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THE IMPACT OF INTERNET INFORMATION FLOW REGARDING 'INNOVATION' ON COMMON STOCK RETURNS: VOLUME VS GOOGLE SEARCH QUARRIES

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ABSTRACT: A number of scholars examine the impact of information flow associated with Google search queries of various search terms on heteroskedasticity of stock return data using the framework of Lamoureux and Lastrapes (1990). This paper examines the role of internet search queries in carrying the new information flow regarding economic innovation to the stock market for ten countries from a sample of top twenty innovative counties (based on Global Innovation Index 2018). When the internet search volume is included in the conditional variance equation of GJR-GRACH model, the ARCH coefficient becomes statistically insignificant for Canada, South Korea, Switzerland and USA (Hong Kong and South Korea to some extent). These findings suggest that the number of internet search volume is a manifestation of residual heteroskedasticity (ARCH type) in stock return data. As such, the internet provides a much-needed infrastructure for carrying the new information flow attached to economic innovation to the stock market as the common stockholder (i.e. capital providers for innovation) expectations reflect such persistent flow of new knowledge to the stock market. Trading volume testifies the specification used and, as such, the internet search queries could possibly be interpreted as an absorptive capacity variable as stock of new knowledge flow of the economy could be successfully traced by volume.

KEY WORDS Innovation; Information Flow; GJR-GARCH; Volume; Google Search Queries; Heteroskedasticity; Conditional Variance; Mixture of Distributions Hypothesis.

JEL Classification: C58, D83, D53, E51, G12, G17; O31

1. INTRODUCTION

In recent years, there has been a significant interest in exploring the impact of internet information flow on common stock returns. Using internet search volume as a proxy for the information content, scholars have established several linkages between stock price changes and time dependence in the information arrival at the stock market. Nowadays, the internet is responsible for facilitating a large part of economic activities of households (e.g. consumption) and researches have shown that the internet increases the probability of household participation in the economic activities (See e.g. Bogan 2008).

In particular, Sprenger et al., (2014) analyze approximately about 250,000 stock-related messages posted on microblogging forums such as Twitter and find an association between tweet sentiment and stock returns (including some association between message volume and trading volume). Also, investor information demand on certain information segments of firms has been examined by a number of scholars (e.g. Bartov et al., 2017; Drake et al., 2012). Drake et al., (2012) investigate the factors affecting investor information demand around earnings announcements using Google search quarries and find that the number of Google searches increase prior to and after the earnings announcements. Zhang et al., (2016) examine the stock market reaction to internet news and find significant positive abnormal stock returns and excessive trading volume during the news arrival time intervals. These findings suggest that the internet provides a much-needed infrastructure for the information arriving at the stock market. Contrarily, some research findings suggest that the frequent access to internet reduces the stock market participation. After controlling for Internet access in the regression model, Liang and Guo (2015) find that there is a negative association between social interaction and stock market participation.

Following the work of Lamoureux and Lastrapes (1990), a number of scholars examine the implications of the information content of internet search volume for heteroscedasticity of stock returns and find that the internet search queries are significantly associated with the type of heteroscedasticity of stock return data (See e.g. Son-Turan 2014; Shen et al., 2016; Shen et al., 2017; Shen et al., 2018) (See also Senarathne (2018) and Senarathne (2019) for the consideration of other proxies such as margin debt value data and investor press reading time). Using internet search queries related to the stock market index (Dow Jones), Dimpfl and Jank (2016) examine the role of internet search queries in predicting stock market volatility and find that the realized volatility of Dow Jones index is strongly correlated with its name search queries. Along these lines, Smith (2012) finds that the number of Google search queries relating to the keywords such as economic crisis, financial crisis and recession is a good proxy for the mixing variable. The findings support the mixture of distributions hypothesis that the heteroscedasticity of stock return is associated with the number of Google search queries which represents the rate at which the information flows into the stock market. The mixture of distribution hypothesis was first put forward by Clark (1973) which is subsequently tested by Epps and Epps (1976), Tauchen and Pitts (1983), Fielitz and Rozelle (1983), Harris (1987), Jain and Joh (1988), Andersen (1996), Senarathne and Jayasinghe (2017). Scholars such as Harris (1987) and Epps and Epps (1976), Belhaj et al., (2015), Takaishi and Chen (2016), Ezzat and Kirkulak-Uludag (2017) demonstrate that transaction volume or number of transactions is a better proxy for the mixing variable while other scholars consider stock volume. Their findings suggest that the number of transaction contains mixed distribution dynamics of stock return data. The following figure shows the association between trading volume and internet search queries. The two variables have shown to provide a close association after 2008 and a weaker association during the world economic and financial crisis period. On observation, it can be seen that the trading volume displays a more finer variation than the number of search queries—but both variables exhibit a uniform direction after the crises cluster (i.e. after November 2011).

