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COVID-19 and volatility in the tourism sector's stocks

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Abstract

This study examines effects of COVID-19 on volatility of hospitality sector stocks in United States. Using a daily dataset, our analysis offers a comparative picture of the sub-sectors, viz. airline, gambling, hotel, restaurant and travel. We use three crucial measures of intensity of pandemic and related stringencies in our analysis. For estimation, we utilize GARCH based models and measured symmetric as well as asymmetric effects. Our findings show for a sizable effect of the COVID-19 outbreak on the volatility of hospitality stocks. Specifically, our results demonstrate that highest level of uncertainty is observed in travel followed restaurant sector.

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1. Introduction

The spread of COVID-19 has led to unprecedented economic impacts and uncertainty around the world. Undoubtedly, the hardest hit industries are the aviation, hospitality, travel and hotel, which are mutually dependent. This is partly because the high transmissibility of COVID-19 and its non-negligible mortality rates have increased the perceived risk of travel and tourism. UNWTO (2020) reports that the ongoing pandemic has led to a 75% year-on-year reduction in international tourist arrivals in 2020Q1, which is the sharpest fall in tourism demand owed to any contagious disease outbreak. Recently, Dube et al., (2020) have presented some statistics which shows that COVID-19 is causing severe losses to restaurant and hospitality industries. Foo et al., (2020) also find similar results for Malaysian tourism industry. Yang et al. (2020) large negative effects of coronavirus-linked health risk on tourism demand. While the focus of most studies remains on the tourism demand response to pandemics, a few scholars show how pandemic-risks affect the financial performance of tourism businesses in the hotel, restaurant and other sectors. For instance, Kim et al. (2020) show negative effects of disease outbreaks in the period 2004-2016 on restaurant firms' value. Similarly, Chen et al. (2007) show negative effects of SARS outbreak on Taiwanese hotel stock price movements. Contrastingly, Harjoto et al. (2020) show evidence of positive abnormal returns that US stock market amidst the pandemic period.

Against this background, we attempt to estimate the effects of COVID-19 on idiosyncratic risk in the tourism and hospitality sector covering five sub-sectors, viz. airline, gambling, hotel, restaurant and travel. Our attempt will help in understanding the level of uncertainty that has prevailed in the tourism sector, which in turn will help in drawing appropriate policy responses.

Within the thematic focus of this stream of literature, this paper contributes by applying news impact theories and concepts on conditional heteroskedastic volatility to examine the impact of the COVID-19 outbreak on the volatility of U.S. hospitality stock prices. We opt to examine U.S. hospitality sector's market performance due to two reasons: first, the U.S. leads the world in international travel and tourism with $1.87 trillion in total travel and tourism output (NTTO, 2019) and U.S. is one of the worst hit economies, second, the U.S. financial market is the largest in the world. In terms of market capitalization, the U.S. comprises 40% of the global market capitalization. Baker et al. (2020) suggest that news regarding COVID-19 spread and related policy responses have exerted a powerful impact on U.S. stock markets.

2. Data and empirical methodology

We extract daily closing values of Dow Jones U.S. hospitality stock prices spanning the period January 21, 2020 to March 31, 2021 from DataStream database. We cover five hospitality indices viz., airline, gambling, hotel, restaurant and travel. To capture the impact of the pandemic, we augment these models by including the $COVID19$ term. Precisely, COVID-19 pandemic effect is gauged using three measures. First, we use the Oxford Coronavirus Government Response Tracker's (OxCGRT) government response index that combines information on common policy responses with respect to 17 key indicators such as lockdown restrictions, school closures, or travel bans that governments took in response to the COVID-19 pandemic (GRI) for United States (Hale et al., 2020). GRI ranges between 0 and 100, with a higher value indicating stricter government action. Second, we use the stringency index (SI) for United States that covers eight closure and containment measures pertaining to public information campaigns taken by the government. These eight measures are weight equally in the overall stringency index, which is scaled from 0 to 100 with higher values pointing towards a stronger government policy response (see Sharma and Khanna, 2022). Third, we employ logarithmic change in the 'total number of confirmed cases' on day t (CONF) (Huynh et al., 2021) [1]. The choice of the beginning period is governed by data availability on various pandemic measures used in this study. Notably, the analysis involving the stringency index covers the period starting March 2, 2022 for the same reason. Further, we cover the period until March 31, 2021 as most of the pandemic restrictions were lifted in the United States after this time. Finally, to include the effect of important pandemic-related events, we introduce a dummy (*Dum*) capturing the declaration of public emergency in the United States. Details of data series and their source are presented in Table 1A, while descriptive statistics are presented in Table 2A of appendix.

