Applied Economics Journal Vol. 26 No. 1 (June 2019): 45-70

ISSN: 2586-9124 (PRINT)
ISSN: 2586-9132 (ONLINE)

Received: 15 October 2018
Received in revised form: 29 January 2019
Accepted: 14 June 2019

The Information Flow Interpretation of Margin Debt Value Data: Evidence from New York Stock Exchange

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Abstract

This paper examines the heteroscedasticity in NYSE Composite index returns using margin debt value data from a sampling period of December 1996 to November 2017. Following Lamoureux and Lastrapes (1990), the lagged margin debt value is included in the conditional variance of GARCH and EGARCH models. The results of EGARCH estimates show that the ARCH effect vanishes and the total volatility persistence is most reduced, confirming that the margin debt value is a reflection of time dependence in the rate of new information arrival on stock market borrowing (i.e. margin borrowing). Further, the lagged margin debt value coefficient is negatively and significantly related to conditional volatility. This implies that—when the new information pertaining to credit risk flows to the market, the investors adjust the risk downward (i.e. downward revision) as their repose to the flow of new information. However, GARCH estimates have shown to provide a weaker reflection of the effect of information pertaining to stock market borrowing (i.e. margin borrowing) on conditional volatility and therefore had little explanatory power of heteroscedasticity in the stock return data. Overall, the results suggest that the form of persistence of new information arrival on margin debt value data in the conditional volatility is a reflection of ARCH type of residual heteroscedasticity of stock return data of the New York Stock Exchange.

Keywords: Margin Debt; Information Flow; EGARCH; Trading Volume.

JEL Classification: C58, D53, E51, G12, G14, G17

1. Introduction

Since the classic seminal work of Lamoureux and Lastrapes (1990), a voluminous literature tests the persistence of ARCH[1] effect in stock return data against various proxies for the flow of information arrives at the stock market. (e.g. internet search quires, patent citations)[2]. This framework offers a realistic methodology to conclude on the informational role of market microstructure variables (e.g. market dollar volume) and has been effectively applied at market level by a number of scholars (Sharma *et al* 1996; Choi *et al* 2012; Zhang *et al* 2014).

Securities collaterals on facilities advanced by banks and financial institutions (BFI) may contain unique (i.e. non-public) information pertaining to the underlying securities portfolios, especially in stock market-related lending (e.g. collateral stock portfolios of margin loans advanced). This is a special case where

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[1] The Autoregressive Conditional Heteroskedasticity (ARCH) model of Engle (1982)

[2] See especially Zhang et al (2014), Shen et al (2016), Senarathne and Jianguo (2018) and Shen et al (2018)

the securities collateral portfolio becomes a part of the total stock portfolio bought by the investors[3]. As such, the BFIs' personnel have access to different types of information about debt securities portfolios of investors, especially, in relation to margin lending. The information that is price sensitive may include undisclosed directors dealing (buying/selling), movements in related party stockholding (Laeven 2001) and deterioration of net worth of major shareholders enjoying facilities, etc. Collectively, this information may impact stock market prices and market performance. The revelation of these types of information in financial services industry by the use of non-public records by informed BFI is not uncommon (See especially Acharya and Johnson 2007). If the insider information pertaining to debt securities portfolios is transmitted to the equity market via financing channels, the BFI may play a significant role in the price formation process of equities (See e.g. Myers and Majluf, 1984). These findings, therefore, suggest that the margin debt may contain persistent flow of information about the stock price increments.

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[3] In the case of other types of lending (e.g. lease, loan or hire purchase) by banks and financial institutions, the type of collateral portfolio may be different from facility advanced. For example, a bank may take houses or vehicles as collaterals on leases advanced to customers. Hence, the bank has no access to different types of information pertaining to collaterals of lease portfolio and its impact on the leasing market. More fully, the collaterals may be unrelated the assets under finance and their markets.