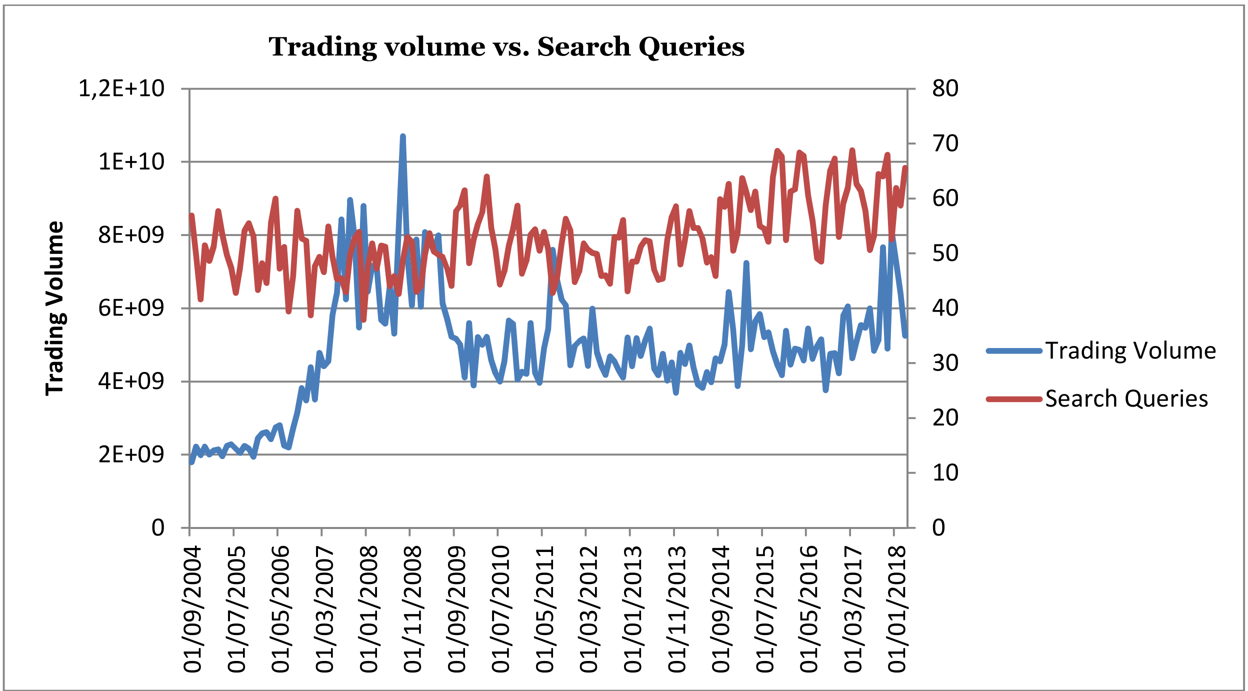

Figure 1. Trading Volume vs. Google Search Queries (Average of Ten Countries). Source: Author's Computation

The literature does not attempt to understand the information flow associated with Google search queries of various search terms pertaining innovation using a common framework (e.g. Lamoureux and Lastrapes, 1990). The objective of this paper is to test the mixture of distribution properties associated with Google search volume data on search terms namely innovation, innovations, economic innovation and economic innovations for ten countries (i.e. within the country search). Since the sample consists of countries ranked 1 to 20 of Global Innovation Index 2018, the heteroscedasticity in stock returns is expected to be associated with the internet information flow regarding the economic innovations in the region (i.e. country). As such, the ARCH effect or the total volatility persistence of GJR-GARCH model (Glosten, Jagannathan and Runkle (1993)) should be negligible when the number of Google search queries is included in the conditional variance of GJR-GARCH model. The remainder of this paper is organized as follows. Section two provides the conceptual framework and section three discusses the data set including sample selection. Section four reports the findings and discusses implications, and section five provides the concluding remarks.

