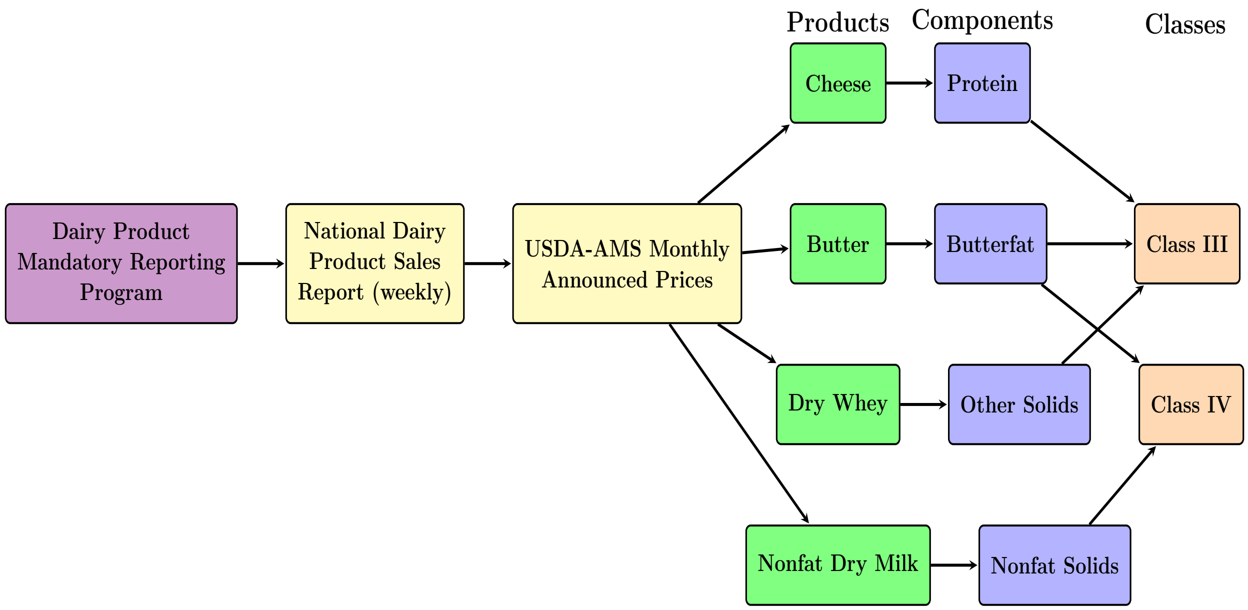
Note: Average daily nearby volume is calculated for a continuous contract described in Section 3 over January 2011-December 2023. The triggering of expanded limits in any commodity within a crush results in expansion for the entire crush complex. Further details can be found in the CME commodity rulebook. https://www.cmegroup.com/rulebook/CME/

The USDA calculates product and fluid milk prices as part of the cash settlement process for futures contracts. Dairy handlers are surveyed weekly to gather information on the value and volume of butter, cheddar, nonfat dry milk, and dry whey sold, with this data being publicly released in the National Dairy Product Sales Report (NDPSR) on a weekly basis. These dairy products are made up of various components such as protein, butterfat, nonfat solids, and other solids. Using specific formulas, the USDA determines the price for each milk class as well as each component.[3] The finalized class, product and component values are then released at the end of each month in the "Announcement of Class and Component Prices", which establishes the cash-settled price for the futures contracts. Figure 2.1 illustrates this pricing mechanism and the interconnections between dairy markets.

The dairy futures markets play a significant role in providing risk management tools for market participants. The high volatility associated with dairy products makes futures a vital risk management tool for many participants. In addition to these markets, several federally available insurance programs offer price and margin protection to dairy farmers.

[2] https://www.cmegroup.com/trading/agricultural/dairy/dairy-spot-call-auction.html
[3] https://www.ams.usda.gov/sites/default/files/media/PriceFormula2019.pdf

Figure 2.1: Federal Milk Marketing Order Price Structure



Note: The FMMO structure dictates CME dairy futures settlement prices. Class I and Class II milk FMMO prices are also driven by component prices. Base Class I skim milk is priced as the average of Class III and Class IV skim milk plus 74 cents, while Class II skim milk is priced as the Class IV skim milk price plus 70 cents.

One such program is the Dairy Margin Coverage (DMC), which is a government-subsidized margin protection product. This program is extremely beneficial for milk producers as it covers the margin between milk price and feed inputs, allowing farmers to obtain coverage for up to 95% of their production, up to 5 million pounds, for a yearly fee of $100 and a premium priced around the coverage level.[4]

Another insurance product available to dairy farmers is the Dairy Revenue Protection (DRP). This government-provided program offers quarterly coverage on the difference between the final revenue guarantee according to FMMO and actual milk revenue. It allows for customization of protection around component or class pricing, providing farmers with a flexible tool

[4]More information can be found at https://www.fsa.usda.gov/programs-and-services/dairy-margin-coverage-program/index.

to protect a significant portion of their milk production. [5]

The popularity of insurance products such as these likely decreases farmer participation in futures markets, as they require less active management. This is in contrast to many other agricultural products, where insurance programs are less protective of producers. This is a further example of the uniqueness of dairy markets compared to other agricultural commodities. Futures trading volume is supported by the heavy presence of dairy handlers and product end users within the markets. Table 2.1 shows the average daily volume for the nearby contracts included in this study. Class III is the most widely used contract, while Class IV and Dry Whey contracts have the lowest average volume. The Class III crush has more volume than the Class IV crush, likely due to cheese being the most popular dairy product. However, even the most heavily traded Class III contract volume is several magnitudes lower than traditional futures contracts' volume that typically ranges in thousands for the nearby contracts, illustrating low liquidity being a serious issue in these markets.

