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Research article

Market Value Volatility and the Volume of Traded Stock for U.S. Industrial Corporations

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Abstract: A novel two-phase econometric approach was used to first obtain the variance (volatility) of the firm's market value adjusted for its common stock repurchases and other determinants (the traditional approach). Then, the variance of some 1,077 firms was used to predict the volume of the firm's common stock traded over a given period of time (the novel approach). The hypothesis was that fast traders in the stock market can use the variance of the firm's market value as a source of risk information, when deciding on what stock to purchase. An unbalanced panel of firms covering the quarterly time periods from 1999 (4) to 2017 (1) was analyzed by the longitudinal method to obtain the variances. Then, linear regression was used to relate the volume of stock traded to the variances. The novel method goes beyond the traditional volatility approach. The statistical results were acceptable for both phases, but with some concern over the use of the variance as an independent determinant in the second phase analysis.

Keywords: firm market value; variance (volatility); panel data; stock repurchases; fast traders; hypothesis tested; volume of common stock traded

1. Introduction

The purpose of this paper is to report on a novel way to examine the volatility of the market value of the firm. The traditional way is to estimate the volatility by a univariate or multi-variate statistical analysis and then make forecasts of the volatility of the firm's market value. The purpose of the novel way is to show how the volatility is key to stock traders (particularly fast traders). For this paper the novel way involves a two-fold approach where first the firm's market value is analyzed using the repurchasing of its common stock (treasury stock) as the key determinant (the traditional way), and then, the variance derived from the first analysis is used as the determinant of the volume of common stock traded over a given period of time (the novel way).

In short, the market value of the firm is first adjusted for (or normalized by) management's stock repurchases, giving from the residuals the variance of its net market value as the risk index. This net market-value variance is then used to explain the volume of common-stock traded. Thus, our key hypothesis is that stock investors, particularly the fast traders will use the volatility of the firm's net market value to determine the volume of common stock to purchase (or sell). For a discussion of fast trading, see Lewis (2014, particularly page 98). Hopefully, the results of this novel approach will be useful to investors for it focuses directly on their use of the variances of the firms' market values in making their stock decisions.

The empirical results are obtained by analyzing the relevant variables for U.S. corporations quarterly over the years 1999 to 2017. From this analysis, we obtain the heteroscedastic variances across firms. These variances are the key to the novel approach, as stated above. Such variance (or volatility) across firms is the index of risk information that fast traders want in order to gain from the fast buying and selling of common stock. Our novel approach goes a step beyond the traditional volatility model, since it focuses on the use of the variance, as opposed to forecasting it. The novel approach is not without concerns (particularly, the problems of estimate bias and consistency), which will be discussed later in the statistical results section.

The two key variables then in the empirical examination are the volume of common stock traded and the heteroscedastic variances. The former is the index of market activity and the latter (as mentioned before) is the index of risk information. We hypothesize that the greater is the volatility, the larger will be the volume of stock market activity. The two-phase econometric approach will be explained in detail in the next section (essentially, for now the first phase involves unbalanced panel data analysis and the second phase involves robust ordinary least squares regression).

The literature on common stock repurchases (CSR's), particularly the financial literature, is quite large. It focuses on various reasons for repurchases (such as an alternative to dividends, used to stabilize its market price, used for employees' pensions and compensation, used to adjust stock owners' equity to the firm's book value or capital, and used in defensive moves on the part of management), but the main thrust of the studies is the effect of stock repurchases on the firm's market value (price of its common stock) (see, for example, Haw et al., 2011; Baker et al., 2011; Sabri, 2003; Woodruff et al., 1995; Sinha, 1991; Tsetsekos et al., 1991; Dann, 1981 and the cites therein for surveys). Our first-phase analysis contributes to this literature.

