Permanent, Transitory, And Non-Fundamental Components Of Returns, Volatility, And Volume

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ABSTRACT

This paper uses a trivariate structural vector autoregressive model to estimate the effects of permanent fundamental, transitory fundamental, and non-fundamental shocks on returns, volatility, and volume. Though each of these three shocks affects all three variables, these effects are not equal. Returns are mostly driven by permanent fundamental shocks, volatility is primarily affected by transitory fundamental shocks, and volume is mainly determined by non-fundamental shocks. This trivariate SVAR model also helps empirically decompose returns, volatility, and volume into the three shock components. Further, we find that the stock market decline in early 2000 was triggered by changes in fundamentals, and was not just the outcome of non-informational trading.

Keywords: permanent and transitory shocks, non-fundamental shocks, trading volume

1. INTRODUCTION AND PREVIOUS RESEARCH

A majority of studies in prior literature find that stock prices are too volatile to be explained only by subsequent changes in dividends. This excess volatility of stock prices suggests that a substantial fraction of stock price variations may arise from non-fundamentals [See Cocharane (1991), Campbell and Shiller (1988), (1989), Campbell (1991), and Campbell and Ammer (1993)] and that investors trade in response to both fundamental and non-fundamental shocks [e.g. Wang (1994), He and Wang (1995), Campbell, Grossman, and Wang (1993), and Lee and Rui (2001)]. Fundamental shocks induce stock price changes by affecting earnings, dividends or discount factors, while non-fundamental shocks induce price changes without affecting earnings, dividends, or discount factors. In other words, fundamental shocks result from innovations that affect fundamentals, while non-fundamental shocks are driven by innovations that do not influence fundamentals[1].

According to Lee (1998), fundamental shocks can be further decomposed into permanent fundamental and transitory fundamental shocks based on their long-run cumulative effects on fundamentals. Dividend change is primarily determined by changes in permanent earnings, but can also be induced by transitory changes in earnings [see Marsh and Merton (1987) and Lee (1996, 1998)]. Permanent fundamental shocks - for example, changes in permanent earnings - have a long-run non-zero cumulative effect on earnings changes, and a long-run non-zero cumulative effect on dividend changes, which in turn induces a long-run non-zero cumulative effect on price changes. Transitory fundamental shocks - for example, transitory changes in earnings - have a long-run zero cumulative effect on earnings changes, which distinguishes them from permanent ones. Transitory fundamental

[1] Note that Campbell, Grossman, and Wang (1993), Wang (1994), and Lee and Rui (2001) use the terms of "informational trading" and "non-informational trading". They defined informational trading as those made by informed traders when they receive information that can affect the stocks future cash flows (exactly as what is defined in this paper as fundamentals). They defined non-informational trades as those for non-informational reasons which do not affect the stocks future cash flows (exactly as what is defined in this paper as non-fundamentals). Therefore, their theoretical foundations for the identifying restrictions can be applied directly in this paper to derive the identifying restrictions. Note that according to Wang (1994), a trade is perceived to be non-informational trade as long as uninformed investors will take one side, even if the other side is informed traders.

shocks induce a long-run zero cumulative effect on earnings changes and a long-run zero cumulative effect on dividend changes, which in turn induces a long-run zero cumulative effect on price changes.

Therefore, stock prices change in response to both permanent and transitory fundamental and non-fundamental shocks. Information is actually a mixture of permanent fundamental, transitory fundamental, and non-fundamental shocks. How these shocks contribute to the generation of returns, volatility, and volume remains largely unexplored. Lee and Rui (2001) are among the first to empirically estimate the effects of non-informational (non-fundamental) and informational (fundamental) shocks on stock returns and trading volume. Using a bivariate SVAR model of stock returns and trading volume, Lee and Rui (2001) distinguish non-informational and informational shocks by imposing an identifying restriction on the bivariate SVAR model: informational shocks have no contemporaneous effects on trading volume[2], while non-informational shocks have contemporaneous effects on trading volume, an assumption based on Campbell et al. (1993). However Lee and Rui (2001) do not further decompose fundamental shocks into permanent fundamental and transitory fundamental shocks, as done by Lee (1998) and herein.

At about the same time, Mixon (2001) proposes a market microstructure model of both returns and trading volume by using separate ARCH-like models to distinguish between news (movement in underlying fundamentals) and noise (caused by the trading process). He also finds that a large body of trading volume is unrelated to the fundamental value of the assets.

Although both papers consider how fundamental and non-fundamental shocks affect returns and volume, neither author breaks down fundamental shocks into permanent and transitory shocks, and neither considers how volatility is simultaneously affected by information flow. Since daily returns, daily volatility, and daily volume[3] are generated by the same information flow and trading process, it makes sense to consider how the three types of shocks affect returns, volatility, and volume simultaneously, especially since the availability of transaction level data makes it possible to determine an informative daily volatility measure.

Clearly, a gap exists in prior finance literature about how the three types of shocks affect returns, volatility, and volume and how to identify the permanent and transitory fundamental and non-fundamental components of returns, volatility, and volume. Our paper tries to fill this void in the literature. By using a trivariate structural vector autoregressive (SVAR) model of daily returns, volatility, and volume with three identifying restrictions, this paper estimates the effects of permanent fundamental, transitory fundamental, and non-fundamental shocks on daily returns, volatility, and volume. Our results show that although each of these three shocks affects all three variables, these effects are not equal, with each shock functioning as the main driving factor for its distinctive target - non-fundamental shocks on trading volume, permanent fundamental shocks on returns, and transitory fundamental shocks on volatility. The duration of the effects also varies: the effects on returns disappear with significant speed (roughly within days), and the impact of various shocks on volatility and trading volume dies off more gradually. Furthermore, by comparing the magnitude of the three shocks, we are able to identify when a specific shock dominates the information flow, and conclude that non-fundamental shocks only dominate the other types of shocks occasionally. Last but not least, we are able to decompose the historical values of returns, volatility, and trading volume into three parts: the permanent fundamental, transitory fundamental, and non-fundamental components.