As uncertainty in hospitality stocks may be a function of the COVID-19 pandemic, we proceed to model the uncertainty directly using the conditional variance of U.S. hospitality stock prices. Thus, we examine GARCH-type processes assuming hospitality stock prices to trail a random walk and estimating the following model:

$$\Delta \log(y_t) = \alpha_0 + \alpha_{1i} \sum_{i=0}^{5} \Delta log(y_{t-i}) + \mu_t \qquad (1)$$

$$\mu_t \sim N(0, h_t) \qquad (2)$$

where, y_t is the daily closing index of each hospitality sector on day t. Further, for each hospitality stock price index, we test the suitability of different GARCH-type models elaborated in Table 1. In the GARCH framework, the conditional variance (h_t) depends upon three terms, namely, the constant (ω), the $ARCH$ term or the one-period lagged squared residuals (μ_{t-1}^2), the GARCH term or the last period's forecast error variance (h_{t-1}). The parameters α and β capture the magnitude effect and persistence in conditional volatility respectively. Next, to capture any asymmetric response[2] of volatility to positive and negative shocks, we explore the exponential-GARCH (EGARCH) specification proposed by Nelson (1991) and the threshold-ARCH (TARCH) specification of Glosten et al. (1993). The parameter capturing asymmetry effect in both EGARCH and TARCH models is γ (Eqs. 3.2 and 3.3). In the EGARCH specification, if γ<0, then this suggests that negative shocks cause higher volatility shocks than positive shocks of similar magnitude (leverage effects), γ>0 suggests that positive shocks generate higher volatility than similar negative shocks (i.e., the EGARCH model accounts for asymmetric response of conditional volatility to unexpected changes in the returns), while γ=0, suggests that the model is symmetric. Contrastingly, the opposite holds for TARCH model i.e. γ>0 implies that significant leverage effects of negative shocks exist.

[1] https://www.who.int/healthinfo/statistics/data/en

[2] An asymmetric relationship exists when the same size of both positive and negative shocks has an unequal impact on the volatility of returns. There is a high possibility that the positive and negative shocks induced from Covid and related measures have different effects on market. For instance, negative shocks may have a larger effect than positive shocks.

Table 1
GARCH-type models employed

$GARCH(1,1)$	$h_t = \omega + \alpha\mu_{t-1}^2 + \beta h_{t-1} + Dum + COVID19_t$	(3.1)
$EGARCH(1,1)$	$\log(h_t) = \omega + \alpha\left[\left\|\frac{\mu_{t-1}}{\sqrt{h_{t-1}}}\right\| - \sqrt{2/\pi}\right] + \beta\log(h_{t-1}) + \gamma\frac{u_{t-1}}{\sqrt{h_{t-1}}} + Dum + COVID19_t$	(3.2)
$TARCH(1,1)$	$h_t = \omega + \alpha\mu_{t-1}^2 + \beta h_{t-1} + \gamma d_{t-1}\mu_{t-1}^2 + Dum + COVID19_t$	(3.3)

For selecting the appropriate volatility model, we apply a battery of criteria, including Akaike Information Criterion (AIC), Schwartz Information Criterion (SIC), and in-sample forecasting performance measured by root mean square error (RMSE), mean absolute error (MAE) and the Theil inequality coefficient (TIC). These criteria along with estimated values are summarised in Table 2. For the airline index, both AIC and SIC prefer EGARCH over other specifications, while TIC suggests for TARCH model. Nonetheless, we employ EGARCH model as the TARCH-asymmetry coefficient is found to be insignificant. For gambling, GARCH specification is found suitable, while for hotel, restaurant and travel indices, TARCH model is found to be the most suitable based on our criteria set.