Figure 1- NYSE Composite Index Vs Margin Debt Value

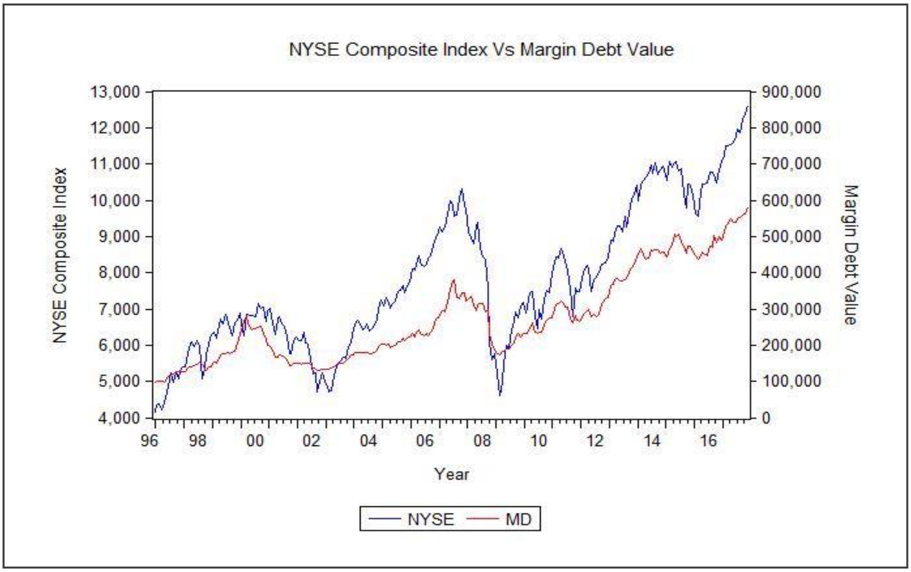

Figure 1 compares the movements of NYSE Composite index and the margin debt values for the entire sampling period. On observation, the line graph exhibits a close association between margin debt values and the NYSE Composite index throughout the sampling period. Any impact of this association on conditional volatility and heteroskedasticity of NYSE index return could be examined within the framework of Lamoureux and Lastrapes (1990).The objective of this paper is to examine the implications of the information content of margin debt value data on heteroscedasticity of equity returns of the New York Stock Exchange (NYSE). The paper is organized as follows. Section 2 provides a brief account of related literature and section 3 provides the theoretical framework including methodology. Section 4 describes the data set and its empirical properties. Section 5 discusses the findings and section 6 concludes the paper.

2. Literature Review

Lamoureux and Lastrapes (1990) examine the implications of the mixture model and find that the variance of the daily price increments is heteroskedastic and positively related to the rate of new information arrival. Taking 20 common stocks, Lamoureux and Lastrapes (1990) show that the ARCH effect vanishes when the stock volume is included in the conditional variance equation. Brailsford (1996), Ali Ahmed *et al* (2005), Oral (2012), Al-Jafari and Tliti (2013), Ananzeh (2015) and Senarathne and Jayasinghe (2017) examine the information flow dependence of stochastic volatility within the framework of Lamoureux and Lastrapes (1990) by imposing restrictions on the asymmetries in the unconditional volatility (i.e. restrictions imposed by GARCH (1, 1)). A thorough understanding of the postulation of Mixture of Distribution Hypothesis (MDH) of Clark (1973) would suggest that the subordinated stock price increment process and the variance of increments are not subject to volatility symmetries because the daily number of new information arrival is an increasing function of operational time of the market (or stock). Another section of scholars examine the role of internet information arrival using internet search volume as a proxy for the information arrival at the market and provide support for MDH within the framework Lamoureux and Lastrapes (1990) (See e.g. Turan (2014), Zhang *et al* (2014), Shen *et al* (2016) and Shen *et al* (2018).