The remainder of this paper is organized as follows. In the next section (section 2), we present the data. In section 3, we outline the SVAR model based on the three identifying restrictions. In section 4, we provide the empirical results showing the relative importance of the three different types of shocks. In section 5, we explain the effects of various shocks on returns, volatility, and volume over time. In section 6, we decompose returns, volatility and volume into three corresponding components. Finally, in section 7, we conclude the paper with a summary of the evidence.

[2] Note that Lee and Rui (2001) still allow non-informational shocks to have some effects on trading volume after the initial period, as we do in this paper.

[3] The sum of returns (log returns) from intra-day transactions constitutes daily return, the sum of volume of intra-day transactions is daily volume, and the volatility of intra-day transactions is daily volatility. Therefore, returns, volatility, and volume are simultaneously determined by the information flow.

2. DATA

To mitigate the thin trading problem and firm-specific risk, this paper focuses on the DJIA index, which is comprised of 30 blue-chip stocks. Daily returns and daily trading volume are obtained from the CRSP database, and the intra-day data are taken from R.C. Research. The sample period covers January 1998 to December 2006.

One potential problem with transaction level data is that "the transaction prices are subject to discrete clustering and bid-ask bounce effects. Such market microstructure features are generally not very important when analyzing long horizon inter-daily returns but can seriously distort the distributional properties of high-frequency intra-day return [Anderson et al., 2001]." In order to minimize this problem, this paper relies on five-minute horizon data, as in Anderson et al. (2001), to identify the highest, lowest, opening, and closing prices in each interval. The five-minute horizon is short enough to maintain the necessary detail in the data but long enough to circumvent the quoted market microstructure problem.

Daily return is calculated using the difference between the natural logarithm of today's closing price plus the dividend and natural logarithm of the previous day's closing price.

$$R_{it} = \log(P_{it} + D_{it}) - \log P_{i(t-1)} \tag{1}$$

where R_{it} is the return of security i on day t, P_{it} is the price of security i on day t, D_{it} is the dividend payment of security i on day t, while $P_{i(t-1)}$ is the price of security i on day t-1.

Daily volatility is measured as sum of absolute returns (SAR) using the following equation based on five-minute horizon returns. The equation is used in Anderson and Bollerslev (1998).

$$\sigma_{it} = \frac{1}{\sqrt{2n/\pi}} \sum_{p=1}^{n} \left| R_{itp} \right| \tag{2}$$

where σ_{it} is the daily volatility of security i on day t, R_{itp} is the return of security i at the pth five-minute horizon on day t, where n is the number of five-minute intervals during the day[4].

Daily trading volume is measured by daily turnover ratio, the ratio of the number of shares traded each day to the number of shares outstanding at the end of the day. The advantage of using daily turnover ratio is that it eliminates the effect of capitalization on trading volume.

3. EMPIRICAL MODEL DESIGN

In this section, we focus on estimating the impacts of the three shocks on returns, volatility, and volume by using a Blanchard-Quah type decomposition in a structural vector autoregressive (SVAR) model. The starting point for a SVAR model is to correctly identify each shock. The following SVAR model is used to simultaneously estimate the impacts of permanent fundamental, transitory fundamental, and non-fundamental shocks on daily returns, volatility, and volume. By the Wold representation theorem,

$$\begin{bmatrix} r_t \\ \sigma_t \\ V_t \end{bmatrix} = \begin{bmatrix} B_{11}(L) & B_{12}(L) & B_{13}(L) \\ B_{21}(L) & B_{22}(L) & B_{23}(L) \\ B_{31}(L) & B_{32}(L) & B_{33}(L) \end{bmatrix} \times \begin{bmatrix} n_t \\ p_t \\ t_t \end{bmatrix} \tag{3}$$

[4] On most days when stock is traded continuously from opening of the exchange to closing of the exchange, n is equal to 78. Sometimes when stock is halted for trading due to an announcement of information, n is less than 78.

where r_t is the daily return, σ_t is the daily volatility, V_t is the daily trading volume, p_t is the permanent fundamental shock, t_t is the transitory fundamental shock, and n_t is the non-fundamental shock. L is the lag operator, $B_{ij}(L)$ is $i, j =$ 1, 2, 3 is a polynomial in the lag operator L.

$$B_{ij}(L) = \sum_k b_{ij}(k)L^k \, with \sum_k \equiv \sum_{k=0}^{\infty} \quad . \tag{4}$$

The above SVAR model can also be written as a VMAR,

$$\begin{bmatrix} r_t \\ \sigma_t \\ V_t \end{bmatrix} = \begin{bmatrix} \sum_k b_{11}(k)n_{t-k} + \sum_k b_{12}(k)p_{t-k} + \sum_k b_{13}(k)t_{t-k} \\ \sum_k b_{21}(k)n_{t-k} + \sum_k b_{22}(k)p_{t-k} + \sum_k b_{23}(k)t_{t-k} \\ \sum_k b_{31}(k)n_{t-k} + \sum_k b_{32}(k)p_{t-k} + \sum_k b_{33}(k)t_{t-k} \end{bmatrix} \tag{5}$$

The three shocks p_t, t_t, and n_t, are serially uncorrelated by construction. They are assumed to be contemporaneously uncorrelated through an orthogonalization. The variance of the vector $e_t = \begin{bmatrix} n_t & p_t & t_t \end{bmatrix}'$ is assumed to be the identity matrix of rank 3 by normalization.

Identifying Restrictions

The VMAR representation in equation (5) implies that returns, volatility, and volume are driven by three types of shocks: permanent fundamental, transitory fundamental, and non-fundamental shocks. In order to uniquely identify the three shocks, three identifying restrictions are needed.

