U.S. Milk Price Leadership among Production Leaders

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Abstract

U.S. fluid milk must be marketed differently from other commodities due to its method of production. Pricing patterns are also different due to historical dairy policy. Federal and state marketing orders create a price floor that combines with market conditions to set prices. This paper uses historical dairy prices from three production leading states, California, New York, and Wisconsin, to identify a price leader in the U.S. We assume since there are no regulations preventing trade between states that state prices will be cointegrated. A vector error correction model and rolling regression both reveal California to be the price leader, indicating that price discovery occurs in California. This information may help policymakers to identify the policies which create effective markets, or those that would inhibit quick price adjustments.

Keywords: Dairy Prices, price leadership, dairy policy, market volatility, and price discovery.

JEL Codes: Q13, Q18.

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1. Introduction

U.S. fluid milk is marketed differently from other commodities. The fluctuations associated with the seasonality of production are often disjoint from consumption patterns, making it difficult to balance supply and demand. A flow commodity like milk is difficult to price efficiently as it is produced daily and must move to market at a similar pace. To stabilize income for members, dairy cooperatives worked to negotiate for a classified pricing system, which stabilized prices paid to producers. Though there have been changes in dairy pricing systems since the 1900's, the dairy policy of today is still shaped by the idea of a classified price support (Blayney and Manchester 2001).

Three major components of the U.S. dairy policy are: border measures creating import barriers and export subsidies, federal and state marketing orders that regulate raw milk prices, and government purchases of dairy products. The marketing orders set a minimum price for milk. This means that the price a dairy farmer receives is based on a federally set minimum as well as market conditions. There are eleven regions of the federal marketing orders, and California operates its own which has several differences from the federal system (Sumner and Balagtas 2002). Differences in policy among these regions may reduce the spatial integration of the regional markets and affect spatial price relationships.

Producers benefit from a well-integrated market because price information is likely to be more accurate, allowing producers to make informed marketing decisions and move their product more efficiently (Goodwin and Schroeder 1991). The speed at which each state can respond to shocks and return to equilibrium is an indicator of market efficiency. Policymakers and other stakeholders are interested in understanding the differences in market efficiency between states for two reasons. The government of a state may want to follow the policy of more efficient states, enabling prices within its state to reflect equilibrium at a quicker rate, allowing producers to make well-informed decisions, or it may want to inhibit this quick adjustment to protect stakeholders from volatility. Understanding which U.S. milk producing region acts as a price leader, and is most efficient in price discovery, is thus an important topic.

In this paper, we examine the differences in market responses of the top milk producing states and attempt to identify a price leader among them. Data were obtained from USDA NASS, including monthly milk prices ($/cwt) and annual milk production (in pounds) by state. The three top producing states by volume in the United States from January 1980 to February 2020 were California, New York, and Wisconsin. As the 1937 Agricultural Marketing Agreement Act has established milk marketing orders that regulate milk prices (Cakir and Balagtas 2012), since milk is transportable at relatively low costs, and there are no inter-state restrictions on trade it is expected that milk prices across states are cointegrated. Our test confirms this, so we estimate a vector error correction model (VECM). From the estimated VECM, we determine which state(s) are price leaders and if leadership has changed over time. To further dissect the price leadership in this market, we test the dynamic changes in price leadership by estimating a rolling regression, which allows us to understand the timeline of price leadership transition among the three states.

From the VECM, we find that California is the price leader among the production leading states in the U.S., California, New York, and Wisconsin. The rolling regression indicated that California has been the primary price leader since the 1990's, with Wisconsin and New York both assuming the role briefly during that period.