[5] See https://www.rma.usda.gov/Fact-Sheets/National-Fact-Sheets/Dairy-Revenue-Protection.

Chapter 3

Data

Dairy futures data, including daily open, close, high, low, volume and open interest, from January 1, 2011, to December 31, 2023, were obtained from Barchart.[1] Dairy futures are traded on the CME from 5:00 p.m. Sunday to 1:55 p.m. Friday. With a break in trading daily from 4:00 p.m. to 5:00 p.m. Central Time. Each contract has a maturity of 24 months, with trading for an expiring contract concluding at 12:10 P.M. Central Time on the trading day preceding the USDA announcement of the weighted average price.

This study examines dairy market's volatility, measured by the daily price return. The daily price returns are computed in annualized terms as follows:

$$R_t = \log\left(\frac{p_t}{p_{t-1}}\right) \times \sqrt{252} \tag{3.1}$$

where R_t represents the return at day t, p_t represents the price of the nearest-to-maturity futures contract for day t, while p_{t-1} is the price of the nearest-to-maturity futures contract at day $t-1$. Returns are calculated for each contract using close-to-close prices to measure the reaction of dairy futures to USDA report releases. The continuous nearby contract is constructed by rolling to the next maturity on the day when its open interest exceeds the one of the previous maturity. The highest volume contract was used when open interest was even between contracts. This approach allowed us to avoid contracts with very little liquidity as

[1] https://www.barchart.com/

they got close to expiration and minimized switching between contracts. [2] Utilizing the dairy futures contract with the highest open interest and volume contract ensures consistency in return values.

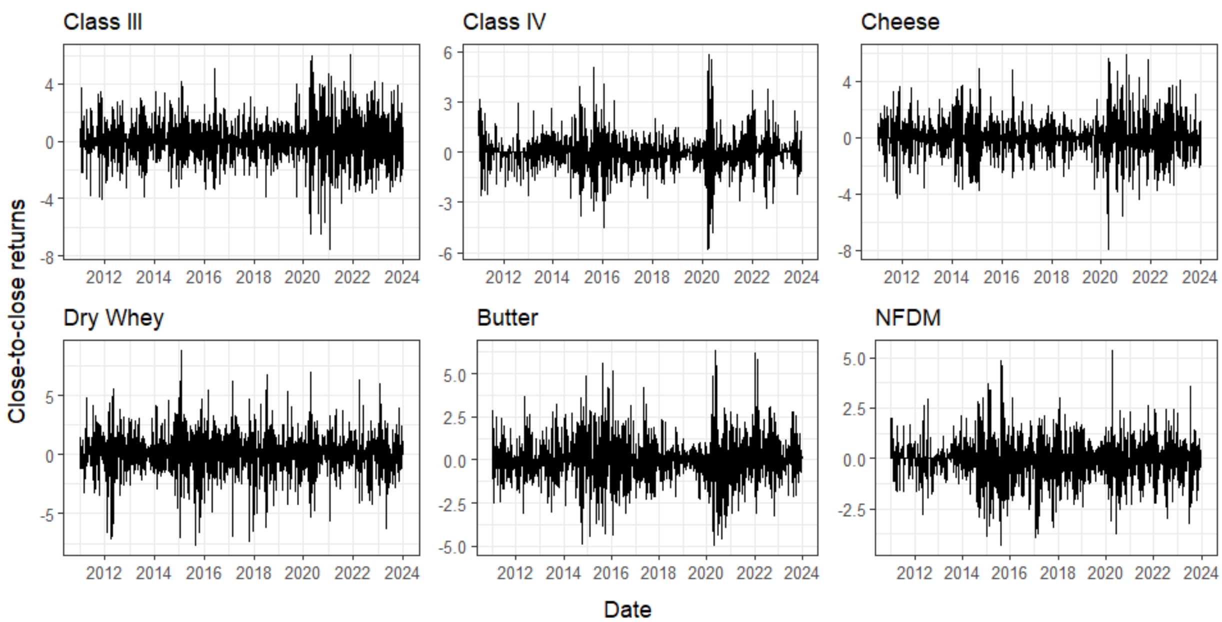
Figure 3.1 shows futures returns for each commodity. Consistent levels of volatility are seen throughout the time horizon, with times of high volatility connected to changes in market conditions. These times of high volatility often occur near each other, indicating volatility persistence. We will explore whether these volatility spikes may be attributed to additional information becoming available to the market from USDA reports. Table 3.1 shows descriptive statistics for logarithmic returns of dairy futures. As expected with financial returns, the mean values are clustered around zero. The returns for the dairy futures contain evidence of a non-normal distribution and serial correlation. The Q^2 values indicate that serial correlation is persistent across all futures.[3] GARCH-type models have been proven effective for modeling such future returns. Futures returns typically possess non-normal, skewed distributions with nonlinear dynamics in variance and mean. These characteristics make a traditional Ordinary Least Squares (OLS) regression incapable of performing meaningful analysis. An EGARCH process can address these atypical data characteristics. To determine whether a EGARCH process is appropriate, a Ljung-Box test was performed on returns for each commodity (Ljung and Box, 1978).