The first identifying restriction is obtained by considering how transitory fundamental shocks affect returns. While permanent fundamental shocks have a long-run nonzero cumulative effect on price changes, transitory fundamental shocks induce a long-run zero cumulative effect. The first identifying restriction we need to impose on the trivariate SVAR model is to render the cumulative effect of transitory fundamental shocks on returns zero, as in Lee (1998). This restriction places a long-run condition on the SVAR system in equation (5). Since $\sum_k b_{13}(k)$ measures the cumulative effect of transitory fundamental shocks, t_t, on the returns, r_t, this restriction implies that $\sum_k b_{13}(k) = 0$.

The second and third restrictions are obtained following Campbell et al. (1993) and Lee and Rui (2001)[5]. Fundamental shocks have no contemporaneous effects on trading volume, while non-fundamental shocks have contemporaneous effects on trading volume. Since fundamental shocks include permanent fundamental and transitory fundamental shocks, our second and third restrictions are that permanent and transitory fundamental shocks have no contemporaneous effects on trading volume. This can be achieved in a world with homogenous informed traders and heterogeneous uninformed traders[6]. These two restrictions impose two short-run

[5] As noted in footnote 1, since the definition of fundamental shocks and non-fundamental shocks are the same as those used in Campbell et al. (1993) and Lee and Rui (2001), we can apply their conclusion here to derive the second and third identifying restrictions.

[6] Suppose we are in a world with informed traders and uninformed traders, just like in the model developed by Wang (1994). We assume informed traders respond only to fundamental shocks, since they can single out fundamental shocks from non-fundamental ones. Uninformed traders respond to both fundamental and non-fundamental shocks since they cannot distinguish between the two types of shocks. Therefore, fundamental shocks, including both permanent and transitory ones, will cause both informed and uninformed traders to trade, while non-fundamental shocks will only cause uninformed traders to trade. Similar to what has been implicitly assumed by Wang (1994), we assume informed traders are homogenous. On the other hand, uninformed traders are heterogeneous.

(contemporaneous) restrictions upon the SVAR system. Since $b_{32}(k)$ and $b_{33}(k)$ measure the effect of the permanent and transitory fundamental shocks, p_t and t_t, on trading volume V_t, these two restrictions imply that $b_{32}(k) = b_{32}(0) = 0$ and $b_{33}(k) = b_{33}(0) = 0$.

Hence, the model of returns, volatility, and volume in equation (5) is characterized by the following three restrictions:

$$\sum_k b_{13}(k) = 0,\ b_{32}(k) = b_{32}(0) = 0,\ b_{33}(k) = b_{33}(0) = 0 \tag{6}$$

The three identifying restrictions are: (1) the cumulative effect of transitory fundamental shocks on returns is zero; (2) permanent fundamental shocks have no contemporaneous effects on trading volume; and (3) transitory fundamental shocks have no contemporaneous effects on trading volume. These restrictions are consistent with Lee (1998), Campbell et al. (1993) and Lee and Rui (2001). The first restriction places a long-run restriction on the SVAR system, while the last two restrictions impose two short run (contemporaneous) restrictions upon the SVAR system. Please note that permanent fundamental shocks and transitory fundamental shocks may still have effects on trading volume after the initial period, and we let the data speak for themselves in this regard.

The trivariate VMAR model in equation (5) with restrictions imposed from (6) is derived by inverting a trivariate SVAR model of returns, volatility, and volume with non-orthonormalized innovations, u_1, u_2, and u_3, and imposing restrictions on the SVAR model. The SVAR model is written as follows:

$$\begin{bmatrix} r_t \\ \sigma_t \\ V_t \end{bmatrix} = \begin{bmatrix} A_{11}(L) & A_{12}(L) & A_{13}(L) \\ A_{21}(L) & A_{22}(L) & A_{23}(L) \\ A_{31}(L) & A_{32}(L) & A_{33}(L) \end{bmatrix} \begin{bmatrix} r_{t-1} \\ \sigma_{t-1} \\ V_{t-1} \end{bmatrix} + \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} \tag{7}$$

where $\left[A_{ij}(L)\right] = \sum_k a_{ij}^k(k)L^k$ for $i, j = 1, 2, \text{and } 3$ with $\sum_k = \sum_{k=0}^{\infty}$ and the innovations are orthonormalized.

First, in a world with homogenous informed traders and heterogeneous uninformed traders, informed traders do not trade with each other since, being homogeneous, they arrive at the same conclusions about the fundamental value of the stock, resulting in their trading directions always being the same. Secondly, informed traders could only trade with uninformed traders. When information comes to the market, it is a mixture of fundamental shocks and non-fundamental shocks. Informed traders have the capability to single out fundamental shocks from non-fundamental shocks, while uninformed traders do not. It is the uninformed trader's susceptibility to non-fundamental shocks that distinguishes uninformed traders from informed traders. Without uninformed traders trading on non-fundamental shocks, there can be no trading at all between informed and uninformed traders since they would have the same belief and would trade in the same direction. Thirdly, uninformed traders could trade with each other. This is because uninformed traders have different beliefs about the future value of the stock due to their heterogeneous responses to non-fundamental shocks. This heterogeneity ensures that uninformed traders can trade with each other. Without uninformed traders responding heterogeneously to non-fundamental shocks, there can be no trading at all among uninformed traders. With informed traders being homogenous and only responding to fundamental shocks, fundamental shocks alone cannot generate trading volume in the absence of non-fundamental shocks.

Furthermore, that fundamental shocks, permanent or transitory, do not generate trading volume contemporaneously does not mean that informed traders do not trade at all. Informed traders trade whenever there is fundamental shock. However, in a world with homogenous informed traders and heterogeneous uninformed traders, the other side of the informed traders' trade is always taken by uninformed traders trading on non-fundamentals, hence only non-fundamental shocks will be considered to generate trading volume. Just as in Wang (1994), a trade from informed traders can be perceived to be non-informational (non-fundamental as the term used in this paper) as long as the uninformed traders will take the other side. Therefore, fundamental shocks, permanent or transitory, do not generate trading volume contemporaneously, though they might have lagged effects on trading volume.

