Volatility Modeling of U.S. Metropolitan Retail Gasoline Prices: An Empirical Note

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Abstract

This empirical note examines the time-varying nature of volatility in retail gasoline prices across ten U.S. metropolitan markets. We employ the exponential GARCH (EGARCH) model to determine the asymmetry and persistence of shocks across metropolitan areas. Our findings indicate the presence of time-varying volatility in metropolitan retail gasoline prices. Furthermore, the results show that persistence associated with volatility shocks ranges from 0.616 (Miami) to 0.968 (Chicago) with the persistence coefficient being statistically less than one across all metropolitan markets. We also observe the presence of asymmetries in the volatility of retail gasoline prices in six of the ten metropolitan markets.

1 Introduction

Casual observation of retail gasoline prices across geographical areas reveals both price volatility and price stickiness. Studies by Bacon (1991), Castanias and Johnson (1993), Borenstein and Shepard (1996), Borenstein et al. (1997), Eckert (2002), Johnson (2002), Davis and Hamilton (2004), Eckert and West (2004a,b), Lewis (2011), Douglas and Herrera (2010, 2014), and Zimmerman et al. (2013) have examined the dynamic pricing behavior of retail gasoline prices, in particular, the presence of asymmetries within various geographical areas. As a result, researchers suggest that the observed price volatility parallels Maskin and Tirole's (1988) Edgeworth price model in which gasoline stations undertake repeated price undercutting in a quest to gain market share. Such price undercutting continues until the price nears marginal cost at which point gasoline stations sacrifice short-term market share by raising prices. On the other hand, the presence of price stickiness within a gasoline market reflects tacit collusion in which gasoline stations, realizing the anticipated response by rival gasoline stations, do not succumb to the competitive pressures to cut prices. In this framework, gasoline stations use "focal point pricing" to reach a price level that facilitates such coordination (Eckert and West, 2004a,b).

Indeed, understanding the fluctuations in retail gasoline prices is relevant in the modeling of such price volatility and its impact on gasoline demand and price elasticity. By incorporating rational habits in the modeling of gasoline demand, Scott (2012) argues that consumer habits such as commuting distance, vehicle design, among other factors, influence gasoline demand. Specifically, consumers reduce their current gasoline demand in response to anticipated future increases in gasoline prices, and reduce their demand further in response to a future price increase perceived as permanent. Lin and Prince (2013) reiterates the importance of price volatility in the modeling of gasoline demand. Lin and Prince (2013) show that as gasoline prices become more volatile gasoline demand decreases in the intermediate run and in the case of heightened price volatility, gasoline demand in both the short- and long-run is less elastic relative to periods of low price volatility.

While a number of studies have estimated volatility models associated with petroleum markets, the vast majority of the studies have focused on the volatility of spot and futures prices at the national level. To the best of our knowledge there are no studies that exclusively focus on modeling the time varying conditional volatility of retail gasoline prices across geographical areas.[1] This empirical note addresses this shortcoming by estimating an exponential GARCH (EGARCH) model in the case of ten large U.S. metropolitan areas. Specifically, our efforts will determine whether or not time-varying volatility is present in metropolitan retail gasoline prices, and if present, the extent to which the persistence in volatility shocks differs across metropolitan retail gasoline markets. Second, unlike previous studies that tend to focus on the asymmetric response of gasoline prices to crude oil prices in the spirit of the "rockets and feathers" hypothesis of Bacon (1991), we investigate the possibility of an asymmetric response in volatility behavior due to shocks. The findings of our inquiry will contribute to the existing literature with respect to the dynamics of retail gasoline prices and the modeling of volatility as a determinant in studies of gasoline demand.

Section 2 describes the data along with the methodology and empirical results. Section 3 provides concluding remarks.

2 Data, Methodology, and Results

Weekly data on retail gasoline prices based on all grades for ten U.S. metropolitan areas from May 26, 2003 to May 22, 2017 were obtained from the U.S. Energy Information Administration. The ten metropolitan areas include Boston, Chicago, Cleveland, Denver, Houston, Los Angeles, Miami, New York City, San Francisco, and Seattle. Table 1 displays the summary statistics for retail gasoline prices for each metropolitan area.