The Jarque-Bera test shows that the returns are nonnormal, as is commonly seen in financial returns. The excess skew and excess kurtosis values permit us to use a student-t distribution, motivating our usage of an EGARCH model with a student-t distribution.

[2] Other methods of calculating the continuous contract were considered. Using the highest open interest to dictate the roll allowed more consistent return values. It is worth noting that when calculated at expiry, the lack of volume led to unusual changes in volatility and abnormal returns. When calculated with the highest volume, gaps appeared in the returns, as zero volume days were persistent.

[3] The Ljung-Box test provided a p-value of >0.01, indicating significance that the null hypothesis of no autocorrelation present can be rejected.

Figure 3.1: Dairy Futures Returns January 2011-December 2023



Note: Continuous returns plotted calculated using equation 3.1.

Table 3.1: Close-to-close descriptive statistics for the returns of all dairy futures January 2011-December 2023.

Commodity	Class III	Class IV	Cheese	Dry Whey	Butter	NFDM
Mean	0.03	-0.00	-0.02	0.04	0.03	-0.04
Standard Deviation	1.19	0.78	1.05	1.28	1.03	0.79
Minimum	-7.59	-5.83	-7.97	-7.68	-4.97	-4.31
Maximum	6.05	5.83	5.86	8.81	6.36	5.37
Excess Skewness	0.06	0.34	-0.04	-0.14	0.29	-0.04
Excess Kurtosis	3.84	11.23	5.63	6.61	4.74	5.43
Jarque-Bera	**1,826.48**	**18,286.00**	**4,493.05**	**5,574.65**	**2,376.38**	**4,261.92**
$Q^2(20)$	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001

Note: N = 3628 for all price return series. The p-values presented for the Ljung-Box test for serial correlation in the squared returns up to 20 lags ($Q^2(20)$). Bold values from the Jarque-Bera test for normality indicate significance at the 1% level.

This study includes USDA reports that contain information relevant for the U.S. dairy market, including the following:

- The World Agricultural Supply and Demand Estimate (WASDE) forecasts the yearly supply and demand of all major U.S. agricultural commodities, including dairy, released monthly. The WASDE occurred 226 times during the analysis period. The WASDE changed release times once over the period, going from an 8:30 a.m. Eastern Time release to 12:00 p.m. Eastern Time in January 2013.[4]

- The Cold Storage report measures the food supply currently in cold storage, such as dairy products. This includes public, private and semi-private refrigerated warehouses and is released monthly. Cold Storage occurred 227 times during the analysis period and can be released on any day of the week at 3:00 p.m. Eastern Time. [5]

- The United States Milk Production report provides the number of milk cows, production per cow, and total milk production for major milk-producing states and nationally and is released monthly. The U.S. Milk Production report occurred 228 times during the analysis period and can be released on any day of the week at 3:00 p.m. Eastern Time. [6]

- The Dairy Products report contains production data for butter, cheese, frozen products, evaporated, condensed, and dry milk and whey products, as well as shipments and stocks of dry milk and whey products released monthly. The Dairy Products report occurred 227 times during the analysis period and can be released on any day of the week at 3:00 p.m. Eastern Time. [7]

[4] https://usda.library.cornell.edu/concern/publications/3t945q76s?locale=en
[5] https://usda.library.cornell.edu/concern/publications/pg15bd892
[6] https://usda.library.cornell.edu/concern/publications/h989r321c
[7] https://usda.library.cornell.edu/concern/publications/m326m1757

- The National Dairy Product Sales Report contains dairy product sales information for butter, cheddar cheese, dry whey, and nonfat dry milk. This data is used in the formulas to calculate fluid milk prices paid by handlers based on the end-use or "classification" of milk. The NDPSR occurs weekly, released on Wednesdays, except during federal holidays, and began in April 2012. There were 606 NDPSR report releases over the time horizon. The wholesale prices and volumes from the NDPSR are used by Federal Milk Marketing Orders (FMMO) when setting the prices of CME dairy cash settled markets.[8]

The dataset contains 1514 unique report releases spanning 4757 business days. There was no significant clustering between any of the report releases. Given the weekly occurrence of the NDPSR, it is the most common report to overlap with other reports. The base scenario is a day with no reports released. The report release dates and times were collected from the archives of their websites. The report dummy variable was created for the day the report impacts the market. Since intraday volatility is not included in the study, no discernible impacts appear from WASDE release time changes.