4. RELATIVE IMPORTANCE OF EACH SHOCK

The empirical results are based on daily returns, volatility, and volume of the DJIA index. Table 1 provides basic statistics about daily returns, volatility, and trading volume.

Table 1: Summary statistics for returns, volatility, and volume

This table provides the summary statistics for returns, volatility, and volume. Volatility is the daily volatility calculated from intra-day returns. Trading volume is measured by turnover ratios. The sample consists of daily data spanning from January 2, 1998 to December 31, 2006. The B-J test is used to test for the normality of the data. ** and * represent significance at the 1% and 5% levels respectively.

		DJIA	
Mean	0.0002	0.0082**	0.0403**
STD	0.0002	0.0001	0.0003
Skewness	-0.1267*	1.9866**	1.0033**
Kurtosis	3.7035**	6.7767**	2.5480**
B-J test	1299.3612**	5818.9081**	991.8714**

Next we examine whether the series of returns, volatility, and trading volume are stationary. Since all variables in a SVAR analysis must be stationary to avoid spurious regression problems, this stationarity test is crucial. If the series is non-stationary, we will have to use first difference or other techniques to achieve the required stationary state. To test the stationarity of returns, volatility, and volume, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are used. The null hypothesis for each of these tests is that the series have a unit root. The results for the unit root tests are unanimous. As seen in table 2, the ADF and PP tests reject the null hypothesis of a unit root for all series in the index, indicating that all three series are stationary and can be used in our SVAR model.

Table 2: Unit root test for stationarity

This table presents t-statistics for the ADF and PP tests respectively. The null hypothesis for the ADF and PP tests is that each series exhibits a unit root. ** and * represent significance at the 1% and 5% levels respectively.

DJIA	ADF Test	Phillips-Perron Test
Trading Volume	-8.4045**	-26.1434**
Return	-15.4794**	-48.2406**
Volatility	-6.0494**	-17.6503**

As a preliminary step before the SVAR estimation, we need to choose the number of lags in each equation in the SVAR system. Using Akaike (1974) information criterion (AIC) and the Schwarz (1978) criterion, we chose 10 lags for each equation in the trivariate SVAR model for the DJIA.

Table 3: Lag selection

This table presents the results of AIC and Schwarz (1978) criterion to choose the number of lags in returns, volatility, and volume series.

	DJIA	
Lags	**AIC**	**Schwarz**
9	-22.9234	-22.7012
10	-22.9373	-22.7102
11	-22.9401	-22.6811
12	-22.9392	-22.6572

After placing the three identifying restrictions in equation (6) onto the SVAR model in equation (5), we can use forecast error variance decomposition to examine the relative importance of each shock for returns, volatility, and volume. The SVAR forecast error decomposition results for the DJIA are presented in table 4 and graphed in figure 1.

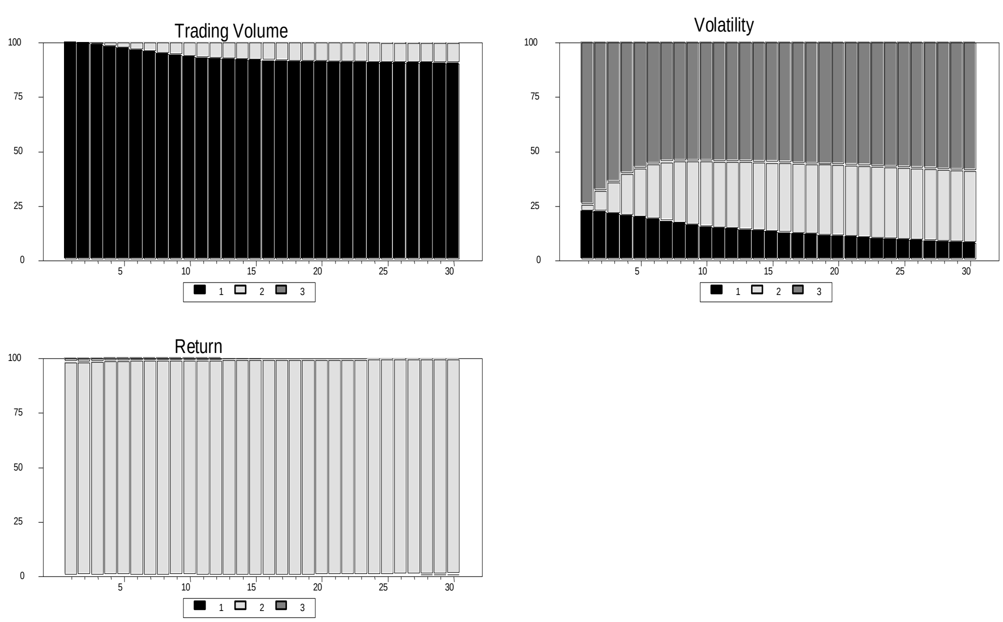
Table 4: Variance decomposition of returns, volatility, and volume

This table reports the relative importance of each shock in explaining returns, volatility, and volume in the SVAR model for various (1 through 30 days) forecasting horizons, as shown in the first column. p_t denotes permanent fundamental shocks, t_t denotes transitory fundamental shocks, and n_t denotes non-fundamental shocks.