2. THEORETICAL SPECIFICATION

Following Lamoureux and Lastrapes (1990) and Zhang et al., (2014) (See e.g. Sharma et al., (1996), Senarathne and Jayasinghe (2017) and Senarathne and Wei (2018)) define δ_{mt} denote the $j^{\,th}$ intraday equilibrium market price increment in day t summed up over a monthly data horizon.

$$\varepsilon_t = \sum_{j=1}^{n_t} \delta_{jmt} \qquad (1)$$

Where n_t is a mixing variable distributed with mean zero and unit variance. This stochastic random variable must be associated with the type of heteroskedasticity accounted for by ARCH and reflects the aggregate amount of new information arrival at the stock market of each country. On the assumption that the new information arrival process is sequential rather than simultaneous, the process of internet information arrival takes the form of;

$$n_t = \theta_0 + b(L)n_{t-1} + \Phi_{t,} \quad n_t \geq 0 \qquad (2)$$

Where n_t is assumed to be serially correlated and evolution to the mixing variable is captured by the lag polynomial operator $b(L)$. $\Phi_{t,}$ is simply a random variable with zero mean and unit variance, which is restricted to be nonnegative by construct. Note that ε_t is subordinated to δ_j and $\Omega = E(\varepsilon_t^2|n_t)$ in the sense of Lamoureux and Lastrapes (1990). The total volatility persistence in the conditional variance is estimated by a GJR-GARCH model in such, $\Omega = \sigma^2 n_t$ and $\varepsilon_t|\, n_t \sim N(0, \sigma^2 n_t)$.

Consider the following regression in the sense of Glosten et al., (1993) (I.e. GJR-GARCH) for the forecast of stock returns.

$$R_{mt} = \varpi + \varepsilon_t, \qquad (4)$$

and $\varepsilon_t = \sigma_t z_t$ in which, z_t is i.i.d with mean zero and unit variance. If the mixture model is valid, $z_t = n_t$ in all respects (i.e. their distributional properties and characteristics). The error term must have the following distributional assumption

$$\varepsilon_t \backslash (\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots..) \sim N(0, h_t), \qquad (5)$$

The following conditional variance equation is used for the estimate of variance of stock returns for each country. The equation (4) does not have a mean and is suppressed given the inherent limitations associated with GARCH modeling as shown by Lamoureux and Lastrapes (1990) and Zhang et al., (2014) (See also Andersen et al., (2001))

$$\sigma_t^2 = \varphi + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 I_{t-1} \varepsilon_{t-1}^2 + \gamma_3 \sigma_{t-1}^2 \quad (6)$$

Where,

σ_t^2 = Conditional variance at time t.

φ = Intercept term of the conditional variance.

γ_1 = ARCH (Autoregressive conditional heteroscedasticity) coefficient.

γ_2 = Asymmetric volatility coefficient.

γ_3 = GARCH (Generalized autoregressive conditional heteroskedasticity) coefficient.

I = A dummy variable employed under the condition, $I_{t-1} = \begin{Bmatrix} 1 \text{ if } \varepsilon_{t-1} < 0 \\ 0 \text{ otherwise} \end{Bmatrix}$

In order to examine the time dependence in the rate of information arrival at the market, the number of Google search queries (Lagged values were considered in order to eliminate any potential simultaneity bias (See e.g. Lamoureux and Lastrapes (1990))) (G) is included in the conditional variance as;

$$\varepsilon_t \backslash (G_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots \ldots) \sim N(0, h_t), \quad (7)$$
$$\sigma_t^2 = \varphi + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 I_{t-1} \varepsilon_{t-1}^2 + \gamma_3 \sigma_{t-1}^2 + \boldsymbol{\lambda} G_{t-1} \quad (8)$$

To test the validity of the framework used, trading volume as a mixing variable for the rate of information arrival is included in the conditional variance as;

$$\varepsilon_t \backslash (V_t, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots \ldots) \sim N(0, h_t), \quad (9)$$
$$\sigma_t^2 = \varphi + \gamma_1 \varepsilon_{t-1}^2 + \gamma_2 I_{t-1} \varepsilon_{t-1}^2 + \gamma_3 \sigma_{t-1}^2 + \varphi V_{t-1} \quad (10)$$

3. DATA

Ten countries are selected from the top twenty innovative countries ranked by Global Innovation Index 2018. Monthly stock index data of each country and the treading volume data are obtained from Yahoo webpage covering a sampling period from 9/30/2014 3/31/2018. Google search queries on search terms *innovation, innovations, economic innovation and economic innovations* are obtained from the Google trend https://trends.google.com/trends/ for each country. Note that Google Trends offers country-wise generation of search queries data. Some descriptive statistics of the sample data are given below.