[8] https://usda.library.cornell.edu/concern/publications/zs25x847n?locale=en

Chapter 4

Methodology

This study investigates the effect of various USDA reports on dairy futures volatility. Previous studies have approached such issues using event studies (Massa et al., 2023). The event study approach attempts to measure if the studied reports cause price movement, indicating that the information is valuable to market participants (Campbell et al., 1998). In dairy markets, the various types of events can be expected to provide price reactions, with potential differences in overall volatility response. For example, the NDPSR is a report that provides direct information for settlement price calculation, as opposed to supply and demand fundamentals, and therefore has been shown to decrease volatility (Fan et al., 2023). The other USDA reports, which are supply and demand-driven, should increase volatility as markets look for a new equilibrium price that would reflect new information from these reports. Some of these reports focus on situation or inventory information. For example, the Dairy Products and Cold Storage reports provide supply data on the production and availability of various dairy products. Milk Production reports on the current U.S. milk supply, which is then used in products. The WASDE is the only forward-looking or outlook report included in this study, as it estimates future milk production and milk and product prices.

Given our focus on dairy futures return volatility and the data characteristics discussed in the previous section, we use EGARCH(1,1) models, derived by Nelson (1991), to fit these returns. This model can be expressed as:

$$\log_e \sigma_t^2 = \left(\omega + \sum_{j=1}^{m} \zeta_j v_{jt}\right) + \sum_{q=1}^{j} (\alpha_j z_{t-j} + \gamma_j(|z_{t-j}| - E|z_{t-j}|)) + \sum_{p=1}^{j} \beta_j \log_e \sigma_{t-j}^2 \tag{4.1}$$

where α_j is a constant associated with past volatility shocks as seen in z_{t-j}. γ_j captures the asymmetrical effect of positive and negative shocks, and β_j is a coefficient of lagged conditional variance values. ζ_j captures the effect of exogenous variables in the model included in the term v_{jt}. Thus, this model allows for asymmetrical responses in variance.[1] We include an Autoregressive (AR) process in the mean equation to capture the impact of previous prices.[2] A student-t distribution accounted for the large kurtosis value, as seen in Table 3.1. This indicates widely distributed tails, which is evidence for using a student-t distribution in the model.

The EGARCH(1,1) models were estimated using the rugarch package in R (Galanos, 2023). We included days of week, months to capture the seasonal movements in dairy market returns. Additional variables for seasonality were also considered; however, their results did not indicate they added additional information to the models.[3] Given the illiquid nature of dairy markets, volume was included as one of the determinants of futures return volatility. A 5-day moving average lagged volume indicator variable was used to capture the impact of volume on volatility while removing the potential risk of endogeneity in the model. This variable takes the value of one when lagged volume was greater than the 5-day moving

[1] Other GARCH-type models were considered; however, the EGARCH provided the most accurate fit.

[2] The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) criteria consistently chose a lag of 1 as being most appropriate across model specifications.

[3] These results are not included here but are available from the authors upon request.

average lagged volume and zero otherwise (Donaldson and Kamstra, 2005), as follows:

$$V_{t-1} = \begin{cases} 1 & \text{if } Volume_{t-1} \geq \dfrac{1}{(n-1)} \sum_{i=2}^{n} Volume_{t-i} \\ 0 & \text{otherwise} \end{cases} \tag{4.2}$$

Other potential methods to capture the effect of volume while minimizing potential endogeneity were considered, including using lagged volume and a 21-day moving average lagged volume indicator variable. The implications of using these alternative measures are discussed in the sensitivity analysis section.

The impact of USDA reports was measured using dummy variables for NDPSR, WASDE, Cold Storage, Milk Production, and Dairy Products reports included in the variance equation. The full model is specified as:

$$R_t = \mu + \phi_1 R_{t-1} + \epsilon \tag{4.3}$$

$$\log \sigma_t^2 = \omega + \sum_{i=1}^{q} \left(\alpha_q z_{t-i} + \gamma_q (|z_{t-i}| - E|z_{t-i}|) \right) + \sum_{i=1}^{p} \beta_p \log \sigma_{t-i}^2 + \delta Volume_{t-1} + \sum_{j=1}^{m} \left(\zeta_{j,t} \cdot Reports_{j,t} \right) + \epsilon_t$$

where $z_t = \dfrac{\varepsilon_t}{\sqrt{\sigma_t^2}}$, and ζ is the coefficient associated with Report releases.

Chapter 5

Empirical Results

The EGARCH(1,1) models were estimated for each set of returns. The conditional variance estimates from the EGARCH model are shown in Figure 5.1, overlaid with the 21-day rolling annualized standard deviation. There are significant differences in the volatility between commodities, with Class III and cheese having less volatility than Butter and Nonfat Dry Milk. This may be due to liquidity differences between markets, as indicated by the average daily volume of nearby contracts shown in 2.1, with less liquid markets having higher volatility. For less volatile markets, such as Class III and cheese, the estimated conditional variance does not overlap with the standard deviation. Across all commodities, the EGARCH(1,1) model appears to represent the movements in daily dairy futures returns adequately.