Our paper makes two major contributions. First, we are one of the first studies that examine price leadership in the U.S. wholesale milk market. Previous studies on milk price leadership have held an international focus, either comparing two nations, or comparing one nation to international prices (Acosta, Ihle and Robles 2014; Bakucs, Fałkowski and Fertő 2012). Price leadership studies that include the United States have focused on wheat (Ghoshray 2007; Janzen and Adjemian 2017). Additionally, the rolling window regression technique offers some advantages over competing methodologies like structural break analysis or smooth transition regressions (Dijk, Teräsvirta and Franses 2002). We will be able to study the dynamics of the price leadership, i.e., how price leadership changed in the wholesale milk market over time. This question could not be answered by a structural break analysis, because a smooth transition regression would only yield two equilibrium price leadership states, with a deterministic functional form on the dynamics of the transition.

2. Literature Review

The identification of price leadership is not a new question. A 1982 study by Spriggs, Kaylen, and Bessler uses Granger causality to attempt to identify who is leading wheat prices, the United States or Canada. The authors find evidence that U.S. wheat prices led Canadian wheat prices over the 1974/1975 crop year, and the 1975/1976 crop year. It is suggested that changes in price leadership could point to changes in market structure (Spriggs, Kaylen and Bessler 1982).

Current literature regarding leaders in price discovery applies high-frequency pricing data and market microstructure methods to the wheat markets to identify the location of world wheat price discovery. Janzen and Adjemian (2017) estimate the proportion of price discovery occurring in the futures markets in Chicago, Kansas City, Minneapolis, and Paris using a reduced form VECM. The study shows that while price discovery is still occurring primarily in the United States, the U.S. share of price discovery has declined, with a greater proportion of wheat price discovery occurring in Paris.

Similarly, Han, Liang, and Tang (2013) examine price discovery and information transfers between the Chicago Board of Trade (CBOT) and China's Dalian Commodity Exchange (DCE) also using a VECM. They find that the DCE plays a significant role in global price discovery, in addition to the dominant effects of the CBOT. Among other commodities, discussion tends to focus on whether discovery occurs in futures or cash markets, finding that futures markets do play a key role in price discovery (Garbade and Silber 1983; Peri, Baldi and Vandone 2013; Xu 2018).

In the dairy sector, analysis on price transmission has largely occurred on a global scale. Global milk prices have become increasingly volatile, and policymakers are attempting to design measures to lessen price swings. This volatility affects different countries and socioeconomic groups at varying magnitudes. Sharp decreases affect small producers disproportionately (Acosta, Ihle and Robles 2014). Acosta, Ihle, and Robles used an Asymmetric Vector Error Correction Model (AVECM) to identify whether the speed of price transmission differed between domestic markets in Panama and international prices obtained from the USDA. Results show the potential for asymmetric price transmission in global and domestic milk prices.

Bakucs, Falkowski, and Ferto (2012) use dairy sector data to compare Hungary and Poland, whose dairy sectors saw a decline similar to the U.S. in number of farms form 1995-2007. Hungary has larger farms than Poland, where the majority of farms had less than 10 cows during this time. There are also differences regarding foreign direct investment, the concentration of processors, the concentration of retailers, and the size of the milk sector. In Poland, milk prices are found to be asymmetrically transmitted along the food supply chain. In Hungary, no asymmetry is found. We see that differences in market structure and policy can have an impact on the milk market.

Looking at the U.S. milk market, Yavuz, Schnitkey, and Miranda (1996) use a spatial equilibrium model to evaluate the impact of supply, demand, and policy variables on the regional distribution of milk production for the years 1970, 1980, and 1991. The authors find that the supply factor variables, including herd size per farm and milk per cow, had the greatest impact for most regions except for the Southeast and the Lake States. The Southeast is most impacted by changes in real milk support prices. The Lake States see a comparable impact from changes to both the per capita consumption and real milk support prices variables when compared to changes in the supply factors variable (Yavuz et al. 1996). Thus, observable differences in supply, demand, and policy variables are found to have differing effects on milk production. It is not a far leap to conclude that those same differences might have an effect on prices as well.

Price transmission has also been studied in the U.S. market. Awokuse and Wang (2009) investigated the effect of nonlinear threshold dynamics on asymmetric price transmission for U.S. dairy products. Using estimates from a cointegration regression, the study estimated TAR and M-TAR models, followed by threshold ECMs. Results show that there is strong evidence of asymmetric price transmission in butter and fluid milk prices, but not for cheese. This paper provides a precedent for analyzing price movements in the dairy sector as a method to identify the impacts of structural differences.