In particular, Shen *et al* (2016) introduce the number of Baidu News events into the conditional variance of GARCH model and find a decreased level of volatility persistence supporting MDH. A number of scholars claim the support of the framework of MDH proposed by Tauchen and Pitts (1983). The central idea of the MDH advanced by Clark (1973) and Tauchen and Pitts (1983) is that the variance of daily returns is driven by a random number of daily information which is sensitive to the stock (in their work, futures) price formation process. The variance of daily price increments is therefore generated from a stochastic process of which the mean is proportional to the mean number of daily transactions. Vlastakis and Markellos (2012) find that the information arrives at the market is significantly and positively related to implied volatility and trading volume. Dimpfl and Jank (2016) study the relationship between volatility and volume of search quarries on 'Dow Jones Industrial Average' and find that the realized volatility and the volume of search queries are positively related. Another most important finding is that the existence of causality in stock market time-series data. The lead-lag relationship between returns and volume of trades using Granger causality has been extended by Smirlock and Starks (1988). Hiemstra and Jones (1994) test for Granger causality using a similar analysis and conclude that there is a positive bidirectional causality between volume of trades and returns in the New York Stock Exchange (See also Renault and Werker 2011; Kumar and Thenmozhi 2012; Gebka and Wohar 2013). The causality between volatility and volume has also been documented by Alizadeh (2013) and Rossi and Magistris (2013). Kumar *et al* (2009) document that there is a positive relationship between trading volume and price changes for fifty Indian stocks.

Fortune (2001) and many others examine the relationship between margin lending and stock market performance (e.g. return and volatility). In particular, Fortune (2001) examines the linkage between the level of margin debt and stock returns for the S&P 500 and NASDAQ during the period 1975 to 2001 and find that the margin loans significantly impact the size of the mean jumps in stock returns and the volatility of NASDAQ. Margin lending increases the buying power of investors or traders, which ultimately increases the market turnover. It also impacts the market liquidity and efficiency as stock market information arrival is accelerated by active trading and quickly reflected in the stock market prices (See Gromb and Vayanos, 2002; Brunnermeier and Pedersen, 2009). The regulatory framework governing the conduct of margin business also impact stock return and volatility (See Salinger 1989; Hsieh and Miller, 1990; Endo and Rhee, 2005; Brumm *et al* 2012; Diaz-Martinez and Fragniere, 2012;. Maggi and Fantazzini, 2012; Brumm *et al* 2015). However, Schwert (1989) finds no evidence for the effect of any changes in margin requirements on subsequent stock return volatility. Another set of scholars show that the excessive margin lending leads to stock market boom and crisis or stock bubbles (See Ricke 2003; Koudijs and Voth 2016). This evidence suggests that margin lending is an influential factor of market performance as it significantly impacts the market performance under bull and bear market conditions. The utilization of margin loans advanced to investors also depends on market conditions. Usually, the utilization of available margins is higher in bull markets than bear markets because the investors find it difficult to cover the cost of margin borrowing under bear market conditions. As such, margin traders are likely to respond asymmetrically to market conditions—for example; margin traders may respond quickly to market downturn than market uptrend (See especially Domain and Racine, 2006).

On the other hand, scholars show that the announcements of bank loans have a positive impact on the borrowers' stock prices and returns. In particular, the famous work of Sharpe (1990, p. 1069) argues '*customer relationships arise between banks and firms because, in the process of lending, a bank learns more than others about its own customers*'. As such, the BFI does possess information about the browsers' profiles which are not publicly available to investors of the stock market. Billett *et al* (1995) show that the banks' announcements of high-quality lenders and their lending have a strong impact on the price change process of underlying stocks. Demiroglu and James (2010) find a larger stock price reaction to the announcement of loans under covenant choice signaling hypothesis. Chava and Gallmeyer (2015) find that the forecastability of stock returns is highly sensitive to credit conditions or standards.

Using data from a sampling period of 1993 to 2009, Albuquerque *et al* (2015) investigate the linkage between trade credits and the cross-border stock returns of international firms. Their findings suggest that the predictability of return is stronger during high credit constraints and low uninformed trading. The quality of the market credit portfolio significantly impacts the stability of the overall market. If the stock market-related lending is not backed up by quality securities collaterals, it is highly likely that the lenders (e.g. margin providers) and the borrowers (i.e. stock market investors) will have to bear significant losses in excesses of cost over market value of stock portfolios (see section three for an extensive discussion). This is apparent in markets where the investors have the option to borrow funds for investments (e.g. delivery versus payment on credit). In line with overpricing hypothesis, Jones and Lamont (2002) study the impact of cost of short-selling on the value of stocks and find that the stocks tend to be overpriced when short-sale constraints are in force[4].