Table 5.1 shows estimation results for Class III milk. Similar results for the other commodities included in this study can be found in the appendix. These tables contain a basic EGARCH (1,1) model results, with no exogenous variables in Model 1. Basic model with a volume indicator in the variance equation in Model 2. Basic model with USDA report variables in the variance equation Model 3. Basic model with both volume and report variables in the variance equation in Model 4. Across all models, various model fit measures, such as the log-likelihood, AIC, and BIC had similar values for Models 2 through 4. However, Model 4 contained an incrementally better fit and will be the primary focus of our discussion of the results due to its inclusion of all variables considered relevant for this study. Across all specifications, the R_{t-1} term provided evidence of a significant correlation between previous

Table 5.1: Class III Futures Exponential GARCH Results

	Model 1	Model 2	Model 3	Model 4
Mean Equation				
μ	0.004^{**}	0.004^{*}	0.004^{**}	0.004^{*}
	(0.002)	(0.002)	(0.002)	(0.002)
R_{t-1}	0.107^{***}	0.110^{***}	0.106^{***}	0.109^{***}
	(0.018)	(0.024)	(0.017)	(0.024)
Variance Equation				
ω	-0.223^{***}	-0.317^{***}	-0.231^{***}	-0.327^{***}
	(0.040)	(0.043)	(0.045)	(0.048)
α	0.008	0.008	0.007	0.005
	(0.025)	(0.024)	(0.026)	(0.025)
β	0.933^{***}	0.938^{***}	0.936^{***}	0.940^{***}
	(0.010)	(0.010)	(0.010)	(0.009)
γ	0.734^{***}	0.670^{***}	0.722^{***}	0.656^{***}
	(0.060)	(0.057)	(0.059)	(0.055)
skew	1.041^{***}	1.040^{***}	1.041^{***}	1.040^{***}
	(0.020)	(0.021)	(0.020)	(0.023)
shape	2.796^{***}	2.808^{***}	2.781^{***}	2.795^{***}
	(0.173)	(0.174)	(0.170)	(0.171)
$Volume_{t-1} > 5$ma		0.231^{***}		0.235^{***}
		(0.046)		(0.046)
NDPSR			0.211^{*}	0.208^{*}
			(0.089)	(0.088)
WASDE			-0.470^{**}	-0.462^{**}
			(0.135)	(0.134)
Cold Storage			0.116	0.099
			(0.145)	(0.145)
Dairy Products			0.166	0.178
			(0.132)	(0.132)
Milk Production			-0.225	-0.279
			(0.146)	(0.147)
Log likelihood	1834.66	1846.54	1846.37	1858.76
AIC	-1.12	-1.12	-1.12	-1.13
BIC	-1.1	-1.11	-1.1	-1.1

Note: The dependent variable is the close-to-close class iii future returns. The sample size contains 3268 observations. Standard errors are displayed below the coefficient values. Significance level is indicated by $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

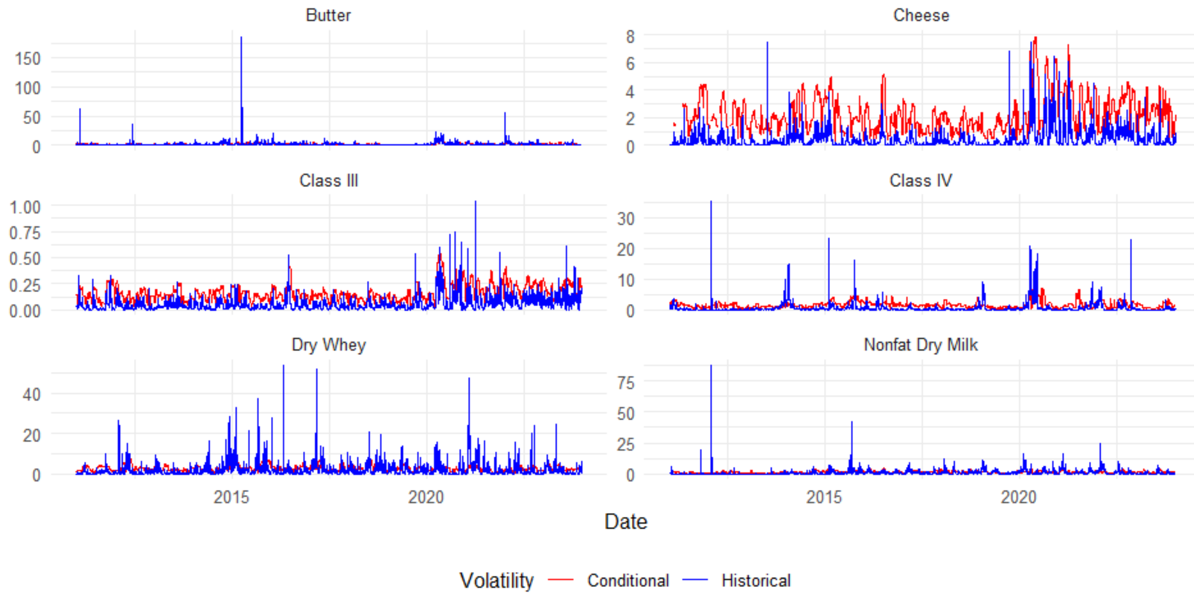
and current-day returns. Additionally, the β shows evidence of long-run volatility persistence. The γ values indicated that a positive shock increases future volatility more than a negative shock. This is the opposite impact seen in many markets with the leverage effect, which indicates that a negative shock will increase future volatility more than a positive shock. The skew and shape also indicate a non-normal distribution with leptokurtic tails. These results can be seen across all commodities.