It is vital to understand that milk prices in the United States do not follow a typical spot market for price discovery. Rather, Chicago Mercantile Exchange (CME) spot markets are used in federally regulated pricing formulas. Buyers and sellers can complete transactions in the spot markets. Additionally, sellers are protected by minimum price regulations enforced by Federal Milk Marketing Orders (FMMO). These regulations are “based on a system of mandatory dairy price reporting, milk pricing formulas, price discrimination based on the end-use of raw milk, and equity payments from a revenue sharing pool" (2019). As milk prices are not completely regulated by the Federal government, there may not be much difference between U.S. states, so identifying a price leader may be difficult.

3. Empirical Design

In this section, we use a VECM to model the long- and short-run relationship between cointegrated variables. For variables to be cointegrated, they must move together, if one cointegrated variable increases, the other cointegrated variable increases as well. However, these cointegrated movements are often not instantaneous, one of the variables can be the "leader." In other words, a movement in one variable results in a similar movement in another variable. We study milk prices in different regions of the United States, represented by the three top producing states in the United States: California, New York, and Wisconsin. It is expected that the milk prices in California, New York, and Wisconsin will be cointegrated. One of the states might be leading price movements for the others.

3.1 Data

The variables used in this study include the monthly prices per hundredweight received for liquid milk in California, New York, and Wisconsin. This dataset begins in January 1980 and ends in February 2020, for a total of 482 monthly observations for each state. Figure 1 plots the prices in each state over the course of the study. We can see that the three price series' generally move together. New York tends to have the highest price throughout the time period, while California has the lowest. It is also clear from the graph that the volatility of prices has increased over time.

[Figure 1 approximately here]

Summary statistics for the milk prices are shown in Table 1. Each state is represented by its conventional state abbreviation: California is CA, New York is NY, and Wisconsin is WI. Newy

York had the highest mean milk price at $15.49, a little less than $2.00 higher than the mean price of California, $13.88. The variance is larger in New York and Wisconsin, both of which have a standard deviation of 3.23, than in California (2.83). This quantifies the large variance that we see in Figure 1.

[Table 1 approximately here]

Figure 2 plots the annual milk production. Before 1992, Wisconsin is the largest producer. California rises from the second largest producer to the largest in 1993 and has been on the top through 2019. New York has continuously produced the least milk, and expanded production the least across this period.

[Figure 2 approximately here]

3.2 Econometric Model

We use Johansen's test (Johansen 1991) to determine whether the price series are cointegrated and thus whether a vector autoregression (VAR) or a vector error correction model (VECM) is appropriate, and find that the system contains one cointegrating vector.

To select the length of lags in the model we use Final Prediction Error values, Aikaike Information Criteria values, Bayesian Information Criteria values, and Hannon Quinn Information Criteria values. The number of lags used is identified by the subscript "t-k." For example, if the milk prices for California is lagged one month, it is represented as CA_{t-1}.

Our dependent variable is the change in price for the respective state's newest observation. For example, the dependent variable for California's equation is $\Delta CA_t = CA_t - CA_{t-1}$. We estimate the following VECM.

$$\Delta CA_t = \gamma_0 + \alpha_1(\beta_0 + \beta_1 CA_{t-1} + \beta_2 NY_{t-1} + \beta_3 WI_{t-1}) + \gamma_1 \Delta CA_{t-1} + \ldots + \gamma_k \Delta CA_{t-k} + \varepsilon_t \qquad (1)$$

$$\Delta NY_t = \gamma_0 + \alpha_1(\beta_0 + \beta_1 CA_{t-1} + \beta_2 NY_{t-1} + \beta_3 WI_{t-1}) + \gamma_1 \Delta NY_{t-1} + \ldots + \gamma_k \Delta NY_{t-k} + \varepsilon_t \qquad (2)$$

$$\Delta WI_t = \gamma_0 + \alpha_1(\beta_0 + \beta_1 CA_{t-1} + \beta_2 NY_{t-1} + \beta_3 WI_{t-1}) + \gamma_1 \Delta WI_{t-1} + \ldots + \gamma_k \Delta WI_{t-k} + \varepsilon_t \qquad (3)$$

To check for model robustness, we estimate a Lagrange multiplier test (LM). This test checks for serial correlation. Additionally, a Jarque–Bera test is used to check if sample data residuals are normally distributed.