3. Theoretical Specification

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) of Bollerslev (1986) has been recognized as one of the most appealing financial market volatility forecasting models. The GARCH takes into account the mean-variance for the entire sample period with a decreasing weight allowing backward from the most recent observations. GARCH demonstrates a better fit for modeling financial time series when the data exhibits heteroskedasticity as the volatility clusters in time (i.e. the tendency that the '*large changes tend to be*

[4] The force-sales instructions are usually served by the margin providers, depending on the conditions of the margin loan covenants.

followed by large changes, of either sign, and small changes tend to be followed by small changes' Mandelbrot (1963 p. 418)). The GARCH models allow prior shocks to have asymmetric effects on the current volatility.

In the sense of Lamoureux and Lastrapes (1990), Sharma *et al* (1996), Choi *et al* (2012) Zhang *et al* (2014) and Senarathne and Jianguo (2018) define δ_{mt} which denotes the m^{th} intraday equilibrium market price increment in day t summed up over a monthly data horizon.

$$\varepsilon_t = \sum_{m=1}^{n_t} \delta_{mt} \qquad (1)$$

Where n_t is the stochastic mixing variable that reflects the aggregate amount of new information arrival on margin debt advanced to investors. In line with Copeland (1976) and Smirlock and Starks (1985) assume that information arrival is sequential rather than simultaneous. Accordingly,

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

in which n_t is serially correlated and the lag operator $b(L)$ captures the evolutions in the new information arrival on margin debt values. $\Phi_{t,}$ is a non-negative random variable with zero mean and unit variance. ε_t is subordinated to δ_m in the sense of Lamoureux and Lastrapes (1990). Let $\Omega = E(\varepsilon_t^2 | n_t)$ where Ω is the persistence of conditional variance estimated by an EGARCH[5] model. Since the mixture model is invoked, $\Omega = \sigma^2 n_t$ and $\varepsilon_t | \; n_t \sim N(0, \sigma^2 n_t)$.

However, the original work of Lamoureux and Lastrapes (1990) studies the implications of information flow on stochastic volatility by employing a plain vanilla Generalized ARCH (1, 1) process of Bollerslev (1986) as,

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[5] Exponential Generalized Autoregressive Conditional Heteroskedasticity

$$R_t = \mu_{t-1} + \varepsilon_t, \quad (3)$$

$$\varepsilon_t \backslash (\varepsilon_{t-1}, \varepsilon_{t-2}, \dots\dots) \sim N(0, h_t), \quad (4)$$

$$\varepsilon_t^2 = \theta + a(L)\varepsilon_{t-1}^2 + \lambda(L)h_{t-1} \quad (5)$$

where θ is the constant and R_t is the NYSE Composite index (P) return computed as $(P_t - P_{t-1})/P_{t-1}$. a is the ARCH coefficient and λ is the return volatility coefficient applicable to GARCH term. h_{t-1} is the conditional variance of the error term (i.e. return) in the prior period ($t-1$). Also, $\theta > 0$, $a > 0$ and $\lambda > 0$ are clearly defended in the literature (See Bollerslev (1986)). μ_{t-1} is the mean of return conditional on past information which is restricted to be zero[6]. The model parameterizes the conditional variance of ε_t as a function of formation set (I) available to investors at time $t-1$. That is to say, $E(\varepsilon_t | I_{t-1}) \sim N(0, h_t)$. If Lamoureux and Lastrapes (1990) is followed, the margin debt value (MD) at time t should be introduced into the conditional variance equation (5) as follows,

$$\varepsilon_t \backslash (MD_{t,} \varepsilon_{t-1}, \varepsilon_{t-2}, \dots\dots) \sim N(0, h_t), \quad (6)$$

$$\varepsilon_t^2 = \theta + a(L)\varepsilon_{t-1}^2 + \lambda(L)h_{t-1} + \Upsilon MD_t \quad (7)^7$$

The GARCH (1, 1) process of Bollerslev (1986) does not account for the possible effect of any negative correlation between lagged returns and contemporaneous volatility (i.e. the leverage effect). In other words, the variance equation does not take into account the asymmetric volatility effect.