In Figure 5.2, the estimated coefficients for exogenous variables included in Model 4 are shown for returns across all commodities. The coefficients have a standard error bar around them indicating the 95% significance level. These values are plotted around 0, where the standard error bar extending across the value of 0 indicates lack of statistical significance at the 95% level . In contrast, if the error bar does not cross over zero line, the variable has a significant impact on return variance. Consistent with our expectations, most of the results indicate that volume is, in fact, a significant positive determinant of dairy futures volatility. While in many more liquid financial markets volume often decreases volatility, given the lack of daily trading in many dairy markets volume here indicates price movement, and subsequently volatility. Cheese is the notable exception, where while still having a positive effect on volatility, the impact of volume is not statistically significant.

NDPSR reports significantly affect all dairy markets volatility except NFDM. As anticipated, these effects were negative in most cases, given that it helps guide futures prices toward settlement. However, Class III milk volatility was found to be positively impacted by the release of the NDPSR reports. This finding is in contrast to Fan et al. (2023) who found that the NDPSR reports decreased volatility in the front-month contract as settlement approached. These differences in results could be due to differences in methodology and the inclusion of volume and other reports in our study.

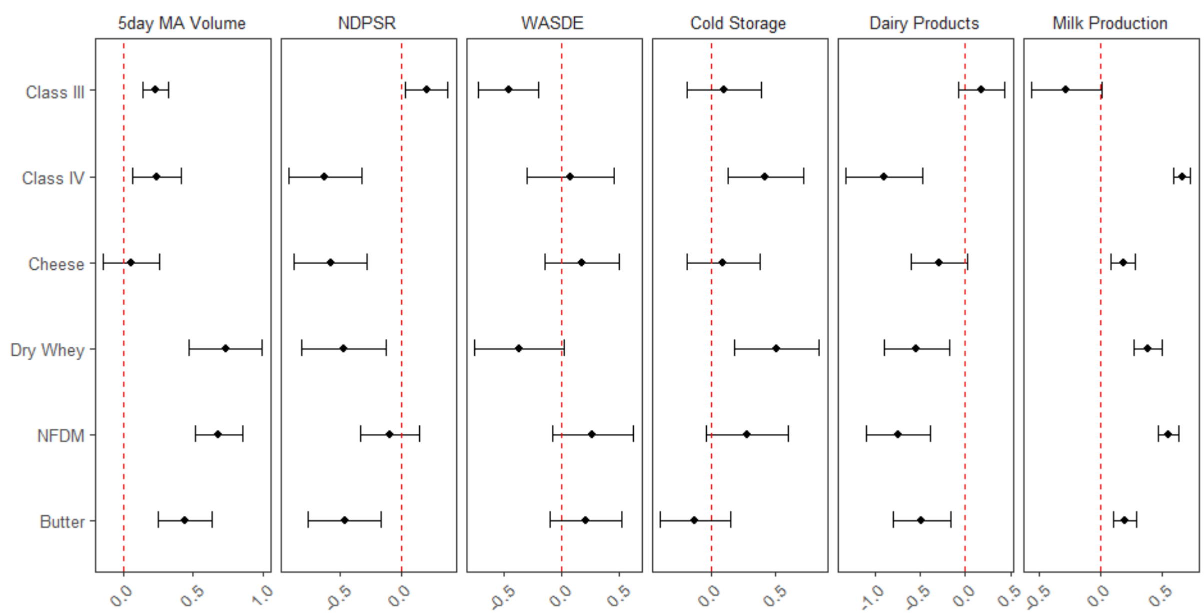
On the other hand, WASDE reports, the only forward-looking reports considered in this

Figure 5.1: EGARCH Conditional Variance vs. 21-day Rolling Annualized Standard Deviation, January 2011-December 2023



Note: Conditional variance values estimated from Model 4 for each commodity, full model results available in the appendix.

Figure 5.2: Reports and 5-day Moving Average Lag Volume Indicator Exogenous Regressor Parameter Values, January 2011-December 2023



Note: Results were obtained from Model 4 with 5-day moving average lag volume indicator to create the 95% confidence interval.

study, had mostly insignificant effects on dairy futures returns. The only commodity it significantly affected is Class III, causing a negative effect on volatility. This finding is consistent with the evidence shown in Isengildina et al. (2006) that situation reports have a stronger market impact than outlook reports. Cold Storage reports also have limited impacts on the dairy markets, significantly affecting only Class IV and Dry Whey volatility despite not containing supply information on either of those commodities. While Cold Storage reports contain supply information for cheese and butter, they did not demonstrate a significant impact on these markets.