Figure 2 shows a gradual evolution in market structure as California's production steadily increases from a low level comparable to New York to surpass Wisconsin by a large margin. For this reason, we suspect that the market may have undergone a gradual shift in its relative pricing structure as well. This contrasts the more common model of change in markets found in the literature. Structural breaks can model a situation where the structure of the market is abruptly altered by a major event, and you essentially estimate a before and after state of the market. In this case the rise of production coming from California is likely to have generated a gradual evolution in market dynamics as California takes a larger and larger market share. We capture this element of the change in market structure by estimating rolling VECM regressions. That is, we start with the beginning third of the sample, estimate a VECM on this subsample, and record the estimated alpha coefficients. Then we drop the first observation in the sample and one observation to the end of the subsample and repeat the process. Since the alpha coefficients estimate the responsiveness of each price to a divergence from the system equilibrium, looking at the evolution of the alpha coefficients over time gives insight into the nature of how price dynamics in this market changed through time as well.

4. Results

A Dickey-Fuller test shows unit-root behavior, indicating non-stationarity. The data is stationary when differenced once. The states are cointegrated at the rank of one according to the Johansen test. The confirmation of cointegration confirms that a VECM is the correct econometric approach. The lag selection criteria indicate that four lags are necessary. Once complete, the LM test indicates that the model still has serial correlation. When a 5^{th} lag is added, the tests no longer detect serial correlation. See Appendix 1 for the stationarity and cointegration testing, as well as the LM test and Jarque-Bera test.

Table 2 below shows the results of the test for short-run causality. This influence of each state is tested on each of the other states in the study, and causality is found in every case. Results are all significant at the 5% level. Linear hypothesis testing determines whether short-run causality exists, confirming that all lags of the independent variable together had causality on the dependent variable.

[Table 2 approximately here]

Table 3 shows the long-run causality results. New York appears to have a long-run causal relationship running from the other states. Wisconsin and California do not show causality from the other two states, however, California's results are not statistically significant. Based on these results, California appears to be the price-leader as it has the lowest α-term in absolute value, indicting California does not respond to deviations from the equilibrium, while New York and Wisconsin prices do.

[Table 3 approximately here]

The results of the rolling regression show that over the time period of this analysis, California has steadily been a price leader with coefficients closest to zero of the three. Approaching the 2000's, Wisconsin and New York begin to reverse roles, with Wisconsin transitioning from price leader to follower (the absolute value of its alpha getting larger), and New York moving from follower to leader (the absolute value of its alpha getting smaller). The progression of the alpha terms is visualized in Figure 3. Please note that the first 10 years are omitted from the rolling regression as there are no previous years of data to incorporate in their estimation.

[Figure 3 approximately here]

5. Conclusions

The results from the vector error correction model show that the milk prices in all three states are cointegrated, and have a degree of causation on each other in the short-run. We find that in the short-run, each state has a statistically significant influence on the prices of the other two states. In the long-run, California has the quickest adjustment speed to deviations from equilibrium prices. This indicates that California is the price leader while New York and Wisconsin prices follow. The rolling regression shows that California has largely maintained price leadership since 1990, with Wisconsin and New York both briefly holding the role throughout the time period. California is the only state of the three tested that is not included in a federal milk marketing order area.

