Heterogeneous Responses to Market Information and The Impact on Price Volatility and Trading Volume: The Case of Class III Milk Futures

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Abstract: Under the theoretical intraday microstructure framework, we analyze the impact of traders' heterogeneous responses to market information on daily futures price and trading activity by utilizing the unique features of Class III milk futures contract. The cash settlement and classified pricing scheme distinguish milk futures from other commodities. We construct two variables, days to maturity and price deviates, to capture the distinctive features. While days to maturity indicate the length of time before cash settlement in the maturity month, price deviates reflect traders' heterogeneous responses to weekly published information on milk prices. A structural price volatility-trading volume model is specified and is estimated using the Bayesian Markov chain Monte Carlo method. The results confirm that (i) the closer to cash settlement, the lower milk futures price volatility, which is opposite to the typical "Samuelson effect" for other commodity futures, and (ii) both price variability and trading volume are increasing functions of traders' heterogeneous responses to market information and therefore are positively associated. The results can be seen as evidence that the USDA weekly published information has significant impact on price and trading activities in the milk futures market.

Keywords: Bayesian methods, classified pricing, microstructure model, stochastic volatility.

JEL codes: C15; G13; Q18.

Introduction

The existing literature (see, e.g., Clark 1973, Tauchen and Pitts 1983, among others) provides strong empirical evidences of a positive relation between price volatility and contemporaneous trading volume in commodity futures market. In explaining the positive association, theoretical models rely on the microstructure framework where price changes with flows of new information, which are assumed to arrive in a random intensity. Theory suggests that volatility and trading volume processes are positively related as they respond to market factors in a similar way. The factors include, for example, rate of information arrival, number of active traders in the market, traders' heterogeneous responses to new information (Tauchen and Pitts 1983), and the interactions between liquidity and informed traders (Kyle 1984; Admati and Pfleiderer 1988). But the microstructure literature focuses only on intraday price patterns and is silent on the relation among these variables at the daily frequency (Anderson 1996). The lack of appropriate proxies representing information flows and traders' responses makes it difficult to match theoretical conjectures with empirical analysis. To fill this gap, the current study utilizes the unique features of the Class III milk futures contract to construct proxy variables and thus build upon the microstructure framework to investigate dynamics of daily price volatility and trading volume.

The volatility of milk price in both spot and futures markets has increased significantly in recent years. From January 2000 to August 2013, the monthly announced Class III milk prices were in the range of \$8.57-\$21.67 per hundred weight (cwt) with standard deviation of \$3.41/cwt (see Figure 1). High price volatility has caused hardship for farm operators as dairy farms tend to be less diversified and more reliant on returns from farm business than other farm types (USDA 2004). While directly increasing market risk, unpredictable high price volatility drives significant farm exits, which contributes to even greater price variation in the short run (Manchester and Blayney 2001). Understanding the source and nature of milk price volatility is the prerequisite for the development of dairy policy.

Milk is produced at the farms every day and then is transported to fluid bottling plants or dairy product manufacturing plants for further processing. About half of the milk supply is processed into cheese, one third used for fluid milk and cream products, and the rest is manufactured to other dairy products such as butter and milk powders. The inherent characteristics such as bulkiness, perishability, and inelastic demand distinguish milk from other agricultural products. Evolved over the years, a classified pricing scheme has been adopted for the U.S. milk market where milk price is determined jointly by market supply, consumer demand and federal and state government policies.[1] Specifically, Federal Milk Marketing Orders (FMMO) set minimum prices paid by handlers for raw fluid-grade milk based on how the milk is used, by which milk is classified into four categories of Class I, II, III, and IV. The minimum price of each class of milk is determined by its linkage with the wholesale prices of manufactured dairy products. For example, Class III milk, which is the focus of this study, is used for producing cream cheese and hard manufactured cheese.[2] The corresponding minimum price is based on the market prices of cheese, butter and dry whey through pricing formula established by the U.S. Department of Agriculture (USDA). The minimum classified prices are announced monthly.[3]

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[1] Please see Manchester and Blayney (2001) for a detailed discussion.

[2] Class I milk is used for beverage products; class II milk is used for soft manufactured products such as cottage cheese, yogurt, and ice cream; class IV milk is used for butter and dry milk products.

[3] The monthly class prices announcements can be found at http://www.ams.usda.gov/AMSv1.0/ams.fetchTemplateData.do?startIndex=1&template=TemplateV&page=MilkPriceAnnouncementsSummariesandProductPrices.

Milk Class III futures contracts trade on the Chicago Mercantile Exchange (CME) and have historically been the most actively traded dairy futures contract. Two unique features distinguish Class III milk futures from most other commodity futures contracts.[4] One is cash settlement. For each calendar month, one specific futures contract is cash settled, which has been trading in the market for about two years. Trading of the maturing contract terminates one day before the announcement day of the Class III price for the maturity month.[5] During the cash settlement, there are no physical delivery and ownership possession of the underlying commodity, Class III milk in this case. Instead, the difference between futures price and the USDA announced price is transferred between buyer and seller. Another distinctive feature is the classified pricing scheme of Class III milk. As discussed above, the USDA announced monthly prices on which futures contracts are settled are computed from prices and volumes of related dairy products, including butter, cheese, nonfat dry milk and dry whey, for the recent four or five weeks based on established pricing formula. The price and volume information on dairy products is collected through manufacturer survey and published weekly by the USDA.[6]

Both cash settlement and classified pricing scheme have important implications on the volatility of milk futures price. As settlement is approaching, information for determining settlement price has been gradually disclosed by the weekly survey reports. With the announcement date and pricing formula on hand, traders adjust their reservation prices and the resulting milk price expectation converges progressively to the settlement price over the maturity

[4] Other cash settled commodity futures traded on CME include lean hogs and feeder cattle.