Table 1: Summary Statistics Metropolitan Retail Gasoline Prices

Metropolitan Area	Mean	Med.	Max.	Min.	S.D.	Skew.	Kurt.	JB
Boston	2.78	2.7	4.11	1.53	0.687	0.119	1.86	41.05 [0.00]^a
Chicago	2.94	2.9	4.52	1.56	0.755	0.117	1.99	32.53 [0.00]^a
Cleveland	2.75	2.69	4.18	1.41	0.691	0.106	1.93	36.42 [0.00]^a
Denver	2.71	2.7	4.06	1.42	0.674	0.081	1.94	35.26 [0.00]^a
Houston	2.62	2.57	3.98	1.38	0.678	0.105	1.93	36.1 [0.00]^a
Los Angeles	3.18	3.13	4.78	1.65	0.722	-0.052	2.19	20.36 [0.00]^a
Miami	2.93	2.88	4.25	1.56	0.683	-0.013	2.06	26.62 [0.00]^a
New York City	2.86	2.79	4.24	1.55	0.701	0.094	1.88	39.46 [0.00]^a
San Francisco	3.17	3.15	4.73	1.67	0.705	-0.076	2.15	22.48 [0.00]^a
Seattle	2.98	2.94	4.4	1.51	0.701	-0.038	2.18	20.51 [0.00]^a

Notes: Mean is the average retail gasoline price per gallon; Med. is the median price; Max. the maximum price; Min. minimum price; SD is the standard deviation of price; Skew. measures skewness of prices; Kurtosis represents the shape of the distribution of prices; and JB is the Jarque-Bera test for normality. "a" denotes statistical significance at the % level. Probability values are in brackets.

As shown in Table 1, we observe that Los Angeles exhibits the highest mean price at $3.18 per gallon with

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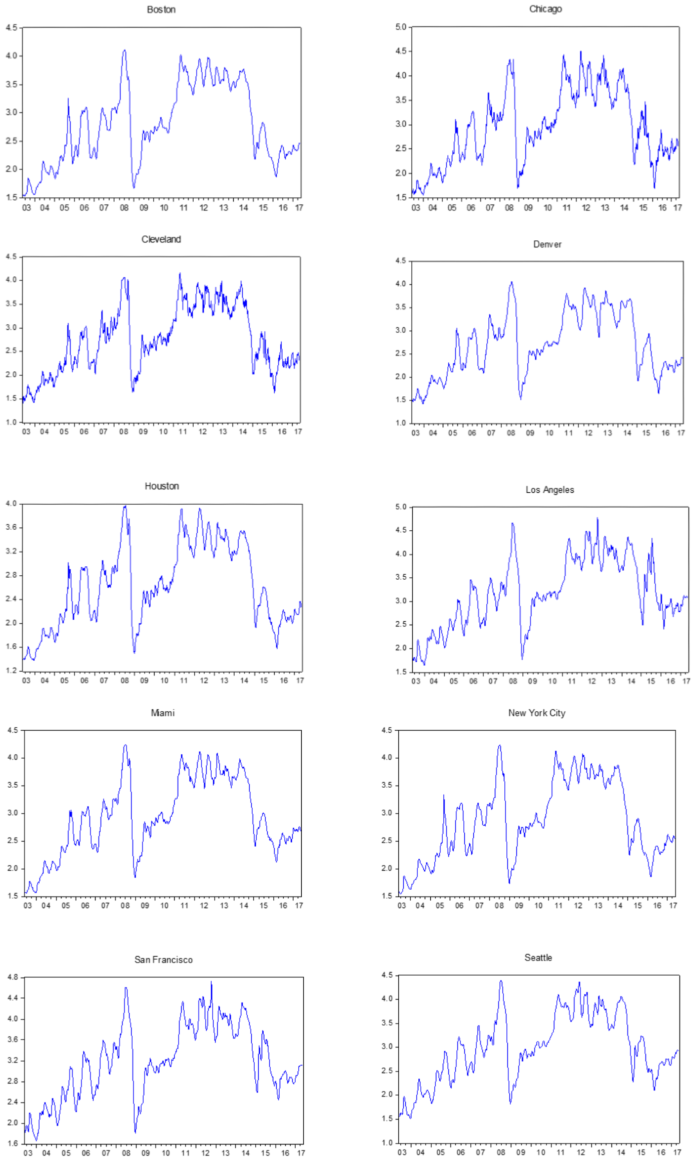
[1] For studies on modeling oil price volatility, and in some cases, gasoline price volatility at the national level, see Ewing et al. (2002), Fong and See (2002), Hammoudeh et al. (2003), Radchenko (2005), Narayan and Narayan (2007), Regnier (2007), Tabak and Cajueiro (2007), Fan et al. (2008), Hung et al. (2008), Wang et al. (2008), Agnolucci (2009), Cheong (2009), Elder and Serletis (2009), Geman and Ohana (2009), Kang et al. (2009), Vo (2009), Chang et al. (2010, 2011), Mohammadi and Su (2010), Wang et al. (2010), Wei et al. (2010), Nomikos and Pouliasis (2011), Arouri et al. (2012), Hou and Suardi (2012), Wang and Wu (2012), Kang and Yoon (2013), and Polemis and Tsionas (2016), among others.