Policymakers looking to reduce variability in milk prices might look to restrict the speed at which the market can respond to equilibrium following shocks. Thus, emulating California's policies would not create the desired effect. If the policy goal is to increase market efficiency, policymakers may wish to emulate California's model regarding federal and state milk marketing orders. Producers outside of California can get some indicator of future market movements based on what occurs in the price leading market.

Additional research might expand the analysis to include one state from each federal milk marketing order area, as well as California. More pronounced differences may be evident if more frequent price data, such as weekly or daily, were obtained and analyzed. It is clear from past research that policy can play a large role in impacting price transmission, and more research is needed to fully understand the impacts in the U.S. dairy market.

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Appendix 1. Pre and Post VECM Estimation Tests

When starting a time series analysis, key information about the data must be established. First, we test the price data to determine if it is stationary or displays unit root behavior using a Dickey-Fuller test. All three price series, California, New York, and Wisconsin show unit root behavior, but are stationary when differenced once. The null hypothesis in the Dickey-Fuller test is random walk. We see from Table A1, we can reject the null with 1% confidence when prices are differenced once.

[Table A1 approximately here]

Our price series' must be cointegrated in order for a VECM to be the appropriate model choice. Table A2 reports the results from three versions of the Johansen test: including no intercept, a constant term, and a trend variable. We see that for all three specifications, we reject the null hypothesis of H0: r = 0 but fail to reject the null hypothesis of H0: r <= 1. This indicates that our variables are cointegrated at a rank of 1.

[Table A2 approximately here]

To determine how many lags should be used in the model, a series of lag-order selection statistics are calculated. These include Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC). These statistics are reported in Table A3. From these results, we conclude that four lags are optimal for this model.

[Table A3 approximately here]

Once the VECM is estimated, we test for serial autocorrelation in the residuals using a Lagrange Multiplier (LM) test. We also check to see if the residuals are normally distributed using a Jarque-Bera test. Table A4 shows that initially, we reject the null hypothesis of no autocorrelation in the LM test. Adding a fifth lag resolves the autocorrelation. In table A5, the results from the Jarque-Bera test show that for all equations, we can reject the null hypothesis that the residuals are normally distributed.

[Table A4 approximately here]

[Table A5 approximately here]

Table 1. Summary Statistics for Milk Price Received for California, New York, and Wisconsin from January 1980 to February 2020 (real)

	Obs.	Mean	Std. Dev.	Min.	Max.
CA	482	8.63	2.41	4.60	15.32
NY	482	9.56	2.34	5.58	15.63
WI	482	9.26	2.25	5.23	15.04

Note: Real prices are reported (base Jan 2000). Source: USDA-NASS Quickstats . https://quickstats.nass.usda.gov/

Table 2. Short-run Causalities

Dependent State	Independent State	Short-run Causality	Prob > Chi-squared
California	New York	Yes	0.03*
California	Wisconsin	Yes	0.05*
New York	California	Yes	0.00***
New York	Wisconsin	Yes	0.05**
Wisconsin	California	Yes	0.00***
Wisconsin	New York	Yes	0.00***

*Note: Short-run causalities are the interpretation of an F-test on the β of the independent variable. Changes in the monthly milk price of the independent state causes changes in the dependent state in the short run if statistically significant. Statistical significance at the 1, 5, and 10% levels are indicated by ***, **, and *, respectively.*

Table 3. Long-run Causalities

Dependent State	Independent States	Long-run Causality	α Coefficient
California	New York and Wisconsin	No	0.01

New York	California and Wisconsin	Yes	-0.01**
Wisconsin	California and New York	No	0.03***

*Note: Changes in the monthly milk price of the independent state causes changes in the dependent state in the long run if statistically significant. Statistical significance at the 1, 5, and 10% levels are indicated by ***, **, and *, respectively.*

Table A1. Dickey-Fuller Test for Unit Root Results

State	Lag	Test Statistic	P-Value
California	0	-2.39	0.14*
California	1	-4.25	0.00***
New York	0	-2.37	0.15*
New York	1	-4.13	0.00***
Wisconsin	0	-2.78	0.06*
Wisconsin	1	-4.60	0.00***