[5] Readers refer to the Chicago Mercantile Exchange (CME) website for the detailed contract specification and settlement procedure http://www.cmegroup.com/trading/agricultural/dairy/class-iii-milk_contract_specifications.html.

[6] The schedule and historical announcements of dairy products prices and volumes (weekly) and class & component prices (monthly) can be found on http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1856.

month. Correspondingly price volatility dies down over the same period. We call this "the settlement effect", which should be contrary to the Samuelson effect evidenced in other agricultural commodity markets that futures prices exhibit increased volatility as they approach the maturity date (see, e.g., Samuelson 1965, Streeter and Tomek 1992).

Between two consecutive weekly announcements, typically four to five trading days in the middle, the deviates between daily futures prices and the previous week milk price indicate heterogeneous responses to newly arrived information among traders, or in other words, the extent to which traders disagree over recently announced price.[7] The heterogeneity in traders' responses can significantly impact price volatility and trading activity, the details of which will be discussed in the theoretical section. We call this "the heterogeneity effect".

The unique features of the milk futures contact, the so-called settlement and heterogeneity effects, provide an interesting setting that enables us to examine the daily price volatility and volume dynamics by linking to the microstructure framework. We also verify the positive association between price volatility and trading volume. For doing so we adopt a multivariate structural price volatility-trading volume model. Besides a stochastic volatility process for capturing the effect of information arrival, the model simultaneously incorporates the volatility-volume linkage. The applied model framework is found to be consistent with main contemporaneous and dynamic features of the data and significantly reduces the estimated volatility persistence (Anderson 1996). A Bayesian Monte carlo Markov Chain (MCMC) procedure is developed for the model estimation, which is proved to perform well and suit particularly for the estimation of the latent volatility process.

[7] Note that Class III milk price is announced monthly and prices and volumes of related dairy products are published weekly. With pricing formula publicly available, information on weekly dairy products should inform traders the corresponding milk price.

In the following section, we summarize the related literature. The theoretical microstructure framework is briefly described in Section 3. Section 4 presents the empirical model and Bayesian estimation procedure followed by the description of data construction. Section 6 reports the empirical results. Concluding remarks are presented in Section 7.

Literature Review

This study draws on the market microstructure literature on the relation between price volatility and trading volume in financial markets. Clark (1973) argues that uncertain information traders shift price expectation to different directions and therefore high price variability is coincident with high trading volumes. Large price changes may also be associated with the public-type of information, which induces all traders to revise price expectations in the same direction and results in relatively low volume. Trading volume can be treated as an “imperfect clock” measuring the speed of price adjustment. Through an intraday price-formation model, Epps and Epps (1976) verify Clark’s hypothesis that volume and price variation are positively related. In the current study, we rely on the theoretical microstructure framework in Tauchen and Pitts (1983) for the empirical setup. The authors establish that both price volatility and trading volume are increasing functions of traders’ heterogeneous responses to newly arrived market information.

Our empirical setting is also closely related to Anderson (1996). He specifies a bivariate structural model of price volatility and trading volume, which is modified from the standard “Mixture of Distribution Hypothesis” (MDH) specification (see, e.g., Clark 1973; Epps and Epps 1976; Tauchen and Pitts 1983). We employ a similar model specification and estimate it using the recently developed Bayesian MCMC methods in studying the relationship between price volatility and trading volume. The applied Bayesian methods has been commonly applied in the literature (see, e.g., Mahieu and Bauer 1998; Abanto-Valle, Migon and Lopes 2009).

A recurring theme in the literature is the commodity price volatility and its determinants. One representative example is Streeter and Tomek (1992). The authors develop a comprehensive model of the futures price volatility by taking into account the effects of variables from three conceptual categories: flow of information including Samuelson effect, current economic condition, and market structure. Although a number of government studies qualitatively analyze important factors causing milk price volatility (e.g., USDA 2011), quantitative analysis of milk price volatility and its determinants has been largely neglected in the literature. One exception is Chavas and Kim (2004) who conducted an econometric analysis of the effects of the dairy support price program on price volatility in U.S. dairy product markets. Focusing on the price support program, they found that the program was effective in reducing price volatility of manufactured dairy products. Similar studies were conducted in U.S. non-fat dry milk (Kim and Chavas 2002), cheese (Chavas and Kim 2005), and butter markets (Chavas and Kim 2006) with the focus on the effect of the price-support program.

A related line of research quantifies the impact of government announced information on commodity markets. For example, in a recent study, Adjemian (2012) quantify the announcement effect of the World Agricultural Supply and Demand Estimates (WASDE) report for cotton, soybeans and hard winter wheat. The results indicate that new announced information is rapidly incorporated into futures prices and impact the commodity prices significantly.