The volatility literature on panel data analysis is also quite large and focuses largely on how to correct for heteroscedasticity to obtain efficient estimates and on the forecasting of the firm's asset market-value variance in volatility models (see, for a review, Hirshleifer and Teoh, 2003; Baldauf and Santoni, 1991; Engle and Patton, 2001, for discussions on the use of volatility models). There does not appear to be any literature on the explicit and direct use of the heteroscedastic variances to explain (or forecast) stock market activity, the point of our phase-two analysis and the testing of the above hypothesize.

In what follows, in the next section the empirical models for panel data analysis and regression analysis are given. The next section contains the sample and the statistical results. The final section has a summary of the paper and includes conclusions.

2. Treasury Stock Model and its Variances Application

2.1. Treasury stock model

Modeling treasury stock and its effect on firm value is complex, particularly if one is trying to differentiate between the effect on firm price of the announcement of repurchases compared to the actual repurchase of stock. In either case, typically, the firm's value is enhanced (see, Baker et al., 2011). In our modeling effort, we use the actual volume of stock repurchases as an exogenous determinant of the firm's market value. Our design takes a limited approach in terms of the number of explanatory variables to facilitate the analysis. This is typical in the literature. Our model, therefore, contains two main variables, q for the market value of the firm (defined shortly) and T for the number of treasury stock shares held by the firm. The basic model has q dependent upon T and this direction forms the regression equation to follow. Other variables are added to the regression (firm size, ASSETS, long-term debt, LTD, and industry dummy variables, DV) and serve as control variables.

The operational form of the treasury stock model is given by

$$q_{it} = a + b_1 * T_{it} + b_2 * T^2{}_{it} + b_3 * ASSETS_{it} + b_4 * LTD_{it} + b_5 * DV_{it} + e_{it}\ , \qquad (1)$$

where q_{it} is defined as the ratio of the market value of the firm to its book value (following, Fama and French, 2001), DV is for industry dummy variables, and e_{it} is the error term. The error term forms the basis for the across-firms' variances. The "i" indexes the ith firm and the "t" is the time-quarter date for the ith firm.

Industry (manufacturing) dummy variables are used to test for the cross-industry effects on the q/T behavior. The reference group is referred to as the light industry group (based more or less on the type of products produced) and is given by DV1 covering SIC 2000 to 2799 (food, tobacco, textiles, apparel, lumber, furniture, paper products, and printing, primarily nondurables). The DV2 is referred to as the medium industry group covering SIC 2800 to 3299 (chemicals, petroleum, rubber, leather, and stone products). The DV3 variable covers the heavy (more or less) industrial sectors of metals, machinery, electrical, electronics, and transportation given by SIC 3300 to 3999. The three-way grouping is somewhat arbitrary but it fits roughly the light, medium, and heavy product criteria.

2.2. *Variances application*

The heteroscedastic variances of the residuals from (1) are used as the predictor variable in the regression relating stock market activity to the variances and given by

$$m_i = a + b_1 * IV_i + b_2 * IVSALES_i + b_3 DV3_i + u_i \,, \tag{2}$$

where m is the average quarterly volume of common stock traded in the market for the ith firm over its full time period (the total number of quarters varies across firms), IV is the inverse of the variance for the ith firm obtained from equation (1) for the full time period and varies across firms, and IVSALES is the inverse of the firm's sales and is used as an index of firm size. The u_i is the error term. The inverse of the variance and the firm's sales produced better statistical results than the variance and sales. The important point to note is that equation (2) uses the means of the ith firm's variables to match the ith firm's variance.

As to the meaning of equation (2), we envision that the fast traders look at the firm's variance (along with other determinants) and decide on how many common stock shares to purchase (in milliseconds, although our data is in aggregated time-quarter periods). The aggregate of these decisions (and, of course, those of other traders) for a given firm determines the mean volume of common stock traded per time-period for the firm. This meaning is the basis of the hypothesis given earlier and implicit in equation (2). As mentioned in the introduction, we have some concern over the use of the variance variable in equation (2) and this concern will be addressed in the results section.