Dairy Products and Milk production are the two situation reports that have the strongest impact on the dairy markets. The Dairy Products report significantly impacts volatility in all commodities except Class III and cheese. Milk production has a significant impact on all except Class III dairy futures. However, these reports tend to move the markets in the opposite directions, with Milk Production releases increasing market volatility, as expected, while Dairy Products decreasing market volatility, contrary to expectations. This finding is likely due to Milk production containing new market information unavailable in the more product-focused monthly reports. On the other hand, Dairy products contain supply information associated with prices reported in the NDPSR.

5.1 Sensitivity Analysis

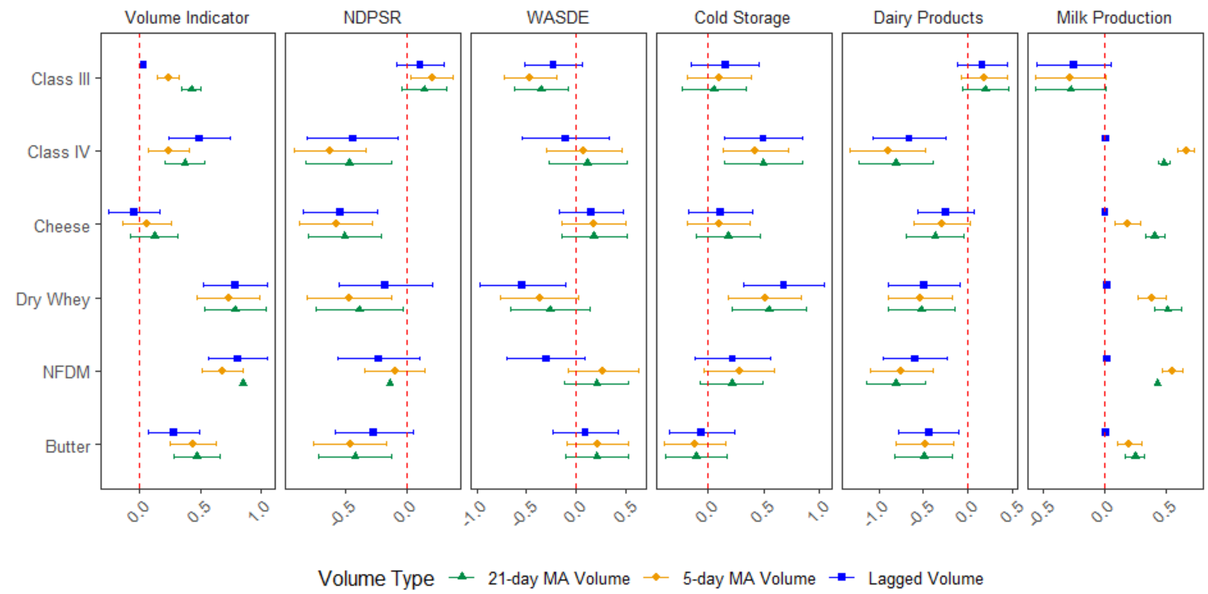
Dairy markets typically lack volume compared to many other futures contracts available, with minimal managed money and other reportables participating in the contracts. This motivated the use of 5-day lagged volume indicator to capture the impact of volume on price volatility. However, other methods of capturing the effect of volume on volatility were considered, including lagged volume and 21-day moving average lag volume indicator.

Lagged volume is calculated here as

$$LagVolume = log(Volume_{t-1}) + 1$$

to account for days when the volume is equal to zero.

Figure 5.3: 5-day Moving Average Indicator vs. Lagged Volume vs.21-day Moving Average Indicator Exogenous Regressor Parameter Values, January 2011-December 2023



Note: Results were obtained from Model 4 with the lag volume, 5-day moving average lag volume indicator, 21-day moving average lag volume indicator to create the 95% confidence interval.

Figure 5.3 shows the results of using the 5-day moving average lagged volume indicator versus lagged volume and 21-day moving average lagged volume indicator. As anticipated, they are very similar, with minimal differences between them. The main difference is that when using lagged volume, Milk Production report has a smaller impact while still statistically significant relative to results using the 5-day lagged volume indicator. Additionally, the significance of some reports varies depending on which indicator is used, such as the impact of NDPSR on Butter and Dry Whey volatility. However, the majority of reports maintain a similar effect on commodities with both volume measures. The same phenomenon can be seen when using the 21-day lagged volume indicator. However, when using the 21-day indicator, the standard error values for NFDM were extremely small for some of the exogenous variables. Still, the relationship with Milk Production remains the same across commodities.

These results provide several insights into the function of CME dairy futures. They indicate that Milk Production is a consistently important report that informs market participants and helps drive volatility. This is particularly noteworthy due to the recent loss of state-specific data on 17 states from the report, which is now being aggregated. NDPSR is found to be not as significant towards overall volatility in dairy futures as previously found, potentially due to the inclusion of lagged volume in our model estimation. Additionally, there appears to be a significant overlap between dairy futures markets. This is likely due to class III and Class IV usage in the other products available on the CME. This potential overlap motivates using a multivariate GARCH approach to measure the volatility interconnectedness between markets in their response to USDA reports.