Theoretical Model

To motivate the empirical analysis, in the exposition to follow we briefly discuss the theoretical foundation of the estimation. The model relies on the microstructure framework of the determination of volatility-volume relation in the intraday futures market developed in Tauchen and Pitts (1983).

When the market moves from the $(i-1)$ th to the i th within-day equilibrium, the corresponding price change and the trading volume can be described as[8]

$$\Delta P_i = \frac{1}{J}\sum_{j=1}^{J}\Delta P_{ij} = \frac{1}{J}\sum_{j=1}^{J} P_{ij} - P_{i-1,j} \quad (1)$$

$$V_i \equiv \frac{1}{2}\sum_{j=1}^{J}| Q_{ij} - Q_{i-1,j} | = \frac{\alpha}{2}\sum_{j=1}^{J}| \Delta P_{ij} - \Delta P_i | \quad (2)$$

where ΔP_i and ΔP_{ij} denote the change in market equilibrium price and trader j 's reservation price in the i th equilibrium, respectively. V_i refers to the trading volume and Q_{ij} is trader j 's position. α is a constant. Eqn. (1) states that the change in the market price ΔP_i is the average change of the trader j 's reservation price ΔP_{ij} $(j = 1, 2, ..., J)$ in the market. Trading volume is the total absolute change of individual traders' position $Q_{ij} - Q_{i-1,j}$, while the position change can be positive or negative. The position itself is defined as proportional to the difference between trader j 's reservation price and the market clearing price, i.e., $Q_{ij} = \alpha(P_{ij} - P_i)$. When the market price P_i is low relative to the reservation price P_{ij}, the trader takes a certain number of long positions depending on how large the price gap is. When the market price is relatively high, the trader will take short positions instead.

[8] Eqns. (2) and (3), Tauchen and Pitts (1983).

Assume the change of trader j 's reservation price ΔP_{ij} has two mutually independent components ϕ_i and ψ_{ij},[9] i.e.,

$$\Delta P_{ij} = \phi_i + \psi_{ij} \tag{3}$$

with the properties $E(\phi_i) = E(\psi_{ij}) = 0,\ \ \mathrm{var}(\phi_i) = \sigma_\phi^2,\ \mathrm{var}(\psi_{ij}) = \sigma_\psi^2$. The component ϕ_i denotes the information common to all traders in the market. The component ψ_{ij} refers to the information affecting individual traders differently. In other words, traders respond in heterogeneous ways to the second type of information by adjusting their reservation prices.

Given the variance-component model in (3) and the market price change defined in (1), the price change and trading volume can be rewritten as[10]

$$\Delta P_i = \phi_i + \bar{\psi}_i,\ \ \bar{\psi}_i = \frac{1}{J}\sum_{j=1}^{J} \psi_{ij} \tag{4}$$

$$V_i = \frac{\alpha}{2}\sum_{j=1}^{J} |\psi_{ij} - \bar{\psi}_i| \tag{5}$$

It can be shown that[11]

$$\mathrm{var}(\Delta P_i) = \sigma_\phi^2 + \frac{\sigma_\psi^2}{J} \tag{6}$$

$$E(V_i) = \left(\frac{\alpha}{2}\right)^2 \sigma_\psi \sqrt{\frac{\pi}{2}} \left(\sqrt{\frac{J-1}{J}}\right) J \tag{7}$$

Notice that the variance of price change and the mean of trading volume in (6) and (7) are for a single equilibrium within a given day. The corresponding daily price variation and trading

[9] Eqn. (4), Tauchen and Pitts (1983).
[10] Eqns. (5) and (6), Tauchen and Pitts (1983).
[11] Eqns. (7b) and (7c), Tauchen and Pitts (1983). Note that the derivation of eqn. (7) requires the normal assumption of the volume V_i. Readers refer to Tauchen and Pitts (1983) for a more detailed discussion.

volume are summed over all intraday equilibria I, the number of which is assumed to be random and depends on the total pieces of new information arriving to the market each day.

More importantly, eqn. (6) indicates that conditional on the number of daily equilibria of I, variability of price changes is determined by (i) the variance of informational component common to all traders σ_{ϕ}^{2}, (ii) the variance of trader specific information σ_{ψ}^{2}, and (iii) the number of traders in the market, J. Similarly, besides the number of daily equilibria and total number of traders in the market, trading volume formulated in eqn. (7) depends on the variance of trader specific component σ_{ψ}^{2}, but not the common information component σ_{ϕ}^{2}. The positive linkage between price variability and trading volume comes from the fact that both price volatility and trading volume are increasing functions of the variance of trader specific information.

For the Class III milk futures market, although there is a slightly increasing trend in the recent years, it is reasonable to assume that the number of traders is constant over the sample period of January 2001-August 2013. Following the theoretical setting, we hypothesize that the milk price volatility responds positively to information common to all traders in the market, which is represented by number of days to settlement representing the “settlement effect”, and traders’ heterogeneous responses to the trader specific information capturing the “heterogeneity effect”. Furthermore the days to maturity is expected to have a negative impact on milk price volatility, which is opposite to the typical Samuelson effect. Trader specific information should have a positive effect on trading volume. We use the difference between the daily futures price and the recent week imputed milk price as a measure of traders’ responses to this type of information. Price volatility and trading volume are positively associated as both of them are increasing function of trader specific information. The corresponding empirical model, Bayesian estimation, and data construction are discussed in the following sections.