The list of stock indexies includes;

1. Switzerland - The Swiss Market Index (SMI)
2. United States - The Dow Jones Industrial Average (DJI)
3. Netherlands - Amsterdam Exchange Index (AEXI)
4. Germany - Deutscher Aktienindex (DAX)
5. Denmark - OMX Copenhagen 20 (OMXC20)
6. Ireland - ISEQ 20 of Irish Stock Exchange
7. South Korea - Korean Composite Stock Price Indexes (KOSPI) for South Korea
8. Hong Kong - Hang Seng Index – (HIS)
9. Japan - Nikkei 225 of Tokyo Stock exchange
10. Canada-S&P/TSX Composite index

Table 1. Empirical Description of the Sample Data

Country	Variable	Mean	Median	Max.	Min.	JB	ML	Q
Canada	R	0.004	0.008	0.106	-0.186	249.84	36.33	34.95
	G	65.3	64	100	39	1.08	NA	822.28
	V	4.0E+09	4.0E+09	7.0E+09	3.8E+07	33.21	NA	401.93
China	R	0.005	0.008	0.243	-0.283	28.44	12.37	49.00
	G	23.55	11	100	4	63.12	NA	1550.3
	V***	1.2E+07	2.1E+06	1.5E+09	1.8E+05	173481	NA	0.009
Germany	R	0.007	0.014	0.155	-0.213	60.52	12.85	30.39
	G	71.45	71.00	100.00	48.00	2.44	NA	566.95
	V	2.5E+09	2.3E+09	6.5E+09	8.9E+07	122.01	NA	526.98
Hong Kong	R	0.005	0.012	0.158	-0.254	47.68	12.75	22.02
	G	56.66	57	100	19	8.08	NA	36.18
	V	3.3E+10	3.4E+10	7.8E+10	5.0E+09	0.52	NA	677.14
Ireland	R	0.001	0.007	0.178	-0.236	75.35	32.12	51.50
	G	32.39	33	59	7	4.83	NA	45.32
	V	1.3E+09	1.0E+09	3.6E+09	3.8E+08	45.62	NA	441.51
Japan	R	0.005	0.009	0.121	-0.272	83.86	7.28	16.42
	G	42.04	41	100	16	154.64	NA	115.58
	V	2.8E+06	2.7E+06	7.2E+06	1.4E+06	379.53	NA	220.63
Netherland	R	0.003	0.012	0.106	-0.220	159.35	20.40	28.24
	G	66.53	66	100	37	4.94	NA	353.93
	V	2.4E+09	2.2E+09	4.9E+09	1.4E+09	176.29	NA	404.74
South Korea	R	0.007	0.009	0.127	-0.263	151.11	1.56	19.38
	G	36.60	27	100	12	34.39	NA	740.06
	V***	1.1E+07	7.4E+06	5.1E+08	3.8E+06	171571	NA	0.189
Switzerland	R	0.003	0.009	0.096	-0.120	13.37	27.60	22.40
	G	61.41	59	100	22	4.45	NA	516.75
	V	1.2E+09	1.1E+09	3.0E+09	5.5E+07	4.18	NA	861.10

USA	R	0.005	0.008	0.091	-0.152	48.37	8.12	44.90
	G	71.31	70	100	51	9.02	NA	1137.30
	V	4.3E+09	4.3E+09	1.1E+10	1.5E+09	8.03	NA	926.29

Note:
JB - Jarque–Bera test statistic for normality. Under null hypothesis for normality, critical value of χ2 (2) distribution at 5% significance level is 5.99.
LM is the ARCH LM test statistic for number of observations multiplied by the R-squared value for 3 lags. Under null hypothesis, critical value of χ2 (3) distribution at 5% significance level is 7.815 (OLS equation $R_t = c + \varepsilon_t$,).
Q (20) is the Ljung-Box Q statistic for serial correlation upto 20 lags, in the return, Google trend data and trading volume series. Under the null hypothesis for no serial correlation, the critical value of χ2(20) distribution at 5% significance level is 31.41.
*Statistically significant at 5% and **Statistically significant at 10%.
Abnormally high volumes of trades were observed during January 2018 for China and July 2008 for South Korea.