Table 2
Criteria for model selection for the GRI model

	Models	AIC	SIC	RMSE	MAE	TIC
Airline	$GARCH$	-3.08	-2.98	2.542	2.098	0.201
	$EGARCH^{\#}$	-3.75	-3.64	0.506	0.454	0.046
	$TARCH$	-3.69	-3.58	0.625	0.586	0.057
Gambling	$GARCH$	-3.99	-3.90	0.034	0.023	0.999
	$EGARCH^{\#}$	-4.03	-3.93	0.034	0.023	0.984
	$TARCH$	-4.00	-3.90	0.034	0.023	0.999
Hotel	$GARCH$	-4.32	-4.23	0.027	0.018	0.993
	$EGARCH^{\#}$	-4.34	-4.24	0.027	0.018	0.993
	$TARCH$	-4.33	-4.23	0.027	0.018	0.941
Restaurant	$GARCH$	-5.51	-5.43	0.019	0.011	0.997
	$EGARCH^{\#}$	-5.63	-5.54	0.019	0.011	0.998
	$TARCH$	-5.53	-5.44	0.019	0.011	0.997
Travel	$GARCH$	-1.79	-1.70	0.207	0.184	0.015
	$EGARCH^{\#}$	-4.38	-4.25	0.199	0.169	0.015
	$TARCH$	-2.01	-1.91	1.92E+13	4.62E+12	1.000

Notes: #denotes the choice of the specification for volatility estimation for the model using GRI as the COVID-19 variable. AIC: Akaike Information Criteria, SIC: Schwarz Information Criteria, RMSE: Root mean square error, MAE: Mean absolute error, TIC: Theil inequality coefficient.

3. The findings

Table 3 reports the parameters of the conditional variance equation capturing the effects of the COVID-19 outbreak in various hospitality sectors. The estimated coefficient of GRI is found to be negative and significant for airline, gambling, hotel, restaurant and travel sectors (columns 1 – 5). This implies that government policy responses to the COVID-19 pandemic helped in significantly mitigating stock volatility in the hospitality sectors. Results imply a fall in the airline index volatility by 0.086% in response to a unit percentage rise in the GRI. Likewise, a unit percentage rise in the index of government response to the COVID-19 pandemic is associated with a corresponding 0.077%, 0.056%, 0.091% and 0.072% fall in the index volatility in gambling, hotel, restaurant and travel sectors respectively. The coefficient for Dum is negative and significant implying that the declaration of public emergency helped allay investors' anxiety regarding the pandemic situation in the country. This result perhaps suggests investors' perception that the government's taking active control of the situation may aid sooner recovery in the future.

Further, the asymmetry parameter (γ) in EGARCH is significant, non-zero and negative for the hotel, restaurant and travel indices. This suggests that negative shocks in the stock returns are associated with a higher conditional variance than positive shocks of the same magnitude. α, which shows the volatility response to unexpected shocks in the returns, is significant. β is quite sizeable and statistically significant suggesting that there is high persistence in the series, i.e., it takes time for volatility to revert back to its long-run average. The parameters α and β appear significant except in a few cases, and $\alpha + \beta < 1$, implying that the stationarity condition is met. Other diagnostic tests reported in the lower panel of Table 3 indicate that the problems of autocorrelation, non-normality and heteroscedasticity are not present with the estimated models.

Table 3
Estimation results for volatility models: impact of COVID-19 using Government Response Index (GRI)

DV: $\Delta\, log(y_t)$	Airline (1)	Gambling (2)	Hotel (3)	Restaurant (4)	Travel (5)
ω	0.271***	0.226***	0.131**	0.215***	-0.090
	(0.055)	(0.051)	(0.058)	(0.077)	(0.178)
α	-0.044	-0.055**	-0.070**	-0.070*	0.212
	(0.033)	(0.025)	(0.033)	(0.040)	(0.162)
γ	0.004	0.003	-0.085***	-0.083**	-0.065*
	(0.014)	(0.018)	(0.020)	(0.035)	(0.037)
β	0.994***	0.987***	0.983***	0.981***	0.972***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.018)
GRI	-0.079***	-0.077***	-0.056***	-0.091***	-0.071***
	(0.016)	(0.013)	(0.015)	(0.019)	(0.021)
Dum	-1.884**	-2.183***	-1.491**	-2.375**	-1.746*
	(0.858)	(0.777)	(0.741)	(1.048)	(1.044)
Log likelihood	572.27	612.92	657.39	849.61	667.10
No. of Observations	300	299	299	299	300
Specification	$EGARCH$	$EGARCH$	$EGARCH$	$EGARCH$	$EGARCH$
(p,q)	(1,1)	(1,1)	(1,1)	(1,1)	(2,1)
Ljung – box (Q12)	0.378	0.018	0.309	0.225	0.216
Ljung – box ($Q^2$12)	0.709	0.012	0.840	0.954	0.996
ARCH(1)	0.918	0.586	0.795	0.693	0.934