Empirical Model and Bayesian Estimation

The Empirical Model

A multivariate structural model of volatility and volume is a natural representation of the theoretical setting in (6) and (7), which is specified as:

$$Y_t = \exp\left(H_t / 2\right)\varepsilon_t,\ \ \varepsilon_t \sim N(0,1) \tag{8}$$

$$H_t = X_t\theta + \phi H_{t-1} + \eta_t,\ \ \eta_t \sim N(0,\sigma_\eta^2) \tag{9}$$

$$M_t \sim Possion\left(m_0 + m_1 \exp(H_t)\right) \tag{10}$$

where Y_t ($t = 1, 2, ..., T$) is the compounded return of Class III milk futures prices, i.e., the difference between logarithm of daily settlement prices in two consecutive days, $\log(P_t) - \log(P_{t-1})$. H_t and M_t denote the log-volatility and the trading volume on day t, respectively. The stochastic volatility model specified in eqns. (8) and (9) has been widely applied in the literature (see, Jacquier, Polson and Rossi 1994, among others). Following the literature (see, e.g., Andersen 1996; Abanto-Valle, Migon and Lopes 2010), the daily trading volume in eqn. (10) is assumed to follow a Poisson process. The intensity of the process is determined by two components, the noise component (m_0) and the informed component, the latter of which is induced by arrival of new information and thus is proportional to price variation and. Eqn. (10) builds up the linkage between price volatility and trading volume. The parameter m_1 is expected to be positive as both price volatility and volume are increasing functions of traders' disagreement about interpretation of new information.

In eqn. (9), $X_t = (X_{1t}, X_{2t}, ..., X_{kt})'$ is a k-dimensional vector including the explanatory variables X_i $(i = 1, 2, ..., k)$. Besides the lagged latent volatility, the variables of days to settlement and price deviates are constructed and included corresponding to the theoretical setting, the details of which will be discussed in the data section. For the model specified in eqns. (8)-(10), we have observations on the compounded return $\{Y_t\}_{t=1}^{T}$ and explanatory variables $\{X_t\}_{t=1}^{T}$. The volatility series $\{H_t\}_{t=1}^{T}$ are latent and need to be estimated together with the parameter vector $\Theta = \{\theta, \phi, \sigma_\eta^2, m_0, m_1\}$. We employ Bayesian Markov chain Monte Carlo (MCMC) methods to estimate the model. Using the data augmentation technique (Tanner and Wong 1987), the applied Bayesian method effectively extracts information from observable data and leads to posterior distributions of latent volatility variables and model parameters, $p(\Theta, H \mid Y, X)$. The Bayesian method has been proven to be able to generate relatively accurate estimates and is well suitable for estimating stochastic volatility models.

The parameters in the vector Θ are assumed to be mutually independent. We employ the conjugate and proper priors for the parameters:[12] $\theta \sim N(\mu_\theta, V_\theta)$, $V_\theta = \sigma_\theta^2 I_{2k}$, $\sigma_\eta^2 \sim IG(a_\eta, b_\eta)$, $m_0 \sim Gamma(a_0, b_0)$ and $m_1 \sim Gamma(a_1, b_1)$.[13] Conditional on the latent volatility variables and the observables, the joint distribution of the returns, the volatility, and the parameters are

$$
\begin{aligned}
& p(\Theta, H \mid Y, X, M) \propto p(Y, H, M \mid \Theta, X)\, p(\Theta) \\
& \propto \prod_{t=1}^{T} \left(\frac{1}{\sqrt{\exp(H_t)}} \exp\left\{ -\frac{1}{2} \exp(-H_t) Y_t^2 \right\} \frac{1}{\sigma_\eta^2} \exp\left\{ -\frac{1}{2\sigma_\eta^2} (H_t - X_t\theta)^2 \right\} \right) \times \\
& \prod_{t=1}^{T} \left(m_0 + m_1 \exp(H_t) \right)^{M_t} \exp\left(-m_0 - m_1 \exp(H_t) \right) \times p(\Theta)
\end{aligned}
$$

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[12] Here we incorporate H_{t-1} into the vector of X and thus ϕ is one of the elements in θ.

[13] Here $N(\cdot)$ and $IG(\cdot)$ denote normal and inverse gamma distribution, respectively.

where $p(\Theta)$ denotes the joint prior distribution of the model parameters. The posterior distributions of the model parameters and latent volatility variables are included in the Appendix. The Bayesian MCMC method repeatedly draws samples from the posterior distribution until it converges to the target distribution. The draws after the initial "burn-in" period are used for model inference. We apply the proposed Bayesian algorithm on simulated data and the algorithm is found to be able to recover the true parameters reasonably well.[14]

Data

We construct two price and volume series for the Class III milk futures contract trading in the Chicago Mercantile Exchange, namely the maturity futures and the composite futures. There is one contract matured and cash settled in each calendar month of a year (January to December), therefore the maturity price (and volume) series consist of the prices (and trading volumes) of the futures contract for the maturity month. The series switches to the next closest-to-maturity contract after the cash settlement of the current month contract.[15]

Following Clark (1973), the composite price and volume series are constructed to aggregate the prices and trading volumes of different maturity months into those for a single composite futures contract. Trading of the contract matured in the current month starts about 24 months ago. In other words, on any given day there are 25 contracts trading in the market with the maturities in every month of the next two years. To utilize the information of all available contracts trading in the market, we construct the weighted average price and volume of the composite futures contract with the weight (denoted by λ_τ) defined as the average proportions of open interest for a given distance to maturity (number of days; denoted by τ). We limit the

[14] The estimation results on simulated data are available upon request.