the lowest mean price in Houston at $2.62 per gallon. Over this period retail gasoline prices ranged from a low of $1.38 per gallon in Houston to a high of $4.78 per gallon in Los Angeles. The variability in retail gasoline prices per gallon (measured by the standard deviation) are quite similar across the metropolitan areas with Denver having the lowest standard deviation at $.678 per gallon and Chicago the highest at $.755 per gallon. With the exception of Los Angeles, Miami, San Francisco, and Seattle, the distribution of retail gasoline prices appear positively skewed with the distribution of prices flat relative to the normal distribution based on kurtosis. Furthermore, the Jarque-Bera test rejects the null hypothesis that retail gasoline prices are normally distributed.

Figure 1 displays the time series behavior of retail gasoline prices for each metropolitan area. From Figure 1, we observe the fluctuations in retail gasoline prices with a notable rise and fall in prices during 2008. With gasoline a refined petroleum product derived from crude oil, the dramatic rise in gasoline prices during the first half of 2008 is due to the significant decrease in non-OPEC oil supply in conjunction with a substantial increase in the global demand for oil. The decline in prices in the second half of 2008 corresponds to the decrease in global demand due to the global financial crisis and ensuing economic decline.

Figure 1: Metropolitan Retail Gasoline Prices



Boston

Chicago

Cleveland

Denver

Houston

Los Angeles

Miami

New York City

San Francisco

Seattle

Using the natural log of retail gasoline prices preliminary unit root analysis of gasoline prices fails to reject the null hypothesis of a unit root in levels for the respective metropolitan areas.[2] However, the null hypothesis of a unit root is rejected for the first-differences in the log of gasoline prices across the respective metropolitan areas. Hence, our modeling of volatility in metropolitan retail gasoline prices will be undertaken using the first-differences of the log of gasoline prices.

We begin with modeling the conditional mean by estimating ARMA models for each metropolitan market. Table 2 reports the respective ARMA models augmented to include a dummy variable for the weeks in 2008 (1.0 for the weeks in 2008 and 0.0 otherwise) along with the residual diagnostics. Each ARMA model satisfies the stationarity (AR terms) and invertibility (MA terms) conditions.[3] The coefficient for the dummy variable, D2008, is negative and statistically significant at the 10 percent level or better with the exception of Denver. Furthermore, each ARMA model is free of autocorrelation based on the Box-Pierce Q-statistic, Q(5), with the exception of Seattle[4]; however, the residuals exhibit autoregressive conditional heteroskedasticity (ARCH) based on the chi-square distributed ARCH(5) statistic (Engle, 1982).