3. Sample and Statistical Results

The useable sample (missing values dropped) consists of 34,382 observations for U.S. industrial corporations (SIC 2000 to 3999) covering quarterly the years 1999 (4) to 2017 (1). All firms (some 1,077) have some treasury stock and have a market value greater than zero. The data are from the Compustat North American files supplied by WRDS, Wharton, UPenn.edu.

The operational equation (1) is the basis for the phase-one q/T regression. The market value q of the firm as indicated above is defined as the ratio of the market value of common stock MVF (given by share prices as of the end of the quarter times the number of common stock shares outstanding at the end of the quarter) to the value of shareholders' book equity (labeled BE). The q is thus MVF weighted by BE. It resembles Tobin's Q and is essentially the q used in the current treasury stock literature. The treasury stock T is the number (in millions of units) of common stock shares recorded in the supplement to the balance sheet of the firm for the quarter. To repeat, only firms with a positive amount of T are used in the sample. The firm's total assets (ASSETS) and long-term debt (LTD) are used as control variables, affecting the market value of the firm and thus q.

The estimation method used for equation (1) is the cross-section/time series generalized least-squares method (XTGLS in Stata) for unbalanced panel data with heteroscedastic variances. The autocorrelations (AR1's) are panel specific (with 1,077 panels). On average, there were 32 observations per panel (firm) with a minimum of 2 and a maximum of 69. The XTGLS method proved to give the best results.

The statistical results for q on T are given in Table 1. All of the coefficients are highly significant and the Wald fit is 243.16 and significant (p=.0000). The mean equation is given by

$$q = 3.46 + .006*T - .0000017*T^2 - .00004*ASSETS + .00007*LTD + 1.65*DV2 - .84*DV3.$$

The equation is non-linear and analogous to the findings of Woodruff et al. (1995). The individual predictor effects on q while significant are, in some cases, relatively small compared to the T effect on q. The firm size (ASSETS) effect is small and negative. The LTD effect is positive but small. The light industry effect (from the constant) is positive and large, and the medium industry (DV2) effect is also positive and large, but the heavy industry effect is negative but large.

Table 1. Statistical results for q (firm value) on T (treasury stock) using the XTGLS method for unbalanced panel data.

Variables	Equation (1)
Constant	3.46 (24.52)
T(treasury stock)	.006 (6.79)
TSQ(T squared)	-1.66e-06 (-4.68)
ASSETS	-.00004 (-9.92)
LTD(long term debt)	.00007 (5.84)
DV2(medium industry)	1.65 (5.56)
DV3(heavy industry)	-.84 (-5.69)
PSAR(1)	
Wald(4 df)	243.16
p	.0000

Notes: Sample size is 34,382 obs and 1,077 firms. Standard errors are in (.) with p < .000. The panel-specific autocorrelations PSAR(1)'s vary in size but are not recorded.

Regardless of the different financial and economic explanations for these effects, they do in the aggregate account for a relatively large Wald ratio. This means that the market value of the firm can be taken as being normalized by these effects, so then the residual-based variances can serve as the risk information needed by the fast trader.

In equation (2) where the firm's common stock market activity is related to the risk information provided by the firm's variance, we considered the possibility that traders would behave differently at different time periods when the market was either rising or falling, in general. Based on the behavior of S&P's 500 stock price index, over our time period, stocks were rising from 1991 (4^{th} quarter) to 2007 (3), then falling from 2007 (4) until 2009 (2), and then again rising from 2009 (3) to 2017 (1). Using dummy variables to capture these time trends, it was found that the dummy variable coefficients were not significant. As a result, time is not in equation (2). As an aside, this result may suggest that fast traders' market behavior is not affected by stock-price trends in the market. What are important to them are the millisecond changes in the variance (our data, of course, is quarterly).