DJIA	Variables Explained								
	Volume			Return			Volatility		
Forecast Horizons	Shocks in			Shocks in			Shocks in		
	n_t	p_t	t_t	n_t	p_t	t_t	n_t	p_t	t_t
1	100.0	0.0	0.0	0.4	97.9	1.7	22.5	3.0	74.5
2	99.1	0.7	0.2	0.4	97.9	1.7	21.5	11.5	67.0
3	98.1	1.8	0.2	0.4	97.6	2.1	20.5	15.8	63.7
4	97.0	2.9	0.2	0.4	97.5	2.1	19.6	19.9	60.5
5	96.4	3.4	0.2	0.5	97.2	2.3	19.2	21.8	59.1
6	95.6	4.2	0.2	0.5	97.1	2.4	18.5	23.5	58.0
7	95.1	4.7	0.2	0.5	97.0	2.6	17.9	23.9	58.2
8	94.4	5.3	0.2	0.5	96.7	2.8	17.3	24.3	58.3
9	94.3	5.5	0.2	0.6	96.6	2.8	16.8	24.4	58.9
10	93.7	6.1	0.3	0.9	96.2	2.8	16.5	24.9	58.7
20	92.7	6.7	0.6	1.1	96.1	2.9	13.5	26.8	59.7
30	92.2	6.6	1.2	1.1	96.0	2.9	12.1	26.9	61.0

Figure 1: Variance decomposition for the DJIA

This figure illustrates the relative importance of permanent fundamental, transitory fundamental, and non-fundamental shocks to returns, volatility, and trading volume using variance decomposition. (Black: non-fundamental shocks; dark grey: transitory fundamental shocks; light grey: permanent fundamental shocks).



As shown in both the table and the graph, permanent fundamental shocks are the most important contributors to the return process. About 97.9% of the returns are due to permanent fundamental shocks in the beginning, a figure which gradually declines to 96% after 30 days. Transitory fundamental shocks play a very minimal role in the return process, since only 1.7% of the returns can be attributed to transitory fundamental shocks in the beginning. As the forecast horizon increases, the effect increases, but it is still less than 3% after 30 days. This finding confirms the result of equation (5) that transitory fundamental shocks have no long-run effect on returns. Non-fundamental shocks play even less of a role in the return process. Their measured effect on returns is only about 0.4% in the beginning and about 1.1% after 30 days. Therefore, even though diversification across the 30 composition stocks of DJIA significantly reduces the effect of non-fundamental shocks on returns, it does not completely eliminate the effect. This is consistent with the argument of De Long et al. (1990) that noise trader risk arising from non-fundamental shocks (noise) is market-wide rather than idiosyncratic, and hence diversification does not eliminate the effect of noise. In summary the results presented here show that return is mostly affected by permanent fundamental shocks. Although non-fundamental shocks and transitory fundamental shocks do contribute to the return process, their impacts are very small.

The relative importance of the three shocks on volatility of the DJIA is also reported. As displayed in table 4 and graph 1, all three types of shocks affect volatility; however, the relative importance of each shock on volatility varies. Transitory fundamental shocks play the most important role. More than 70% of the volatility can be explained by transitory fundamental shocks in the beginning, while more than 20% of the volatility can be explained by non-fundamental shocks. The influence of permanent fundamental shocks on volatility is about 3% in the beginning, but as the forecast horizon increases, their impact increases to more than 25% in 30 days. Overall, transitory fundamental shocks are the most important contributor to volatility[7].

Finally, let us look at the relative importance of the three shocks on trading volume. As presented in the table and graph, trading volume is mostly induced by non-fundamental shocks. The influence of non-fundamental shocks on volume is still about 92% after 30 days. Even though permanent fundamental shocks and transitory fundamental shocks do not affect trading volume contemporaneously, as the forecast horizon increases, both shocks start to show some influence on trading volume, though the influence is very minimal, roughly 6.6% and 1.2% respectively after 30 days. The finding that permanent and transitory fundamental shocks can affect trading volume in the long run does not contradict the identifying restrictions in equation (6). These identifying restrictions only state that permanent fundamental shocks and transitory fundamental shocks do not affect trading volume contemporaneously. They do not exclude the possibility that permanent fundamental and transitory fundamental shocks have a lagged effect on trading volume, as proven by the empirical results in this paper.

In summary, permanent fundamental shocks are the main drivers for returns, while transitory fundamental shocks are the main drivers for volatility. Non-fundamental shocks mainly drive the trading volume[8]. Since noise trading risks that arise from non-fundamental shocks are market-wide and could not be diversified away, as suggested by De Long et al. (1990), this paper provides one approach to measuring how sensitive the stock returns are to non-fundamental shocks. Therefore, investors can identify those stocks with higher/lower noise trader risk and choose stocks according to their preference.

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[7] The fact that transitory fundamental shocks only play limited roles on returns, but are the most important contributors to volatility is not surprising. By definition, transitory fundamental shocks do not have a long-run cumulative effect on earnings and dividend changes. Therefore, transitory fundamental shocks shouldn't have a great impact on price changes, though the trading activities from informed and uninformed traders based on transitory fundamental shocks will definitely contribute to the daily volatility.