The leverage effect is not only caused by Black and Scholes's (1973) type of corporate borrowing. They explain a class of asymmetries associated with the stock price volatility and the degree of leverage in the underlying firm's capital structure. The leverage effect may also be caused by excessive investor borrowing

[6] As this is a market level study.

[7] Mean equation (6) is recalled as incidental.

and subsequent constraints imposed by the lenders (i.e. margin providers). For example, the volatility may respond asymmetrically to the sign of stock price movements during a financial or economic crisis. In particular, a credit crisis usually results in a follow of bad news to the stock market than good news, which usually creates an investor panic in the market. In the case of a stock market crisis, the investors are more concerned about the quality and value (including liquidity) of the collateral securities portfolios than other market conditions because the leverage effect is more pervasive in crisis- markets[8]. The investors usually tend to realize these facts when the symptoms of a market crisis are perceived. Therefore, the leverage effect may also be caused by the information pertaining to stock market borrowing rather than corporate borrowing—especially in the case of a market crisis situation.

From an empirical front, the volatility may also react asymmetrically to the increase and decrease in margin borrowing, particularly, because of the conditions imposed by the margin loan covenants or margin trading agreements (e.g. margin calls and force-sale of securities etc.). As such, the standard GARCH model fails to capture this asymmetric effect on conditional volatility.

Consider the following specification in the sense of Nelson (1991) which accounts for the asymmetric effect of innovations on volatility;

$$R_t = \mu_{t-1} + \varepsilon_t, \tag{8}$$

$$\varepsilon_t \backslash (\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\ldots) \sim N(0, h_t), \tag{9}$$

[8] Senarathne *et al* (2017) show how systematic and collateral specific risk could impact the return required by the investors (i.e. equity owners of stockbrokerage firms) of the stockbrokerage firms. They find a close association between systematic risk and firm's leverage, and its significant impact on return required by the stockholders.

$$\ln(\sigma_t^2) = \omega + \eta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (10)$$

where ω is the constant of the conditional variance equation above and σ_t^2 is the conditional variance at time t. η is the coefficient corresponds to the previous period ($t-1$) volatility or lagged conditional variance and γ is the coefficient applicable to leverage effect. γ is expected to be negative if a negative shock has a greater impact on volatility than the positive shocks of the same magnitude. α explains the effect of long term volatility. μ_{t-1} is the mean of return conditional on past information. Although the other models of GARCH family such as Threshold GARCH (TGARCH) and Power GARCH (PGARCH) are capable of modeling leverage effect, the EGARCH model of Nelson (1991) is chosen as it has been shown to provide a parsimonious representation for the interpretation of heteroscedastic mixture model of Lamoureux and Lastrapes (1990).

Introducing margin debt value[9] MD at time $t-1$ to the conditional variance, the equation (10) can be written as[10],

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[9] In order to avoid any possible simultaneity bias, lagged margin debt values are considered (Lamoureux and Lastrapes (1990, p. 228).

[10] μ_{t-1} is constrained to zero in line with Lamoureux and Lastrapes (1990, p. 222). In some work implementing GARCH or other models from GARCH family, the mean of the return is usually set to zero. Although this is quite unorthodox, it arises from the fact that with finely-sample data, the mean does not become easier to estimate, while the volatility does. Therefore a number of empirical papers concerning GARCH (or EGARCH) volatility estimates constrain conditional mean to zero, which often benefits from sampling at higher frequencies (see, for example, Andersen & Bollerslev 1998, and Senarathne and Jianguo 2018). For these reasons, Lamoureux and Lastrapes (1990) and many of their successors do model volatility constraining the conditional mean to zero (See e.g. Zhang et al 2013). ARCH modeling is based upon the fact that the large and small errors tend to cluster together (see Engle 1982, p. 989, paragraph

$$\varepsilon_t \backslash (MD_{t,}\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\ldots) \sim N(0, h_t), \quad (11)$$

$$\ln(\sigma_t^2) = \omega + \eta \ln(\sigma_{t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \lambda MD_{t-1} \quad (12)$$