Notes: The table summarizes results of the variance equation using *GARCH*-type specifications. *p*-values are reported in parentheses. Dum captures the effect of public emergency declaration in the United States, i.e., Dum = 1 if date is February 3 2020, 0 otherwise. For all diagnostic tests, *p*-values are reported. DV: dependent variable, JB: Jarque-Bera normality test.
$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p< 0.10$

Next, we assess the robustness of these results using two alternate measures of the pandemic effect, viz., SI and CONF (see Table 1A) and report the results in Tables 4 and 5, respectively. Table 4 results indicate that the stringency of containment and closure measures taken by the government mitigate stock market volatility across all the five sectors, albeit in differing magnitudes. λ, which captures the asymmetry effects, is negative and significant in the case of hotel and gambling sectors pointing towards significant leverage effects in these sectors. This implies that negative shocks in the returns precipitate larger changes in the conditional volatility compared to positive shocks of similar magnitude. Further, the β coefficient is quite sizeable suggesting high persistence in the volatility series. The diagnostic tests show that there is no serious concern regarding autocorrelation and heteroscedasticity in the estimation of these results.

Table 4
Estimation results for volatility models: effects of COVID-19 via Stringency Index

DV: $\Delta\, log(y_t)$	Airline (1)	Gambling (2)	Hotel (3)	Restaurant (4)	Travel (5)
ω	0.336*** (0.069)	0.157 (0.114)	0.312*** (0.069)	0.255*** (0.072)	0.033 (0.284)
α	-0.048 (0.035)	-0.032 (0.056)	-0.084** (0.035)	-0.075* (0.040)	0.098 (0.168)
γ	0.024 (0.024)	-0.086** (0.042)	-0.050* (0.028)	-0.043 (0.032)	-0.057 (0.036)
β	0.996*** (0.000)	0.987*** (0.004)	0.980*** (0.000)	0.982*** (0.000)	0.967*** (0.019)
SI	-0.090*** (0.014)	-0.063** (0.028)	-0.107*** (0.016)	-0.096*** (0.015)	-0.122* (0.076)
Log likelihood	512.40	421.21	598.02	777.79	601.45
No. of Observations	274	213	274	299	274
Specification (p,q)	$EGARCH$ (1,1)	$EGARCH$ (1,1)	$EGARCH$ (1,1)	$EGARCH$ (1,1)	$EGARCH$ (2,1)
Ljung − box (Q12)	0.216	0.521	0.319	0.146	0.173
Ljung − box ($Q^2$12)	0.853	0.210	0.651	0.898	0.999
ARCH(1)	0.751	0.478	0.584	0.469	0.858

Notes: The table summarizes results of the variance equation using *GARCH*-type specifications. The time period covered in this regression is March 3, 2020 to March 31, 2021. Accordingly, Dum, which captures the effect of public emergency declaration on February 3 2020 in the United States, is dropped here. *p*-values are reported in parentheses. For all diagnostic tests, *p*-values are reported. DV: dependent variable, JB: Jarque-Bera normality test.
$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.10$

As a final step, we include daily growth in the number of confirmed COVID-19 cases in the model (see Table 5). The results indicate negative and statistically significant effects of the disease spread on the conditional volatility of tourism stocks in these five sectors. Results further imply a 0.328% airline index volatility in response to a unit percentage rise in growth of the COVID-19 confirmed cases. Likewise, a unit percentage rise in the growth of COVID-19 confirmed cases leads to a corresponding 0.745%, 0.407% and 0.828% rise in the volatility of the gambling, hotel and restaurant, respectively. The negative sign of the estimated coefficient appears reasonable as it suggests that the spread of COVID-19 precipitates fear among the investors that ends up driving up the volatility of these sectors. This is contrary to the mitigating effects of government response measures that perhaps help towards allaying investor stress and worry by indicating the government’s commitment towards the future of individuals, businesses and the economy. The coefficient of Dum is negative and significant for the hotel sector implying risk mitigating effects of public emergency declaration in the United States, which is line with the previous results. However, the dummy coefficient is positive and significant for the airline sector. Notably, unlike the other two pandemic measures, number of confirmed cases perhaps works as an outcome variable capturing the efficacy of government policy response and stringency. If despite these restrictive measures the number of cases remain high, such restrictions may not work towards allaying down investor anxiety. On the contrary, in the worst scenario, investor fears might be precipitated further upon such announcements by the government. Thus, the positive coefficient of the dummy variable in some cases may be justified in the same light. Regarding the diagnostic tests, the results remain the same.