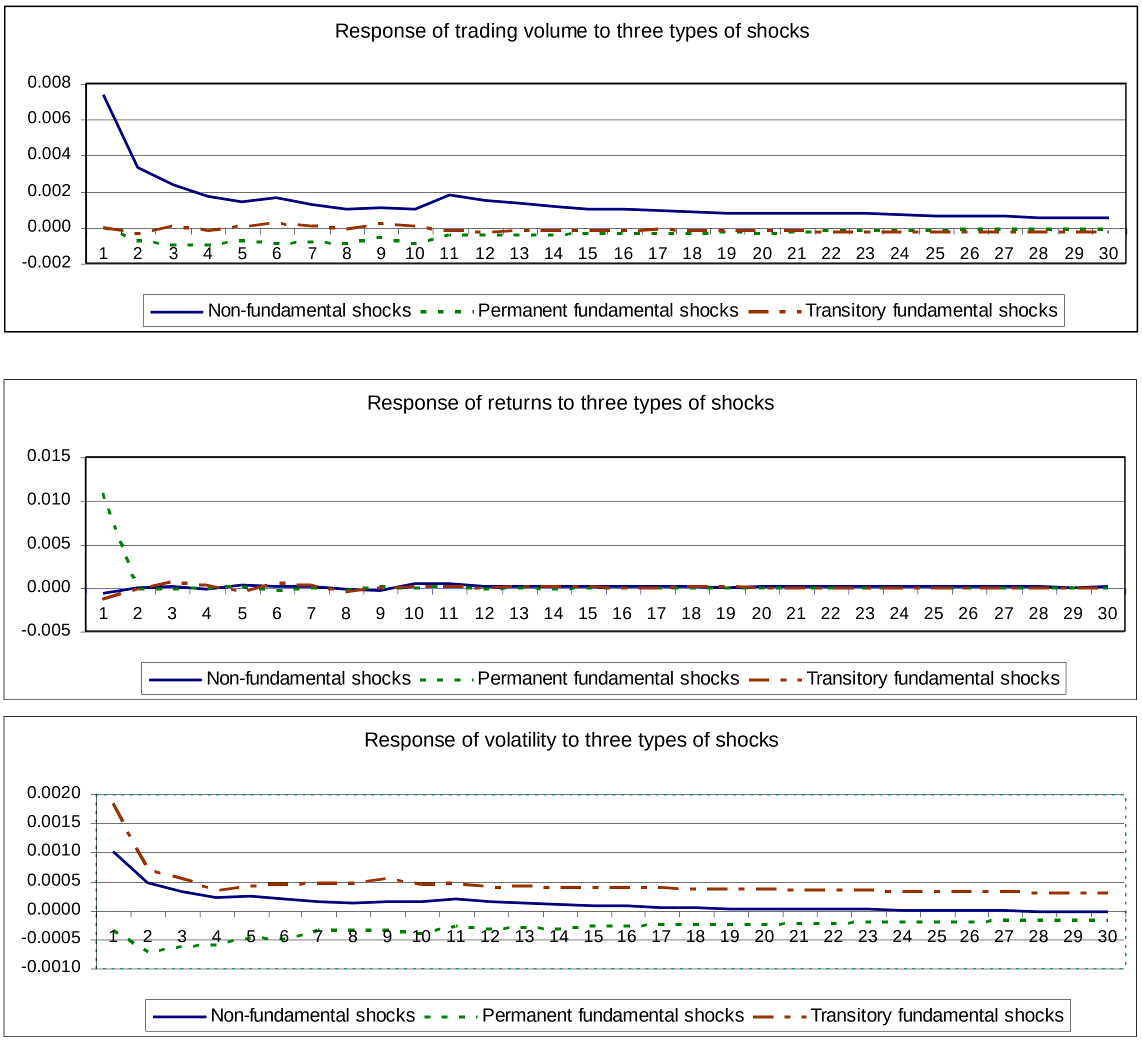
[8] The finding that non-fundamental shocks and transitory fundamental shocks do not have a significant impact on returns does not mean that these two types of shocks never greatly affect stock returns. The results presented in table 4, just like any other statistic inference, only provide us with a picture of how the market responds to the three types of shocks in general. We do recognize the fact that non-fundamental shocks and transitory fundamental shocks can greatly affect stock returns at certain days, which is essentially the spirit of section 6 of this paper. Section 6 shows that some times stock returns can be mostly driven by fundamental shocks, while other times stock returns can be mostly affected by non-fundamental shocks. That is actually why stock market bubbles only occur occasionally.

5. DYNAMIC EFFECT OF EACH SHOCK

In addition to evaluating the relative importance of each shock, we also investigate how each shock affects returns, volatility, and volume over various horizons. Figure 2 illustrates the dynamic responses of returns, volatility, and volume to one standard innovation in permanent and transitory fundamental shocks, and non-fundamental shocks for the DJIA.

Figure 2: Responses of returns, volatility, and trading volume to permanent fundamental, transitory fundamental, and non-fundamental shocks for the DJIA

This figure illustrates the responses of trading volume, returns, and volatility to a one-standard shock over 30 days.



As seen in the graph, non-fundamental shocks play highly significant roles in determining trading volume. Trading volume has a strong positive initial response to non-fundamental shocks, but the effect dies off gradually in the long run. The initial effect of volume to both permanent and transitory fundamental shocks is zero, consistent with the identifying restrictions that permanent fundamental shocks and transitory fundamental shocks do not have any contemporaneous effects on volume. They do however have lagged effects on volume, though the cumulative effect tapers off gradually in the long run. This finding is not surprising since returns, volatility, and volume are simultaneously determined in an autoregressive system.

Figure 2 also shows how returns respond to various shocks. Permanent fundamental shocks have a significant positive initial effect on returns but the effect dies off very quickly, in fact in just two days. This indicates that the influence of permanent fundamental shocks on returns is usually absorbed easily and quickly. The effect of transitory fundamental shocks on returns is initially negative, but the accumulated effect dies off quickly in the long run. This finding is consistent with our identifying restriction imposed on the SVAR model that transitory fundamental shocks have no long- run effects on stock prices. Non-fundamental shocks have a significant negative initial effect on returns and this effect also diminishes quickly in the long run, causing stock price to exhibit mean reversion.

The response of volatility to various shocks is also presented in figure 2. Volatility shows a strong positive initial response to non-fundamental shocks, a strong negative response to permanent fundamental shocks, and a strong positive response to transitory fundamental shocks. However, the effect of non-fundamental shocks on volatility tapers off more quickly in the long run than the effects of permanent fundamental and transitory fundamental shocks.