[15] The exact switching time is one day before the USDA announces the Class III price for that contract month.

distance to maturity to 252 days (one trading year), i.e., $\tau \in \{1, 2, ..., 252\}$, because that going further back typically doesn't add in much information when open interest is quite low and daily prices have low variation. Figure 2 presents the weights for each of the 252 days.[16] The weight curve shows an expected shape, rising first to the maximum around 15 days, staying at the peak for about 40 days, and then falling toward zero. It indicates that approximately fifteen to fifty days before maturity is the most active trading period for the Class III milk futures, which is consistent with our observation on trading activities of individual contracts. The composite futures price is calculated as $P_t = \sum_{\tau=1}^{252} \lambda_\tau P_t^\tau / \sum_{\tau=1}^{252} \lambda_\tau$.[17] Average trading volumes weighted by λ_τ's are computed similarly for the composite futures.

The Class III futures prices and trading volumes are compiled from the database maintained by the Commodity Research Bureau.[18] The sample covers the period of January 5, 2001 to August 30, 2013. One major objective of the current study is to quantify the responses of futures price volatility and trading volume to market information flows. For doing so, two explanatory variables are constructed and included in the vector of X in eqn. (9) including days to maturity (D_t) and price deviates (PD_t).The cash settlement date (or the USDA milk price announcement date) for each month in the sample are employed to calculate how many days left before maturity for each trading day.[19] The variable of days to maturity intends to capture the "settlement effect" described in the previous section, whose coefficient in eqn. (9) is hypothesized to be positive. It means that the closer to the maturity date a futures contract in the

[16] A simple weighted average method is applied to remove small irregularities and make the curve smooth.

[17] Readers are referred to Clark (1973) for more details on the construction of the composite futures price and volume.

[18] The data description can be found at http://www.crbtrader.com/datacenter.asp.

[19] The monthly Class III prices are announced by USDA by the 5th of the following month.

maturity month, the lower price variability. In addition, as "days to maturity" is public information commonly available to all traders in the market, this variable also indicates the response of price volatility to the information component that is common to all traders.

The variable of "price deviates" is constructed as the price difference between the close price of each trading day and the most recent weekly price of Class III milk. The procedure is illustrated in Figure 3. As in panel (a), for each month, there are four to five reports of prices and sales quantities for the final dairy products of Class III milk including butter, cheese, non-fat dry milk (NFDM), and dry whey. They are published weekly in the National Dairy Products Sales Report (NDPS) by the USDA.[20] The prices and sales of these dairy products are used to calculate USDA monthly announcement price, which is also the futures settlement price, by following the established formulas.[21] Specifically, the monthly announced Class III milk price is based on the prices of its components including butterfat, protein, and other solids. The component prices are calculated from average weekly prices weighted by sales of final dairy products of butter, cheese, NFDM, and dry whey over the four or five weeks in a given month. For example, the price of butterfat, one of the milk components, is calculated as

$\text{Butterfat Price} = (\text{Butter Price} - 0.1715) \times 1.211$, in which

$$\text{Butter Price} = \frac{\sum_{j=1}^{4 \text{ or } 5} \left((\text{Weekly Butter Price})_j \times (\text{Weekly Butter Sales})_j \right)}{\sum_{j=1}^{4 \text{ or } 5} (\text{Weekly Butter Sales})_j}.$$

[20] The National Dairy Products Sales Reports can be found on the website of Agricultural Marketing Service, USDA: http://www.ams.usda.gov/AMSv1.0/ams.fetchTemplateData.do?startIndex=1&template=TemplateV&page=MilkPriceAnnouncementsSummariesandProductPrices.

[21] In the sample period, the Class III milk pricing formulas have been changed four times, 01/31/2001, 04/01/2003, 02/01/2007, and 10/01/2008. We incorporate these changes in the data construction.

In our study, we calculate the weighted average dairy product price for each week in a given month based on the weekly NDPS reports and then compute the component prices and corresponding milk price for that week (see panel b in Figure 3). Note that for the first week of the month, there is only one weekly report available, while for the later weeks multiple weekly reports are available and contain more information before the end of month when the settlement price is announced. So we incorporate gradually increasing information into the constructed weekly milk price using prices and sales data available for all previous week(s) in a month. For the days between two weekly announcements, typically four to five days, the price deviates variable is calculated as the difference between the daily close price and the weekly imputed milk price. The price deviates reflect traders' heterogeneous responses to the newly released information on milk prices. Higher deviates indicate traders respond diffusely to the information and are expected to be associated with higher price volatility and trading volume.