Table 5
Estimation results for volatility models: effects of COVID-19 pandemic via confirmed cases

DV: $\Delta\, log(y_t)$	Airline (1)	Gambling (2)	Hotel (3)	Restaurant (4)	Travel (5)
ω	-0.161*** (0.022)	-0.970** (0.394)	-0.211*** (0.016)	-0.420*** (0.021)	-0.673*** (0.247)
α	-0.111*** (0.028)	-0.024 (0.180)	-0.129*** (0.023)	0.219 (0.140)	0.230 (0.168)
γ	-0.056** (0.023)	-0.034 (0.060)	-0.072** (0.028)	-0.068 (0.042)	-0.057 (0.043)
β	0.968*** (0.000)	0.892*** (0.050)	0.959*** (0.000)	0.938*** (0.001)	0.932*** (0.031)
$CONF$	0.328*** (0.058)	0.745** (0.332)	0.407*** (0.058)	0.828*** (0.079)	0.350 (0.223)
Dum	0.239*** (0.487)	-1.299 (1.570)	-0.975** (0.384)	-1.586 (0.467)	0.819 (1.432)
Log likelihood	654.84	617.77	653.96	843.63	660.78
No. of Observations	299	300	300	299	299
Specification	$EGARCH$ (1,1)	$EGARCH$ (2,1)	$EGARCH$ (1,1)	$EGARCH$ (2,1)	$EGARCH$ (2,1)
Ljung − box (Q12)	0.194	0.270	0.127	0.198	0.176
Ljung − box ($Q^2$12)	0.682	0.065	0.281	0.271	0.995
ARCH(1)	0.904	0.612	0.811	0.369	0.878

Notes: The table summarizes results of the variance equation using *GARCH*-type specifications. Dum captures the effect of public emergency declaration in the United States, i.e., Dum = 1 if date is February 3 2020, 0 otherwise. *p*-values are reported in parentheses. For all diagnostic tests, *p*-values are reported. DV: dependent variable, JB: Jarque-Bera normality test.
$^{***}p$<0.01, $^{**}p$<0.05, $^{*}p$< 0.10

4. Conclusion

The hospitality stocks have become highly volatile and risky due to the COVID-19 spread. Our results show for a sizable effect of the COVID-19 outbreak on the volatility of hospitality stocks. This is an indication of the fear and widely prevailing insecurity in the hospitality sector. Specifically, our results show that highest level of volatility or uncertainty is observed in travel followed restaurant sector. Administrative responses such as travel restrictions, physical confinement and lockdowns have an unprecedented impact on the market (Baker et al., 2020). Thus, policymakers should avoid giving time-inconsistent guidance and assure the market for a reasonable policy response, rescue package and stimulus for effectively dealing with the situation. Further, as more data becomes available, future research can focus on firm-level financial volatility and the role of factors such firm size, age, innovation efforts, etc. in mitigating any uncertainty.

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Appendix

Table 1A
Hospitality Dow Jones US stock indices and data source

Variable	Description	Source
Airline	Logarithmic returns on Dow Jones US Airlines Index	DataStream
Gambling	Logarithmic returns on Dow Jones U.S. Gambling Index	DataStream
Hotel	Logarithmic returns on Dow Jones U.S. Hotels Index	DataStream
Restaurant	Logarithmic returns on Dow Jones U.S. Restaurants & Bars Index	DataStream
Travel	Logarithmic returns on Dow Jones U.S. Travel & Leisure Total Stock Market Index	DataStream
GRI	Logarithm of the COVID-19 government response index	OxCGRT

SI	Logarithm of the COVID-19 stringency index	OxCGRT
CONF	Logarithmic growth rate in daily number of confirmed COVID-19 cases	WHO website