*Note: H0: Random walk without drift, d=0 Statistical significance at the 1, 5, and 10% levels are indicated by ***, **, and *, respectively.*

Table A2. Johansen Test for Cointegration Results

Specification	H0:	Test Statistic	10%	5%	1%
None	r = 0	38.50	18.90	21.07	25.75
None	r <= 1	10.36	12.91	14.90	19.19
Constant	r = 0	38.53	19.77	22.00	26.81

Constant	r <= 1	10.38	13.75	15.67	20.20
Trend	r = 0	38.81	23.11	25.54	30.34
Trend	r <= 1	20.19	16.85	18.96	23.65

Note: If test stat > critical value, we reject the null hypothesis.

Table A3. Lag Selection Criteria Results

Lag	LL	LR	dF	p-value	FPE	AIC	HQIC	SBIC
0	-2196.65				2.24	9.32	9.33	9.35
1	-997.295	2398.7	9	0.00	.01	4.28	4.32	4.38
2	-832.488	329.61	9	0.00	.01	3.62	3.69	3.80*
3	-812.585	39.81	9	0.00	.01	3.57	3.67*	3.83
4	-799.753	25.67	9	0.00	.01*	3.55*	3.69	3.90
5	-797.413	4.68	9	0.86	.01	3.58	3.75	4.01
6	-790.005	14.82	9	0.10	.01	3.59	3.79	4.09
7	-783.142	13.73	9	0.13	.01	3.60	3.83	4.18
8	-768.403	29.48	9	0.00	.01	3.57	3.83	4.23
9	-760.828	15.15	9	0.09	.01	3.58	3.87	4.32

*Note: * indicates optimal lag*

Table A4. Lagrange Multiplier Test of Serial Autocorrelation

Lag	Chi-squared	Degrees of Freedom	Prob > Chi-squared
1	28.11	9	0.00

2	25.80	9	0.00

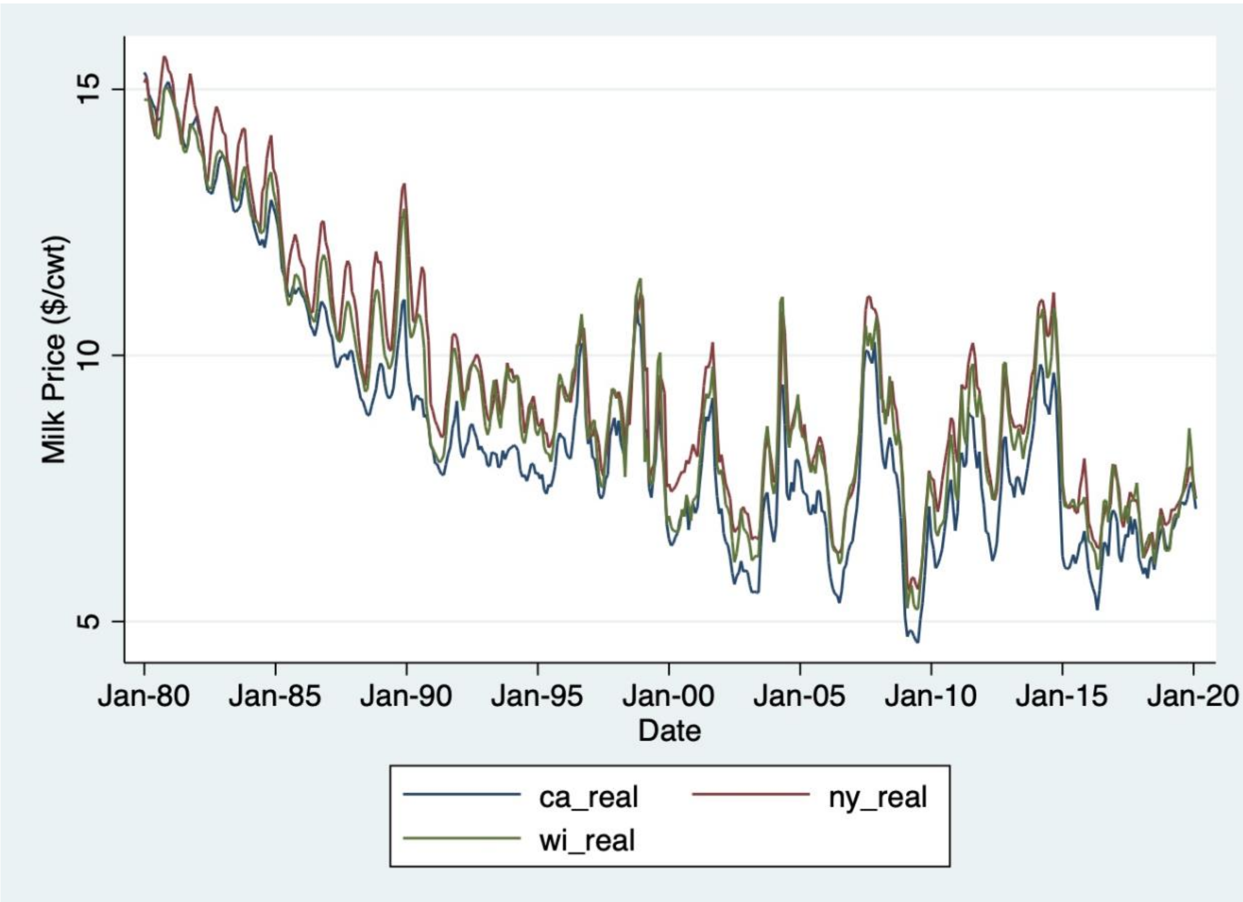
Note: H0: no autocorrelation at lag order