Under null hypothesis of margin debt value reflects the amount of new information arrival at the market on credit risk, the total persistence (ARCH effect in particular) in the conditional variance as captured by ($\eta + \gamma + \alpha$) should be negligible when accounting for uneven flow of information arrival under serial correlation in the presence of EGARCH (See Lamoureux and Lastrapes (1990, p. 223).

4. Data and Empirical Results

Monthly index[11] and margin debt value data are obtained from the New York Stock Exchange (NYSE) covering a sampling period from December 1996 to November 2017[12]. Some descriptive statistics of these sample data are as follows.

Table 1 – Empirical Description of the Sample Data

Table 1 - Statistical Properties of Sample

Variable	Mean	Median	Max.	Min.	Skewn.	Kurtos.	JB	ADF	ML	Q (36)
R_t	0.004	0.009	0.108	-0.217	-0.985	5.873	126.96	-13.923	21.62	35.62
MD_t	272284	235998	580945	97400	0.71	2.38	25.50	0.166	NA	4305

Note:

1. JB - Jarque–Bera test statistic for normality. Under the null hypothesis for normality, critical value of $\chi 2$ (2) distribution at 5% significance level is 5.99.
2. ADF- Augmented Dickey-Fuller test statistic for stationarity of data for maximum of 18 lags. Under null hypothesis for data having unit root, the critical value at 5% significance level is -2.87.

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5). As such, too idiosyncratic errors may not reflect the clusters in errors which ARCH should factually account for.

[11] NYSE Composite Index. Data are available at https://finance.yahoo.com

[12] NYSE notes that NYSE member firms' margin data will no longer be updated after December 2017. Hence, December 2017 has been eliminated from the sample.

3. LM is the ARCH LM test statistic for number of observations multiplied by the R-squared value for 3 lags. Under the null hypothesis, critical value of χ2 (3) distribution at 5% significance level is 7.815 (OLS equation $R_t = c + \varepsilon_t$,).
4. Q (36) is the Ljung-Box Q statistic for serial correlation up to 36 lags, in the margin debt values. Under the null hypothesis for no serial correlation, the critical value of χ2(36) distribution at 5% significance level is 49.80.
5. *Statistically significant at 5% and ***Statistically significant at 10%

Nonnormality of return distribution is witnessed by the Jarque–Bera test statistic. The null hypothesis of normality of return and margin debt values is rejected as test statistic exceeds the critical value of 5.99 under 5 percent significance level. Nonstationarity of margin debt values is confirmed as ADF test statistic does not exceed the critical value of -2.87 at 5 percent significance level. NYSE monthly returns are however stationary. Regression residuals generated from OLS specification as in Note 3 to Table 1 are serially correlated as null hypothesis of no ARCH effect is clearly rejected. However, the test results of Ljung-Box Q statistic for serial correlation show that the index return is not subject to serial correlation (See Table 1) as Q statistic is less than the critical value. Margin debt value data are however highly serially correlated.

Table 2 – Estimation Results

Table 2 Maximum Likelihood Estimation of GARCH Model

Description	a	t-statistic	λ	t-statistic	Υ	t-statistic	$(a + \lambda)$
h_t without MD	0.1666**	1.6872	0.8086*	8.4130	NA	NA	0.9751
h_t with MD	0.2079	1.3103	0.5374*	2.2363	-1.3E-09***	-1.4918	0.7453

Note:

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

3. The residual diagnostics tests for the estimation equations (5) and (7) (under the same specifications used for descriptive statistics); JB 69.59* and 49.91*; LM 0.929 and 0.642; Q (36) 23.66 and 28.40. The Walk coefficient restriction, t-statistic (for single restriction) for null hypothesis $\Upsilon = 0$ and $\chi 2$ (2) statistic for null hypothesis $a = \Upsilon = 0$ is -1.491 and 2.677 respectively. The Log-likelihood ratios of the two models are 446.75* and 448.66* respectively.