In Table 2, we report the statistical results from running equation (2) using robust OLS. All the coefficients are statistically significant at p =< .022. The negative sign on the coefficients for IV and IVSALES, since these variables are in the inverse form of variance and sales, means that as the variance increases (given the size of the firm), the index of common stock activity, our m, also increases. This result is to be expected.

Table 2. Statistical results for m (stock volume) on IV (1/variance) using OLS robust.

Variables	Equation (2)
Constant	4.43e+07 (5.41)
IV(1/variance)	-9,319.8 (-2.30)
IVSALES(1/sales)	-54,266.5 (-4.68)
DV3	3.22e+07 (2.57)
RSQ	.0052
p > F = 28.17	.0000

Notes: Sample size is 1,058 firms. The t ratios are in (.) with p < .023.

Although the significant RSQ (.0052) is small, our concern is with the hypothesis given above, its common stock traded (by fast traders and other traders) over a given period of time. Of interest is the industry effect. The DV2 coefficient was not significant and the variable was excluded from equation (2). The DV3 industry coefficient was significant and positive along with the significant and positive intercept (in effect, DV1). These results suggest that the light industries and the heavy industries have a significant role in determining the effect on the firm's common stock activity as the result of the variance of its market value, and by implication the result of fast trading.

As indicated earlier, there may be some concern over the design of equation (2), in that the independent variable, IV (the inverse of the variance) is stochastic or random, since it is derived from the residuals of equation (1). Using the stylized X notation, define $\mathrm{X} = X^* + \mathrm{v}$, where v is a random measurement error. It can be shown that the v error will be transferred to the residual u by virtue of the X coefficient b, giving $\mathrm{y = a + bX + (u - bv)}$, where $\mathrm{w = (u - bv)}$ is a compound random variable. As such, X is not independent of the error term w in the stylized equation $\mathrm{y = a + bX + w}$. The use of OLS regression results in a biased and inconsistent X coefficient. In other words, the covariance between X and w is not zero. But, since the $\mathrm{COV(X, w)} = -bS_v^2$, if b is relatively small, a small COV may not matter.

In regards to equation (2), other regression methods such as Instrumental Variables and Errors in the Variables were not feasible for various reasons (no suitable instrument and no known reliability index). In any case, the correlation between IV and u is quite weak ($-.256$), suggesting that IV and u in equation (2) are weakly independent. The sample size for the correlation is quite large (1,058 firms), so any bias is apt to be quite small and the estimated coefficient weakly consistent. So, for all intents and purposes, we stand by the statistical results and accept the hypothesis, admittedly with some trepidation.

4. Summary and Conclusions

Using a novel two-phase econometric approach to analyze longitudinal data on U.S. industrial corporations over the quarterly time periods 1999 (4) to 2017 (1), we first obtained the variances (volatility) of the firms' net market values adjusted for the effect on them of the firms' common stock repurchases (treasury stock) and other determinants. This represents the traditional approach. Then, in the second phase, the novel approach, the firm's volume of common stock (averaged over its time quarters) was regressed on the firm's variance and other variables. This regression was the basis for the hypothesis that fast traders (and others) will use the variance (volatility) of the firm's net market value to make their stock buying/selling decisions. The approach was novel in that it goes beyond the traditional volatility model approach as given in the literature and uses the variance as a predictor variable.

The first-phase statistical results were quite significant, so the variances obtained were considered a useful surrogate for the risk information used by fast traders. The second-phase results were also quite significant, even though the RSQ fit was small.

Nevertheless, in conclusion, while there was some trepidation over the use of the variance as an independent variable (necessary, nonetheless, for the purpose of our model), the statistical results were considered sufficiently good to verify, at least tentatively, our hypothesis. In any case, given the large number of firms in our sample and the generally good statistical results, this conclusion seems reasonable. It remains for other researchers to design and run their own tests of the hypothesis.

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Conflict of Interest

All authors declare no conflicts of interest in this paper.

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