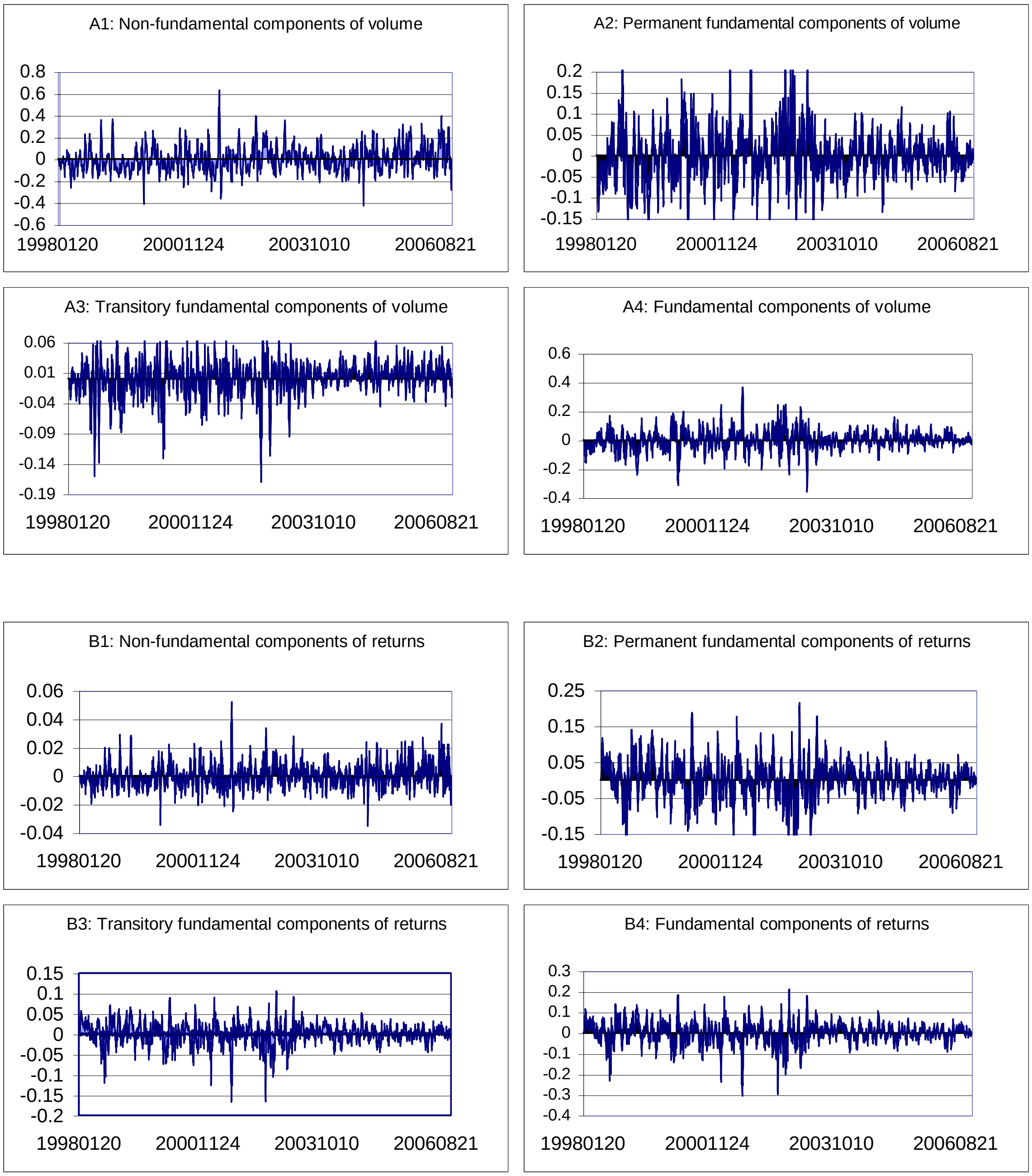
Overall, we find that the effects of these three shocks on returns dissipate fast, while the impact of various shocks on volatility and trading volume dies off more gradually.

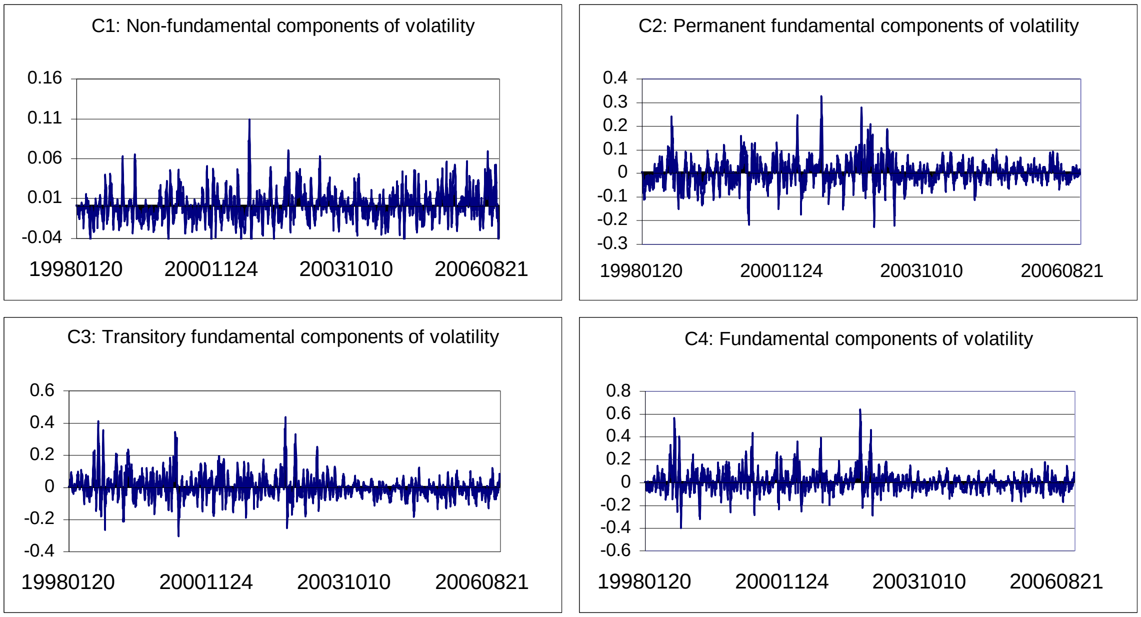
6. DECOMPOSITION OF RETURNS, VOLATILITY, AND VOLUME

By imposing the three identifying restrictions in equation (6) upon the SVAR model in equation (5) and setting two types of shocks equal to zero at one time, we can decompose returns, volatility, and volume into three components: the first one arises from the effects of permanent fundamental shocks, the second one results from the effects of transitory fundamental shocks, and the last one is due to the effects of non-fundamental shocks. Figure 3 plots the permanent fundamental, transitory fundamental, and non-fundamental components of returns, volatility, and volume of the DJIA index.