Table 2: ARMA Models

ARMA Terms	Boston	Chicago	Cleveland	Denver	Houston	Los Angeles	Miami	New York City	San Francisco	Seattle
AR(1)	0.539 (0.032)^{a}	0.526 (0.097)^{a}	0.126 (0.037)^{a}	0.525 (0.036)^{a}	0.697 (0.048)^{a}	0.545 (0.031)^{a}	0.720 (0.042)^{a}	0.639 (0.056)^{a}	0.632 (0.029)^{a}	0.648 (0.037)^{a}
MA(1)		-0.243 (0.111)^{b}			-0.232 (0.065)^{a}		-0.185 (0.059)^{a}	-0.129 (0.067)^{c}		0.209 (0.048)^{a}
MA(2)				0.139 (0.034)^{a}						
MA(3)	0.206 (0.038)^{a}			0.191 (0.037)^{a}				0.125 (0.043)^{a}		
D2008	-0.012 (0.006)^{b}	-0.014 (0.007)^{b}	-0.013 (0.006)^{b}	-0.008 (0.006)	-0.015 (0.007)^{b}	-0.012 (0.006)^{c}	-0.012 (0.005)^{b}	-0.012 (0.006)^{b}	-0.011 (0.006)^{c}	-0.011 (0.006)^{c}
Model Diagnostics										
Q(5)	3.26 [0.33]	3.69 [0.30]	2.10 [0.72]	0.33 [0.85]	5.67 [0.13]	6.71 [0.15]	1.55 [0.67]	0.12 [0.94]	3.11 [0.54]	6.26 [0.10]^{c}
ARCH(5)	136.62 [0.00]^{a}	23.44 [0.00]^{a}	49.87 [0.00]^{a}	94.24 [0.00]^{a}	104.08 [0.00]^{a}	52.23 [0.00]^{a}	69.74 [0.00]^{a}	107.93 [0.00]^{a}	76.93 [0.00]^{a}	44.73 [0.00]^{a}
Log Likelihood	1939.59	1495.85	1340.82	1874.86	1787.70	1744.21	2025.69	1955.30	1885.73	2071.11

Notes: AR(.) represents the autoregressive terms and MA(.) the moving average terms. Q(5) is the Box-Pierce Q-statistic distributed as chi-square with 5 degrees of freedom to test the null hypothesis of no autocorrelation in the residuals up to 5 lags. ARCH(5) is distributed as chi-square with 5 degree of freedom to test the null hypothesis of no autoregressive conditional heteroscedasticity of the residuals. Significance levels denoted as follows: a(1%), b(5%), and c(10%). Standard errors are in parentheses and probability values are in brackets.

With the presence of autoregressive conditional heteroskedasticity resulting from the estimation of the respective mean equations for retail gasoline prices, we proceed with examining the time-varying nature of the residual variance. As the standard GARCH model of Bollerslev (1986) assumes a symmetrical response

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[2] While the augmented Dickey-Fuller (Dickey and Fuller, 1979), Phillips-Perron (Phillips and Perron, 1988), and the generalized least squares version of the Dickey-Fuller (Elliott et al., 1996) indicate retail gasoline prices by metropolitan area are integrated of order one, we also examined the Lumsdaine and Papell (1997) and Lee and Strazicich (2003) unit root tests with allowance for structural breaks given the dramatic fluctuation in retail gasoline prices during 2008 to find the respective metropolitan retail gasoline prices were still I(1). Results are available upon request.

[3] Cosimano and Jansen (1988) reiterate that the absence of autocorrelation in the residuals is important before testing for the presence of autoregressive conditional heteroscedasticity (ARCH) in the residuals to avoid falsely identifying ARCH effects.