Table A5. Jarque-Bera Test Results

Equation	Chi-squared	Degrees of Freedom	Prob > Chi-squared
Wisconsin	77.24	2	0.00
California	66.24	2	0.00
New York	179.50	2	0.00
ALL	322.98	6	0.00

Note: H0: residuals are normally distributed

Figure 1. Average Monthly Milk Price Received for California, New York, and Wisconsin from January 1980 to February 2020 (real)



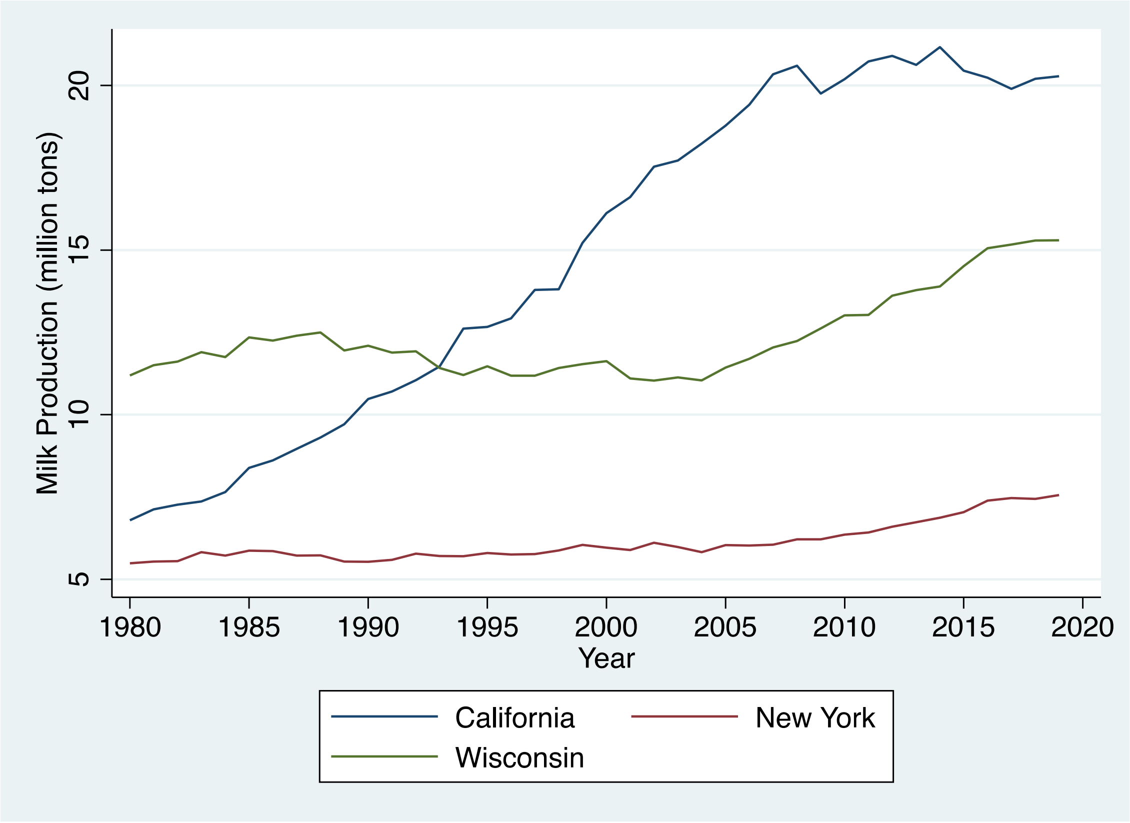


Figure 2. Annual Milk Production for California, New York, and Wisconsin from 1980 to 2019

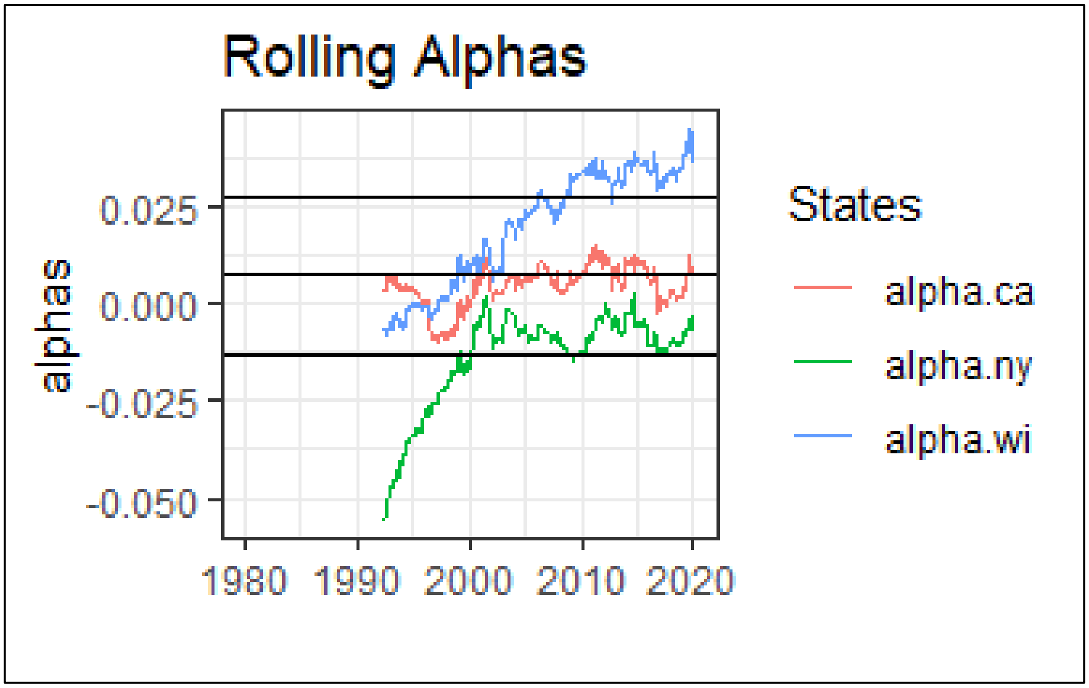


Figure 3. Rolling Alpha Estimation from 1980-2020 Depicting Milk Price Leadership if Close to 0.000