Chapter 6

Conclusion

This study follows previous event study frameworks for measuring the value of USDA information using the unique pricing structure of dairy futures. It estimates the relationship between price volatility, trading volume, and USDA reports related to the U.S. dairy market. The event study focuses on five major USDA reports related to dairy markets: NDPSR, WASDE, Cold Storage, Dairy Products, and Milk Production. Daily futures returns from January 2011 through December 2023 are used in the analysis. This time horizon contains a variety of market conditions, allowing for accurate estimation of information impacts from reports.

The study employs an EGARCH model, with dummy variables, to measure the impact of lag volume and USDA reports on close-to-close returns for dairy futures. While alternative returns were considered, the close-to-close returns emerged as the most accurate model fit. In a departure from traditional finance literature, the return series reacted more strongly to 'good' news than 'bad' news. Based on BIC results, lag volume remained a primary indicator for overall model fit; however, in some of the future reports, the model fit improved.

The results indicate that NDPSR has a less significant impact than previously found when lagged volume is included; however, it still has a largely negative effect on volatility, which is within expectation. Additionally, many of the other reports positively impact the volatility of dairy futures. Specifically, the Milk Production report is estimated to positively impact the price volatility of five of the six dairy futures.

Given the interconnected nature of dairy markets as outlined in Figure 2.1, there is likely a heavy amount of volatility spillover between markets. The relationships between Class III and Class IV crush components are expressed in USDA-derived equations. Measuring the spillover between Class III, cheese, and dry whey would allow us to determine how the different components of the crush impact each other. It allows us to examine whether the products or the fluid milk causes larger market ripples, possibly giving a directional sense of which market is more relevant. The same approach can be used for Class IV, butter, and nonfat dry milk.

Overall, we find that USDA reports significantly impact volatility in dairy futures markets. These findings further our understanding of the relationship between the USDA information and dairy market dynamics. However, it is important to recognize that we examine these effects separately for each individual commodity. Since dairy market are heavily interconnected through physical relationships, a joint examination of the relationship between dairy markets and USDA reports would be an interesting area for future research.

Bibliography

Campbell, J. Y., Lo, A. W., MacKinlay, A. C., and Whitelaw, R. F. (1998). The Econometrics of Financial Markets. *Macroeconomic Dynamics*, 2(4):559–562.

Donaldson, R. G. and Kamstra, M. J. (2005). Volatility Forecasts, Trading Volume, and the ARCH Versus Option-Implied Volatility Trade-Off. *Journal of Financial Research*, 28(4):519–538.

Du, X. and Dong, F. (2016). Responses to Market Information and the Impact on Price Volatility and Trading Volume: The Case of Class III Milk Futures. *Empirical Economics*, 50:661–678.

Dykes, M. (2018). U.S. Dairy Industry's Economic Impact Totals $753 Billion. https://www.idfa.org/news/u-s-dairy-industrys-economic-impact-totals-753-billion.

Fan, Z., Jump, J., Tse, Y., and Yu, L. (2023). Volatility in US Dairy Futures Markets. *Journal of Commodity Markets*, 29.

Galanos, A. (2023). *rugarch: Univariate GARCH Models.* R package version 1.5-1.

Isengildina, O., Irwin, S. H., and Good, D. L. (2006). The Value of USDA Situation and Outlook Information in Hog and Cattle Markets. *Journal of Agricultural and Resource Economics*, 31(2):262–282.

Ljung, G. M. and Box, G. E. (1978). On a Measure of Lack of Fit in Time Series Models. *Biometrika*, 65(2):297–303.

MacDonald, J. M. (2020). Consolidation in us agriculture continues. *Amber Waves: The Economics of Food, Farming, Natural Resources, and Rural America*, 2020(1).

Massa, O. I., Karali, B., and Irwin, S. H. (2023). What Do We Know About the Value and Market Impact of the US Department of Agriculture Reports? *Applied Economic Perspectives and Policy*, 46(2):698–736.

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica: Journal of the Econometric Society*, pages 347–370.

Nguyen, D. B. B. and Prokopczuk, M. (2019). Jumps in Commodity Markets. *Journal of Commodity Markets*, 13:55–70.

Prentice, A. M. (2014). Dairy Products in Global Public Health. *The American Journal of Clinical Nutrition*, 99(5):1212S–1216S.

Staugaitis, A. J. (2019). The Effect of Diary Futures Trading Activity on Their Price Volatility: Literature Review. *Science & Studies of Accounting & Finance: Problems & Perspectives/Apskaitos ir Finansu Mokslas ir Studijos: Problemos ir Perspectyvos*, 13(1).

Tejeda, H. A., Trujillo-Barrera, A., and Fortenbery, T. R. (2021). Identifying the Purpose and Success of Dairy Futures Contracts: Are Class III and Cheese Futures Contracts Serving Distinct Markets?

Xie, R., Isengildina-Massa, O., Dwyer, G., and Sharp, J. (2016). The Impact of Public and Semi-public Information on Cotton Futures Market. *Applied Economics*, 48(36):3416–3431.