[4] Further examination reveals additional lags in the Box-Pierce Q-statistic suggests the absence of autocorrelation in the case of Seattle.

of volatility to shocks, we explore the possibility of asymmetry in the conditional variance using the exponential GARCH (EGARCH) model set forth by Nelson (1991). The exponential GARCH(1,1) specification augmented with the dummy variable, D2008, is given as follows:

$$log(\sigma_t^2) = \mu + \phi D2008 + \alpha|\frac{\epsilon_{t-1}}{\sigma_{t-1}}| + \gamma(\frac{\epsilon_{t-1}}{\sigma_{t-1}}) + \beta log(\sigma_{t-1}^2) \quad (1)$$

The EGARCH specification does not place restrictions on the α, β, and γ parameters and allows for oscillatory fluctuations in the conditional variance as the coefficient for β maybe either positive or negative. The degree of persistence attributed to shocks on the conditional variance is measured by β with β closer to one exhibiting greater persistence. The coefficient, γ, determines the asymmetry in the volatility of retail gasoline prices. If $\gamma \neq 0$, the impact of shocks are asymmetric. If $\gamma > 0$, positive (higher prices) shocks will increase volatility more so than negative shocks. On the other hand, if $\gamma < 0$, negative (lower prices) shocks will have a greater impact on volatility than positive shocks. Finally, the coefficient, α, captures the impact of the conditional shock on the conditional variance of retail gasoline prices. Table 3 displays the results from the EGARCH model for the respective metropolitan retail gasoline prices.

Table 3: ARMA-EGARCH(1,1) Models

ARMA Terms	Boston	Chicago	Cleveland	Denver	Houston	Los Angeles	Miami	New York City	San Francisco	Seattle
AR(1)	0.700	0.512	0.081	0.783	0.612	0.716	0.670	0.720	0.744	0.652
	(0.026)^a	(0.098)^a	(0.039)^b	(0.026)^a	(0.050)^a	(0.022)^a	(0.039)^a	(0.032)^a	(0.022)^a	(0.033)^a
MA(1)		-0.215			-0.080		-0.079	0.088		0.229
		(0.111)^b			(0.063)		(0.056)	(0.049)		(0.045)^a
MA(2)				0.007						
				-0.033						
MA(3)	0.111			0.078				0.039		
	(0.033)^a			(0.028)^a				(0.031)		
D2008	-0.003	-0.002	0.007	0.009	-0.001	-0.011	-0.005	-0.008	-0.007	-0.005
	(0.005)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)^b	(0.005)	(0.005)^c	(0.006)	(0.005)
μ	-1.716	-0.360	-0.850	-2.896	-0.768	-3.028	-3.569	-2.503	-3.396	-1.106
	(0.507)^a	(0.126)^a	(0.246)^a	(0.562)^a	(0.258)^a	(0.810)^a	(0.932)^a	(0.597)^a	(0.663)^a	(0.313)^a
ϕ	0.145	0.046	0.05	0.234	0.089	0.037	0.350	0.137	0.268	0.067
	(0.094)	(0.022)^b	(0.052)	(0.152)	(0.051)^c	(0.107)	(0.178)^b	(0.152)	(0.125)^b	(0.072)
α	0.338	0.169	0.236	0.512	0.232	0.331	0.356	0.430	0.375	0.343
	(0.093)^a	(0.047)^a	(0.058)^a	(0.108)^a	(0.052)^a	(0.097)^a	(0.108)^a	(0.115)^a	(0.092)^a	(0.075)^a
γ	0.134	-0.031	-0.037	0.285	-0.020	0.216	0.146	0.179	0.327	0.022
	(0.058)^b	(0.030)	(0.028)	(0.071)^a	(0.044)	(0.067)^a	(0.069)^b	(0.069)^a	(0.071)^a	(0.046)
β	0.830	0.968	0.901	0.697	0.926	0.647	0.616	0.750	0.628	0.903
	(0.055)^a	(0.016)^a	(0.033)^a	(0.064)^a	(0.031)^a	(0.099)^a	(0.104)^a	(0.063)^a	(0.077)^a	(0.034)^a
GED Parameter	1.044	1.674	2.164	0.982	1.227	0.943	1.166	1.027	1.029	1.133
	(0.054)^a	(0.088)^a	(0.147)^a	(0.061)^a	(0.073)^a	(0.041)^a	(0.073)^a	(0.050)^a	(0.060)^a	(0.074)^a
Model Diagnostics										
Q(5)	2.89	2.25	1.50	4.25	1.69	5.18	0.67	1.43	3.02	3.54
	[0.41]	[0.52]	[0.83]	[0.12]	[0.64]	[0.27]	[0.88]	[0.49]	[0.55]	[0.32]
ARCH(5)	1.80	3.11	5.81	1.02	7.85	0.41	1.57	0.89	2.54	4.78
	[0.88]	[0.68]	[0.33]	[0.96]	[0.16]	[0.99]	[0.91]	[0.97]	[0.71]	[0.44]
Log Likelihood	2138.10	1544.41	1368.84	2023.99	1879.12	1895.86	2101.78	2189.40	2034.7	2176.54