The coefficient a applicable to ARCH term is positive and statistically significant at the 10 percent significance level in the GARCH (1, 1) model (equation 5). GARCH term λ is positive and statistically significant at 5 percent significance level and the sum of the total volatility coefficient is recorded at 0.9751. However, the inclusion of margin debt value in the conditional variance results in the reduction of total volatility persistence by 0.2298 to record at 0.7453 (estimation equation 7). Although the ARCH term becomes statistically insignificant, the reduction in the total volatility persistence is not quite significant. The coefficient applicable to margin debt value is negative and statistically significant at 15 percent significance level. These findings are not significant enough to conclude that the margin debt value data reflects the type of heteroscedasticity in stock returns accounted for by the ARCH model. However, this conclusion does not take into account the volatility asymmetries that may impact the heteroscedasticity in stock returns, through the time dependence in the rate of information arrival on margin debt value data (i.e. good or bad news pertaining to the updates on credit risk). This is particularly due to the fact that the standard GARCH (1, 1) model fails to account for any asymmetric effect of stock market borrowing (e.g. due to force-selling or margin calls) on conditional volatility.

JB test for normality rejects the null hypothesis that the residuals are normally distributed for two GARCH (1, 1) scenarios as the test statistics substantially exceed the critical value. However, the residuals are serially uncorrelated and homoscedastic as per the results of the Ljung-Box Q test and the

ARCH-LM test. More importantly, the null hypotheses (two separate hypotheses) of Wald coefficient restrictions for $\Upsilon = 0$ and $a = \Upsilon = 0$ are accepted for the estimation equation 7 and, as such, the margin debt value alone or lagged squared errors and margin debt value jointly does not appear to have an effect on the conditional volatility.

Table 3 Maximum Likelihood Estimation of EGARCH Model

Description	η	t-statistic	γ	t-statistic	α	t-statistic	λ	t-statistic	$(\eta + \gamma + \alpha)$
h_t without MD	0.2350*	2.2296	-0.3006*	-4.2708	0.8227*	14.2834	NA	NA	0.7572
h_t with MD	0.1183	0.9467	-0.4131*	-5.3357	0.6996*	8.1132	-1.09E-06*	-3.0718	0.4048

Note:

1. *Statistically significant at 5% assuming returns are conditionally normally distributed. **Statistically significant at 10%.
2. The coefficients are estimated using the methods described by Bollerslev and Wooldridge (1992) for obtaining quasi-maximum likelihood (QML) covariances and robust standard errors.
3. The residual diagnostics tests for the estimation equations (10) and (12) (under same specifications used for descriptive statistics); JB 42.23* and 20.16*; LM 0.720 and 0.807; Q (36) 22.03 and 26.67. The Walk coefficient restriction, t-statistic (for single restriction) for null hypothesis $\lambda = 0$ and $\chi 2$ (2) statistic for null hypothesis $\eta = \lambda = 0$ are -3.07* and 30.98* respectively. The Log-likelihood ratios of the two models are 458.7* and 465.73* respectively.

The lagged volatility coefficient (η) is positive and statistically significant at 5 percent significance level as in equation (10), and the coefficient (γ) applicable to leverage effect is negative and statistically significant at 5 percent significance level. This confirms that the negative shocks have a greater impact on volatility than positive shocks of the same magnitude. The long-term volatility coefficient (α) is positive and statistically significant.