Estimation Results and Analysis

We run the Bayesian MCMC algorithm for 20,000 iterations. The first 10,000 runs are discarded as "burn-in" and we use the last 10,000 iterations for the reference of the model parameters. Table 1 reports posterior mean, standard errors, and probabilities of being positive for each element of the parameter vector Θ. The top panel of Table 1 reports the estimation results for the maturity futures, while those for the composite futures are presented in the lower panel.

For the maturity futures, all estimated coefficients are highly concentrated around the estimated mean with relatively small standard errors, which verify the validity of the model specification. The estimated lagged effect confirms the time dependence of the volatility process. More importantly, both days to maturity and price deviates have positive and significant effects on price volatility, which imply that (i) the days to the cash settlement in the maturity month are positively related to price variation, and (ii) the greater discrepancy in traders' responses to the weekly milk prices, the higher the price variability. It is also consistent with the hypotheses from the microstructure model that price volatilities are increasing function of both the common information and trader specific information flows captured by the constructed days to maturity and price deviates variables, respectively.

For the composite futures, days to maturity lose its explanatory power for price volatility. It makes sense because the variable indicates the time before settlement for the closest-to-maturity contract only, this contract specific information should not induce responses from traders holding contracts further away from settlement. Price deviates still play a significant role in determining price variation, which indicates that traders of the contracts with different maturity months are still sensitive to the weekly USDA announced prices.

The estimated volume coefficients, m_0 and m_1, indiate the strong and positve linkage between price volatility and trading volume for both the maturity and the composite futures. This indicates the positive volatility-volume linkage as both of them respond positively to the information flowing into the market.

To verify the relation between trading volume and information flows, we run the OLS regression of trading volume on the two information variables, days to maturity and price deviates, for the composite futures. The results are reported in Table 2. We focus only on the composite futures because that trading in the second half of the maturity month (less than 15 days before maturity) is relatively thin. This decreasing trend of trading activity is coincident with the days to maturity variable and thus blur the relation between volume and market information. The regression results indicate that the traders' responses to trader-specific market information, represented by the price deviates variable, show a positive and significant effect on their trading activities. The effect of days to maturity is only marginally significant.

Conclusion

Under the typical microstructure framework, both price volatiltiy and trading volume of futures contracts are considered to be increasing functions of trader specific market information and therefore are positively associated. Our study utilizes the unique features of the Class III milk futures contract including cash settlement and classified pricing scheme to confirm the hypothesized relation between price volatility, trading volume and market information flows. For doing so, we construct two distinct variables, days to maturity and price deviates, to capture the "settlement effect" and "heterogeneity effect", the latter of which represents traders' heterogeneous response to newly arrived market information. The Bayesian MCMC methods are applied on a bivariate structural model for stochastic volatility and trading volume of the Class III milk futures. The estimation results confirm that (i) the closer to settlement the futures contract is, the lower the price variation, and (ii) both price volatility and trading volume are increasing functions of trader specific informaiton and thus are positively linked. We can also interprete the resutls as evidence that the USDA weekly published information has a significant impact on price and trading activities in the milk futures market.

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Table 1. Estimation results.

Variable	$E(\cdot \mid y)$	$Std(\cdot \mid y)$	$\Pr(\cdot > 0 \mid y)$
The maturity futures			
θ			
Constant	-2.42	0.12	0.00
Days to maturity	0.14	0.007	1.00
Price deviates	0.02	0.008	1.00
Lagged effect (ϕ)	0.05	0.02	0.99
σ_η	3.20	0.04	1.00
m_0	3.06	1.74	1.00
m_1	0.32	0.96	0.99
The composite futures			
θ			
Constant	2.06	0.11	1.00
Days to maturity	-0.006	0.005	0.11
Price deviates	0.01	0.007	0.95
Lagged effect (ϕ)	0.07	0.02	1.00
σ_η	2.55	0.04	1.00
m_0	4.47	2.57	1.00
m_1	0.47	0.38	1.00

Table 2. The OLS regression results of trading volume (standard errors are in the parentheses).

Variable	Estimates	P-value
Days to maturity	-1.92*	0.08
	(1.09)	
Price deviates	5.05***	0.002
	(1.67)	
Constant	890.44***	<0.001
	(44.60)	
R^2	0.0043	

Figure 1. The Monthly Announced Class III Milk Prices ($/cwt), January 2000-August 2013.