AR(.) represents the autoregressive terms and MA(.) the moving average terms. Q(5) is the Box-Pierce Q-statistic distributed as chi-square with 5 degrees of freedom to test the null hypothesis of no autocorrelation in the residuals up to 5 lags. ARCH(5) is distributed as chi-square with 5 degree of freedom to test the null hypothesis of no autoregressive conditional heteroscedasticity of the residuals. GED is the Generalized Error Distribution. Significance levels denoted as follows: a(1%), b(5%), and c(10%). Standard errors are in parentheses and probability values are in brackets.

Each model in Table 3 is free of both autocorrelation and autoregressive conditional heteroscedasticity in the residuals. The degree of persistence in volatility, measured by β, is statistically significant and less than one in magnitude. However, the β coefficient estimates vary across metropolitan areas from 0.616 in Miami to 0.968 in Chicago. The coefficient estimate, α, representing the impact of a shock on conditional variance ranges from 0.169 in Chicago to 0.512 in Denver. Moreover, the asymmetry parameter, γ, is statistically significant in six of the ten metropolitan areas (statistically insignificant for Chicago, Cleveland, Houston, and Seattle). Of the six metropolitan areas in which asymmetry is present, positive shocks will increase volatility more so than negative shocks for Boston (0.134), Denver (0.285), Los Angeles (0.216), Miami (0.146), New York City (0.179), and San Francisco (0.327). The turbulence in gasoline prices during 2008, captured by the dummy variable, D2008, has a positive and statistically significant impact on volatility in only four metropolitan areas: Chicago (0.046), Houston (0.089), Miami (0.350), and San Francisco (0.268).

3 Concluding Remarks

While research has been undertaken to explore the dynamic pricing behavior of retail gasoline markets, in particular, the observed volatility and stickiness of prices, the modeling of the time-varying nature of price volatility in retail gasoline prices at the metropolitan level has not been examined using GARCH-type specifications. Such modeling efforts are relevant in light of the recent literature on the modeling of gasoline demand and the role that price volatility has upon gasoline demand and price elasticity. This empirical note addresses this shortcoming with the estimation of EGARCH models for retail gasoline prices by U.S. metropolitan area. Our results indicate variation across metropolitan markets with respect to the persistence of volatility shocks and the presence of asymmetry.

In particular, we find that persistence associated with volatility shocks ranges from 0.616 in Miami to 0.968 in Chicago with the persistence coefficient being statistically less than one across all metropolitan markets. As for the presence of asymmetries in the volatility of retail gasoline prices we observe the absence of asymmetry in four metropolitan markets (Chicago, Cleveland, Houston, and Seattle) with positive and statistically significant asymmetry in the remaining six metropolitan markets (Boston, Denver, Los Angeles, Miami, New York City, and San Francisco). Thus, as the literature on modeling gasoline demand continues to investigate the role of price volatility as a determinant of gasoline demand, it is particularly important to recognize the heterogeneous nature of the retail gasoline markets with respect to the presence of time-varying volatility along with the degree of persistence and asymmetry in volatility shocks.

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