Table 2A

Summary statistics and ARCH effects of the tourism indices returns

Variables	Airline	Gambling	Hotel	Restaurant	Travel	CONF	SI	GRI
Mean	0.000	0.000	0.000	0.000	0.001	0.000	3.220	3.400
Median	0.000	-0.001	0.000	0.002	0.000	0.000	3.219	3.355
Maximum	0.188	0.115	0.141	0.156	0.139	0.188	3.637	3.652
Minimum	-0.227	-0.269	-0.158	-0.170	-0.134	-0.227	2.924	3.221
Std. Dev.	0.045	0.040	0.033	0.024	0.031	0.045	0.200	0.137
Skewness	-0.352	-1.204	-0.179	-0.374	-0.121	-0.352	-0.222	0.078
Kurtosis	7.854	10.997	6.924	19.546	7.389	7.854	1.773	1.502
Unit root (level)	-1.200	-1.595	-1.501	-1.636	-1.540	1.256	-1.483	-3.25
Unit root	-21.87***	-14.43***	-21.77***	-8.85***	-23.47***	-3.80*	-3.94***	-5.22***
Jarque-Bera	1075.71**	2015.83***	725.89***	12078.80***	445.03***	52165.16***	363.7***	2384.41***
LB-Q12	0.210***	0.167***	0.151	0.239***	0.228***	-	-	-
ARCH effect	6.172***	12.143***	4.193***	3.841***	6.085***	-	-	-

Notes: Unit root (level) denotes the unit root test results for stock prices. Unit root denotes the stationarity test for returns. LB denotes Ljung-Box test statistic for autocorrelation. While the null hypothesis of non-stationarity is not rejected for stock prices, daily stock returns are found to be stationary for all the sectors.

$^{***}p<0.01$, $^{**}p<0.05$, $^{*}p< 0.10$

The summary statistics of hospitality stock returns are presented in Table 2A. It is evident from this table that the maximum daily return during the sample period is 18.8% for the airline sector and the minimum return is -26.9% for the gambling sector. Similarly, a maximum growth of 18.8% and a maximum fall of 22.7% are observed in the daily total confirmed cases of COVID. The ADF test results suggest that stock price series is integrated of order 1, while stock returns are found to be stationary. Further, most return series exhibit auto-correlation as implied by Ljung-Box statistics, and autoregressive conditional heteroscedasticity (ARCH) effect as indicated by the ARCH test. Moreover, the Jarque-Bera values are high and statistically significant. The distribution of the returns is fat-tailed as kurtosis is greater than 3. ARCH-LM test results confirm the presence of significant auto-regressive conditional heteroscedasticity effects in these series. As a result, GARCH-type models seem suitable in our set up as they can account for time-varying volatility shocks in our data.

Table 3A

Estimation results for volatility models: effects of COVID-19 via Stringency Index

DV: $\Delta\, log(y_t)$	Airline (1)	Gambling (2)	Hotel (3)	Restaurant (4)	Travel (5)
ω	0.336*** (0.069)	0.157 (0.114)	0.312*** (0.069)	0.255*** (0.072)	0.033 (0.284)
α	-0.048 (0.035)	-0.032 (0.056)	-0.084** (0.035)	-0.075* (0.040)	0.098 (0.168)
γ	0.024 (0.024)	-0.086** (0.042)	-0.050* (0.028)	-0.043 (0.032)	-0.057 (0.036)
β	0.996*** (0.000)	0.987*** (0.004)	0.980*** (0.000)	0.982*** (0.000)	0.967*** (0.019)
SI	-0.090*** (0.014)	-0.063** (0.028)	-0.107*** (0.016)	-0.096*** (0.015)	-0.122* (0.076)

Log likelihood	512.40	421.21	598.02	777.79	601.45
No. of Observations	274	213	274	299	274
Specification (p,q)	$EGARCH$ (1,1)	$EGARCH$ (1,1)	$EGARCH$ (1,1)	$EGARCH$ (1,1)	$EGARCH$ (2,1)
Ljung − box (Q12)	0.216	0.521	0.319	0.146	0.173
Ljung − box ($Q^2$12)	0.853	0.210	0.651	0.898	0.999
ARCH(1)	0.751	0.478	0.584	0.469	0.858

Notes: The table summarizes results of the variance equation using *GARCH*-type specifications. *p*-values are reported in parentheses. For all diagnostic tests, *p*-values are reported. DV: dependent variable, JB: Jarque-Bera normality test. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.10$