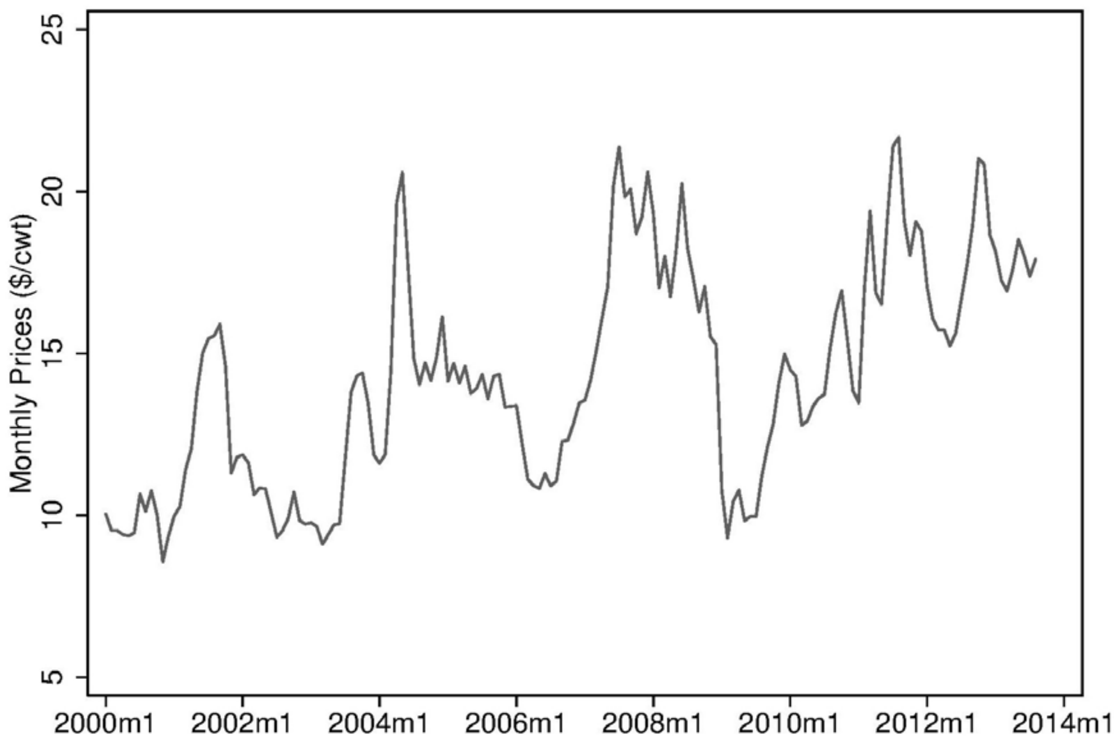


Figure 2. The Constructed Weights for the Composite Futures Price and Volume

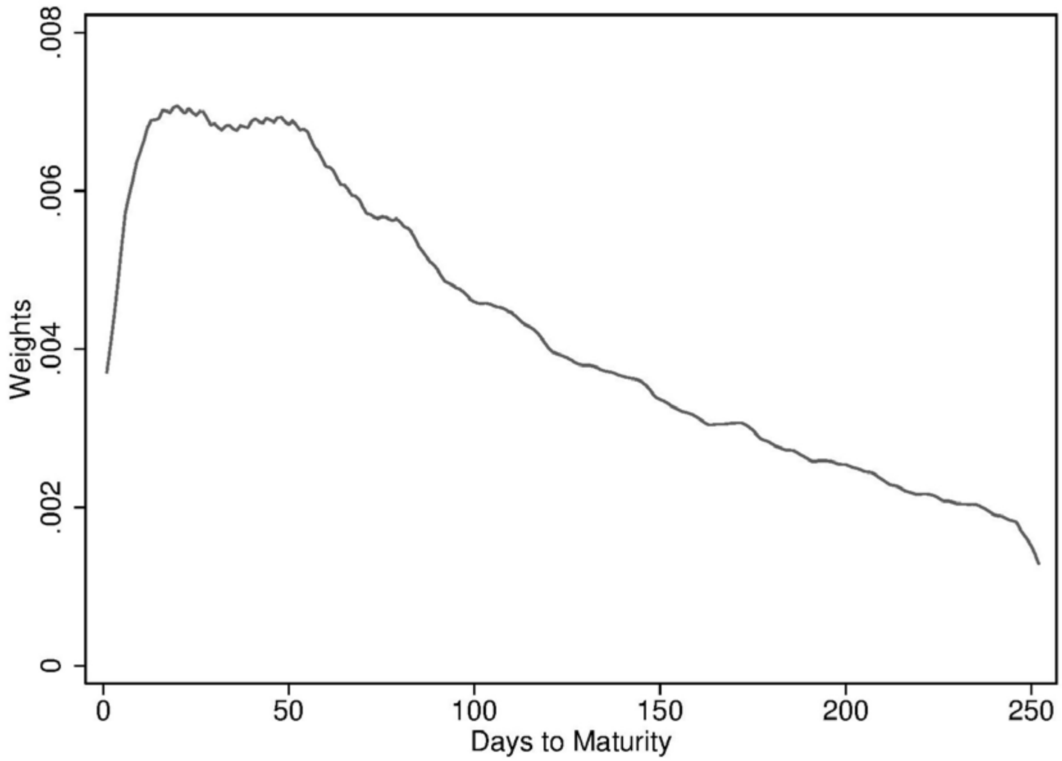
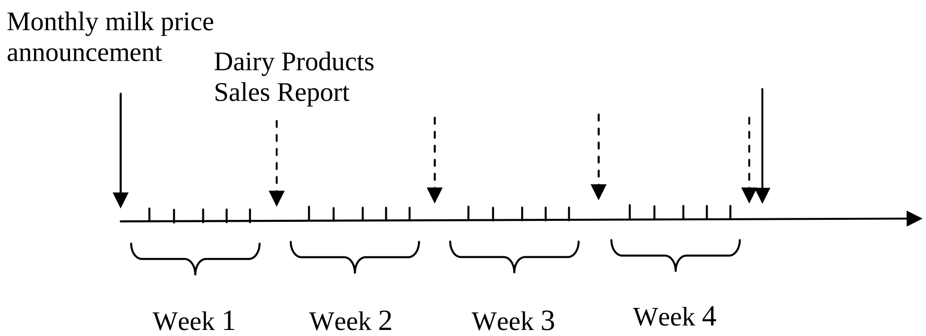
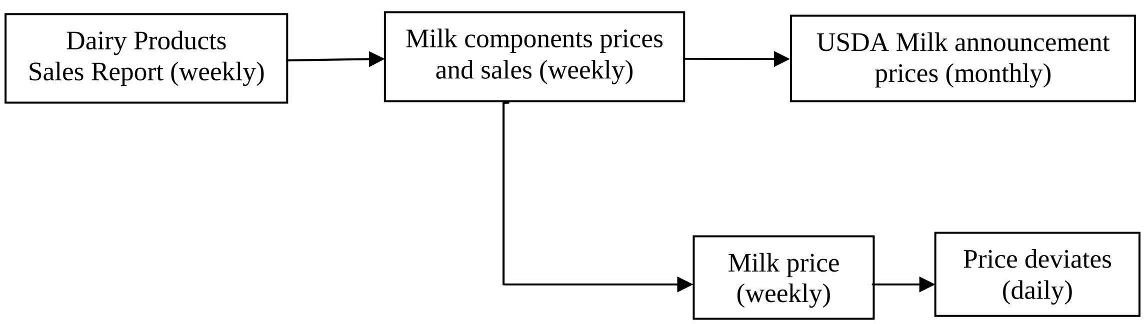