4. EMPIRICAL RESULTS AND DISCUSSIONS

Jarque–Bera test statistic exceeds its critical value of 5.99 for stock returns of all countries, displaying the nonnormality of their distributions. Except for the Google search query data of Canada, Germany, Ireland, Netherlands and Switzerland, the null hypothesis of normality of distributions is rejected for all other countries. Trading volume data are nonetheless normally distributed only for Hong Kong and Switzerland. ARCH effect exists in data for all countries, except for Japan and South Korea whose test statistics fall below the critical value under ARCH LM test for three degrees of freedom. Ljung-Box Q test for serial correlation upto 20 lags shows that the Google search query data are serially uncorrelated for China, Germany, Japan, Netherland, South Korea and Switzerland. Data are serially correlated for all other countries as the test statistic exceeds its critical value of 31.41. Trading volume data are highly serially correlated except for China and South Korea.

Table 2. Maximum Likelihood Estimation of GJR-GARCH Model (Without Proxy)

Country	γ_1	t-stat	γ_2	t-stat	γ_3	t-stat	@trend	t-stat	Total volatility persistence
Canada	0.255*	6.882	-0.511*	-4.657	0.809*	15.336	-2.5E-06*	-5.419	0.553
China	0.278*	2.499	-0.210***	-1.525	0.817*	10.365	NA	NA	0.885
Germany	0.132**	1.880	-0.317*	-2.140	0.768*	4.684	NA	NA	0.583
Hong Kong	0.141**	1.708	0.168	1.254	0.652*	5.619	NA	NA	0.961
Ireland	0.082	1.374	-0.222*	-3.004	0.868*	15.267	NA	NA	0.728
Japan	0.045	0.539	0.155	0.889	0.719*	4.638	NA	NA	0.919
Netherla nd	0.149	1.059	0.050	0.298	0.597*	3.128	-9.4E-06*	-2.049	0.796
South Korea	0.137*	2.254	-0.037	-0.296	0.878*	21.118	NA	NA	0.978
Switzerla nd	0.065***	1.422	-0.272*	-2.949	0.716*	5.921	NA	NA	0.509
USA	0.153*	3.042	-0.298*	-2.675	0.904*	18.069	4.3E-07**	1.782	0.759

Note:
*Statistically significant at 5% assuming returns are conditionally normally distributed. **Statistically significant at 10%. ***Statistically significant at 15%.
The coefficients are estimated using the methods described by Bollerslev and Wooldridge (1992) for obtaining quasi-maximum likelihood (QML) covariances and robust standard errors.

The maximum likelihood estimation results of GJR-GARCH show that the coefficient γ_1 is highly statistically significant at 5 percent significance level for Canada, China, South Korea and USA. Coefficient γ_1 is statistically significant at 10 percent for Germany and Hong King and 15 percent for Switzerland. The initial estimations of GJR-GARCH for Canada, Netherland and USA showed a deterministic increase in the conditional variance as the sum of the GJR-GARCH coefficients exceeded unity. Hence, a time trend was included in the conditional variance equations of such regressions as a possible solution. The ARCH coefficient of the regressions for Ireland, Japan and Netherlands is statistically insignificant at 5 percent in the initial regressions. The coefficients of the GJR-GARCH model are reported with the coefficients of the time tend in Table 2. The leverage effect exists for Canada, Germany, Ireland, Switzerland and USA at 5 percent significance level and, for China at 15 percent significance level.