Once the legged margin debt value is included in the conditional variance equation of the EGARCH model (equation 12), the ARCH effect vanishes and the coefficient becomes highly statistically insignificant at 5 percent significance level. Also, the total volatility persistence reduces substantially to 0.4048 from 0.7572[13]. These findings suggest that the margin debt values reflect the time dependence in the rate of information arrives at the stock market. More importantly, the difference in the amount of reduction of total volatility persistence under GARCH and EGARCH is better explained by leverage effect. The difference may largely be due to the impact of the asymmetries caused by the information pertaining to stock market borrowing rather than the corporate borrowing. Also, the lagged margin debt value coefficient is negative and statistically significant at 5 percent significance level. This unearths a stylist fact about the relationship between credit risk of borrowing[14] and the required rate of return of common stockholders. When margin debt values are increased[15], the BFI have more access to new margin traders (investors), their profiles and portfolios (types of information have been discussed under section 1 and 2). As the new information pertaining to credit risk of margin borrowing flows into the stock market, investors learn about the implications of such risk on their value of equity investments and return[16]. Since the investors are more informed about the credit risk than ever before, the volatility is reduced as the uncertainty of future stock price changes is perceived. Li and Ongena (2015) show that the abnormal stock returns of corporate borrowers are

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[13] See Lamoureux and Lastrapes (1990, p. 228). The coefficients are estimated using the methods described by Bollerslev and Wooldridge (1992) for obtaining quasi-maximum likelihood (QML) covariances and robust standard errors.

[14] In this case, margin borrowing.

[15] I.e. when new margin clients (customers or investors) are facilitated, the BFI have more information about credit risk profiles pertaining to facilities advanced to investors, which may impact the credit risk at the market level.

[16] Demiroglu and James (2010) argue that the future operating performance should be negatively correlated with the credit risk. They attribute this relationship to customer profile and characteristics of the credit.

reduced with US bank loan announcements. Friewald *et al* (2014) find essential facts about the credit risk premia and find that the stock returns are increased with the increase in credit risk premia estimates.

Except for the nonnormality of residual distributions of EGARCH models (two scenarios) estimated by equations (10) and (12), the residuals are homoscedastic and serially uncorrelated. The null hypothesis (two separate hypotheses) for the coefficient, $\lambda = 0$ and $\eta = \lambda = 0$ under Wald coefficient restriction test are soundly rejected. The variability in margin debt value individually and jointly with legged squared residuals is significant for the forecast of conditional volatility. The goodness of fit of the two models is very high as the Log-likelihood ratios are highly significant.

5. Conclusion

The information content of stock market-related borrowing (e.g. margin borrowing) should be reflected in the stock market prices if the market is efficient. Although not clearly documented in the literature, the importance of information flows to the stock market on market borrowing has been identified by Myers and Majluf, (1984). However, the issue of whether the margin borrowing (i.e. margin debt) reflects the time dependence in the new information arrival has not been addressed using a common framework. Personnel attached to BFI have access to all relevant information pertaining to debt securities portfolios of customers. If this piece of insider information[17] is reflected in the stock market prices, the market can be recognized as a strong form efficient market (Fama (1965, 1970).

ARCH effect vanishes and the total volatility persistence as captured by the sum of volatility coefficients has most reduced when lagged margin debt value is included in the conditional variance equation of the EGARCH model. The

[17] Together with other relevant insider information

empirical results reveal that the margin debt value replicates the time dependence in the rate of information arrival on credit risk of stock market borrowing. Further, the lagged margin debt value is negatively and significantly related to volatility, which implies that the investors adjust their risk[18] (i.e. h_t) as the new information pertaining to credit risk flows to the market.

Although the ARCH effect is eliminated by the inclusion of margin debt values in the conditional variance of GARCH (1, 1) model, the total volatility persistence is reduced marginally. This inability could be attributed to the fact that the GARCH (1, 1) model fails to accounts for the asymmetric effect of information pertaining to stock market borrowing (i.e. margin borrowing) on conditional volatility.

Overall, the results suggest that the form of persistence of new information arrival on margin debt value data in the conditional volatility is a reflection of ARCH type of residual heteroscedasticity of stock return data of the New York Stock Exchange.

Acknowledgment

The author would like to thank the Editors for the opportunity to revise the manuscript. Useful and constructive comments from two anonymous reviewers shall be gratefully acknowledged. As usual, any errors or omissions remain the author's sole responsibility.

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[18] See Engle *et al* (1987).

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