Figure 3. Construction of the Variable of "Price Deviates".



(a) Price announcement and reports



(b) Price construction

Appendix: The Bayesian MCMC Sampling Algorithm

In what follows, $N(\mu,\sigma^2)$ denotes the normal distribution with mean μ and variance σ^2, $IG(a,b)$ denotes the inverse gamma distribution with parameters a and b.

Step 1. Drawing from $p(\theta \mid \Theta_{-\theta}, Y, V)$

$\theta \mid \Theta_{-\theta}, Y, V \sim N(D_\theta d_\theta, D_\theta)$,

where $D_\theta = \left(Z_t{}' Z_t \sigma_\eta^{-2} + V_\theta^{-1} \right)^{-1}$, $d_\theta = Z_t{}' V_t \sigma_\eta^{-2} + V_\theta^{-1} \mu_\theta$.

Step 2. Drawing from $p(\sigma_\eta^2 \mid \Theta_{-\sigma_\eta^2}, Y, V)$

$\sigma_\eta^2 \sim IG\left(T/2 + a_\eta, \left(b_\eta^{-1} + \sum_{t=1}^{T} (V_t - Z_t{}'\theta)^2 \right)/2 \right)$.

Step 3. Drawing from $p(V_t \mid \Theta, Y)$ $(1 < t < T)$

$$p(V_t \mid \Theta, Y) \propto \exp\left(-\frac{V_t}{2} \right) \exp\left(-\frac{Y_t^2}{2} \exp(-V_t) \right) \exp\left(-\frac{1}{2\sigma_\eta^2} (V_t - Z_t{}'\theta)^2 \right) \exp\left(-\frac{1}{2\sigma_\eta^2} (V_{t+1} - Z_{t+1}{}'\theta)^2 \right)$$

As the posterior density is not in any known distribution form, a random walk Metropolis-Hastings (M-H) step is employed.

Step 4. Drawing from $p(V_1 \mid \Theta, Y, V_{-1})$ and $p(V_T \mid \Theta, Y, V_{-T})$

$$p(V_1 \mid \Theta, Y, V_{-1}) \propto \exp\left(-\frac{V_1}{2} \right) \exp\left(-\frac{Y_1^2}{2} \exp(-V_1) \right) \exp\left(-\frac{1}{2\sigma_\eta^2} (V_2 - Z_2{}'\theta)^2 \right)$$

$$p(V_T \mid \Theta, Y, V_{-T}) \propto \exp\left(-\frac{V_T}{2} \right) \exp\left(-\frac{Y_T^2}{2} \exp(-V_T) \right) \exp\left(-\frac{1}{2\sigma_\eta^2} (V_T - Z_T{}'\theta)^2 \right)$$

Both posterior densities are not in any known distribution form, so a random walk M-H step is applied.

Step 5. Drawing from $p(m_0 \mid V)$ and $p(m_1 \mid V)$

$$p(m_0 \mid V) \propto \exp\left(-\frac{m_0^2}{2\sigma_0^2} + \frac{\mu_0 m_0}{\sigma_0^2} - \sum_{t=1}^{T} \exp(m_0) + \sum_{t=1}^{T} m_0 Y_t \right)$$

$$p(m_1 \mid V) \propto \exp\left(-\frac{m_1^2}{2\sigma_1^2} + \frac{\mu_1 m_1}{\sigma_1^2} - \sum_{t=1}^{T} \exp(m_1 V_t) + \sum_{t=1}^{T} m_1 V_t Y_t \right)$$

Similarly, a random walk M-H step is used to generate draws from the above posterior densities.