Table 3. Maximum Likelihood Estimation of GJR-GARCH Model (With Proxy)

Country	Proxy	γ_1	t-stat	γ_2	t-stat	γ_3	t-stat	λ or φ	t-stat	@trend	t-stat	Total volatility persistence
Canada	G	0.122	0.768	0.076	0.469	0.596*	3.836	-1.2E-05	-1.370	-3.6E-07	-0.318	0.794
	V	0.15	0.781	0.05	0.204	0.600*	2.443	-2.4E-13**	-1.681	-1.1E-12	-4.9E-07	0.800
China	G	0.133*	3.773	-0.275*	-3.623	1.015*	38.325	-2.9E-06*	-2.503	NA	NA	0.873
	V	0.150	0.947	0.050	0.271	0.600*	2.979	-1.3E-11*	-10.659	NA	NA	0.800
Germany	G	0.124**	1.677	-0.311*	-2.080	0.782*	4.803	8.3E-06	1.387	NA	NA	0.595
	V	0.150	0.595	0.050	0.192	0.600*	2.655	-6.3E-13**	-1.700	NA	NA	0.800
Hong Kong	G	0.145**	1.657	0.142	1.146	0.663*	5.878	-1.3E-05	-0.838	NA	NA	0.950
	V	0.150***	1.525	0.050	0.488	0.600*	2.711	-6.3E-14*	-2.613	NA	NA	0.800
Ireland	G	0.089	1.431	-0.216*	-2.912	0.877*	14.985	-6.9E-06	-0.731	NA	NA	0.750
	V	0.150	0.661	0.050	0.194	0.600*	4.458	-1.3E-12*	-17.642	NA	NA	0.800
Japan	G	0.094	0.849	0.051	0.460	0.744*	4.581	2.0E-05	0.936	NA	NA	0.889
	V	0.150	1.164	0.050	0.377	0.600*	5.157	-6.5E-10*	-51.03	NA	NA	0.800
Netherland	G	0.116*	2.631	-0.480*	-3.269	0.709*	9.304	-5.2E-06	-0.837	-4.6E-07	-0.358	0.345
	V	0.150	0.561	0.050	0.216	0.600*	3.545	-6.1E-13*	-5.960	-1.2E-13	-2.1E-08	0.800
South Korea	G	3.9E-04	0.007	0.011	0.194	0.901*	17.035	1.1E-05**	1.727	NA	NA	0.912
	V	0.125**	1.826	-0.132**	-1.784	0.905*	19.542	1.4E-11*	2.810	NA	NA	0.898
Switzerland	G	0.078	1.190	-0.251**	-1.647	0.752*	5.157	-3.4E-06	-1.123	NA	NA	0.579
	V	0.150	0.544	0.050	0.212	0.600*	3.741	-5.8E-13*	-13.319	NA	NA	0.800
USA	G	0.158	3.165	-0.310	-2.777	0.865	13.958	-2.3E-05	-3.5E+00	4.4E-06	3.189	0.713
	V	0.150	0.756	0.050	0.145	0.600	2.577	-2.1E-13	-1.4E+00	-2.2E-14	-1.5E-08	0.800

Note:
*Statistically significant at 5% assuming returns are conditionally normally distributed. **Statistically significant at 10%.
The coefficients are estimated using the methods described by Bollerslev and Wooldridge (1992) for obtaining quasi-maximum likelihood (QML) covariances and robust standard errors.

The ARCH coefficient is statistically significant for Canada, China South Korea and USA at 5 percent significance level and, for China and Hong Kong at 10 percent. The ARCH coefficient for Switzerland is only significant at 15 percent significance level. The total volatility persistence is less than unity in all regressions, suggesting that the basic volatility modeling conditions of GJR-GARCH were met. The GARCH coefficient is highly significant for all counties.

When the lagged number of Google search queries is included in the conditional variance of the GJR-GRACH model, the ARCH coefficient becomes statistically insignificant for Canada, South Korea, Switzerland and USA. When the lagged trading volume is included in the conditional variance equation, the ARCH coefficient becomes highly statistically insignificant at 5 percent significant for all countries—whose ARCH coefficient was statistically significant in the initial regression (i.e. the GJR-GARCH without a proxy in the conditional variance)—except for Hong Kong and South Korea.

However, the significance of the ARCH coefficient for Hong Kong and South Korea regressions has reduced to a certain extent after the inclusion of volume in the conditional variance equation. The GARCH coefficients of all country- level regressions are highly statistically significant. However, USA reports insignificant GARCH coefficients for both regressions with Google search queries and trading volume in the conditional variance equation.

Table 4. The Residual Diagnostics of GJR-GARCH estimations and Coefficient Restriction Test Results

Country	Eq.	JB(2)	LM(3)	Q(20)	Wald ($\gamma_1 + \gamma_3 = 0$)
Canada	6	20.59*	0.42	16.16	NA
	8	27.80*	1.21	16.98	27.39*
	10	116.01*	3.55	20.64	10.06*
China	6	3.65	1.68	38.17	NA
	8	0.05	0.12	32.88	1165.17*
	10	16.62*	1.40	45.73	15.17*
Germany	6	70.68*	0.51	16.86	NA
	8	52.43*	0.68	18.43	19.14*
	10	246.61*	0.15	27.32	8.90*
Hong Kong	6	3.52	1.11	23.85	NA
	8	3.81	1.25	23.59	62.22*
	10	21.48*	12.64*	26.27	11.65*
Ireland	6	8.24*	0.53	29.91	NA
	8	10.29*	0.60	27.31	220.88*
	10	46.31*	1.88	30.55	9.67*
Japan	6	10.14*	1.76	13.59	NA
	8	9.65*	1.15	13.48	34.92*
	10	12.13*	2.91	13.70	16.41*
Netherland	6	20.27*	1.76	16.29	NA
	8	16.15*	1.57	12.31	97.89*
	10	175.84*	15.20*	17.02	13.07*
South Korea	6	33.61*	2.74	10.23	NA
	8	25.96*	1.45	8.64	199.94*
	10	5.38	4.00	10.20	796.17*
Switzerland	6	5.31	3.64	24.72	NA
	8	7.09*	4.31	23.11	17.64*
	10	23.34*	2.53	26.58	12.47*
USA	6	11.96*	0.49	19.61	NA
	8	10.85*	4.07	15.53	70.94*
	10	72.40*	18.99*	33.69	9.35*

Note:
*Statistically significant at 5% assuming returns are conditionally normally distributed. **Statistically significant at 10%.
Wald is the F-statistic from the Wald coefficient restriction test under null hypothesis of ARCH and GRACH coefficients of interest are simultaneously equal to zero.

Jarque–Bera test statistic for normality is less than the test critical value for equations six and eight of GJR GARCH regression for China and Hong Kong (i.e. normally distributed). The residuals of the equation ten for South Korea and equation six for Switzerland are normally distributed. The ARCH effect or the residual heteroskedasticity exists for equation ten of Hong Kong, Netherland and USA regressions as the test statistic of ARCH-LM test substantially exceeds the critical value. The residuals of other regressions are however homoscedastic (i.e. serial correlation based homoscedasticity). The residuals of all regressions for China are serially correlated as per the Ljung-Box Q test. The test statistic exceeds the critical value substantially. The residuals of the equation ten of Ireland and USA are also serially correlated. The null hypothesis of Wald coefficient restriction test is soundly rejected for all regression equations. Total volatility persistence is therefore significant in all regressions —given the persistence of strong GARCH effects—although the ARCH effect becomes insignificant when the proxy variables are included in the conditional variance equation as in Lamoureux and Lastrapes (1990).

5. CONCLUSION

Not only investor behavior is influenced by the flow of internet information but also the consumer internet search behavior influences the way consumers behave in the market place (Peterson and Merino 2003). As such, the number internet search volume of interest may contain much valuable information about the disequilibrium dynamics and market asymmetries.

When the internet search volume is included in the conditional variance equation of GJR-GRACH model, the ARCH coefficient becomes statistically insignificant for Canada, South Korea, Switzerland and USA (including Hong Kong and South Korea to a certain extent). These findings suggest that the number of internet search volume reflects the type of heteroskedasticity in stock return data. As such, the internet provides a much needed infrastructure for the new internet knowledge flow—regarding economic innovation—to the stock market as the common stockholder (i.e. capital providers for the innovation) expectations manifest such persistent flow of new knowledge to the stock market.

Inclusion of stock volume in the conditional variance equation testifies the framework used. Although the total volatility persistence is not reduced substantially due to strong GARCH effect in the conditional variance, ARCH coefficient becomes highly statistically insignificant when the trading volume is included in the conditional variance equation of GJR-GARCH model. As such, the internet search queries could possibly play the role of absorbing the internet information flow pertaining to the economic innovation of the respective countries as trading volume does.

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