Figure 3: Decomposition of returns, volatility, and trading volume for the DJIA

This figure decomposes returns, volatility, and volume into three components: permanent fundamental, transitory fundamental, and non-fundamental components.



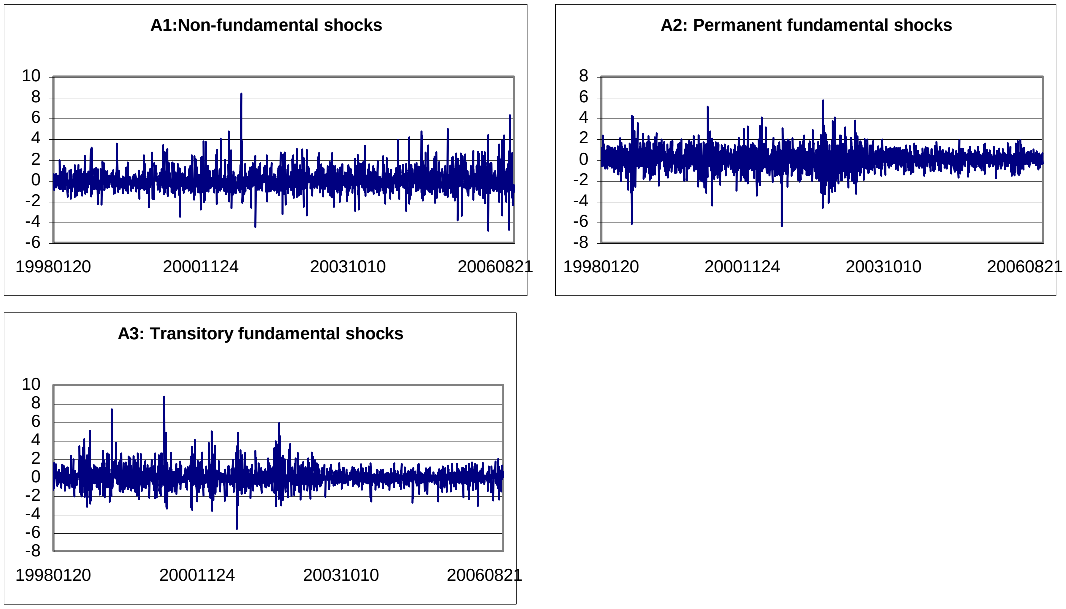


A comparison of figures A1, A2, A3, and A4 reveals that the non-fundamental component dominants the other two components in trading volume. Similarly an examination of figures B1, B2, B3, and B4 indicates that the permanent fundamental component is the dominant component for returns. A comparison of the magnitude of the three components in figures C1, C2, C3, and C4 shows that the transitory fundamental component is the most significant component for volatility. Our results confirm Karpoff (1987) and Lee and Rui (2001) that the majority of return movements reflect common fundamental information about the company or economy while volume indicates the extent to which investors disagree about the meaning of the information. These findings are consistent with our previous observations about the relative importance of the three shocks.

As mentioned above, information is a mixture of permanent fundamental, transitory fundamental, and non-fundamental shocks. At a given time, it is not easy to separate non-fundamental shocks from both types of fundamental shocks. Hence how to decompose information into the three shock components becomes an imperative task. The SVAR model used in this paper helps us achieve this separation. Permanent fundamental, transitory fundamental, and non-fundamental shocks over the sample period are plotted in figure 4 for the DJIA index. A further look at figure 4 reveals that on some occasions, non-fundamental shocks dominate other types of shocks, while at other times, fundamental shocks are dominant. This figure helps us determine when non-fundamental shocks dominate the market. In other words, this graph helps us identify the occurrence of extremely high-level non-fundamental shocks in the market.

Figure 4: Structural innovation for the DJIA

This figure illustrates the permanent and transitory fundamental shocks, and non-fundamental shocks for the DJIA.



These figures are also helpful in ascertaining whether a particular extreme return event is driven by fundamental shocks or non-fundamental shocks. For instance, figure 4 shows that in the beginning of the stock market decline in the year 2000, the transitory fundamental shocks dominate the other two shocks. Permanent fundamental shocks rank second, and non-fundamental shocks score last. This implies that the tech bubble burst in 2000 was triggered mostly by fundamental changes, and it was not just the outcome of non-informational trading.

To summarize, the trivariate SVAR model helps us separate information into its three shock components and can be used to decompose historical returns, volatility, and volume into the three components. It also helps us determine when the information flow is dominated by non-fundamental or fundamental shocks.

7. CONCLUSION

This paper uses a trivariate SVAR model to empirically estimate the effects of permanent fundamental, transitory fundamental, and non-fundamental shocks on returns, volatility, and volume. We find that permanent fundamental shocks primarily affect returns, transitory fundamental shocks mostly impact volatility, and non-fundamental shocks mainly drive trading volume. The SVAR model is also used to decompose information into its three shock components. Based on the decomposition, we can investigate whether a particular extreme return event is driven by fundamental shocks or non-fundamental shocks. The SVAR model also enables investors to identify stocks more susceptible to noise trader risk. Investors can use this model to choose stocks according to their sensitivity to noise trading and to determine when information flow is dominated by either non-fundamental or fundamental shocks.

REFERENCES

1. Akaike, H. (1973), Information theory and the extension of the maximum likelihood principle, in 2nd International Symposium on Information Theory, B. N. Petrov and F. Csaki, eds., Budapest.

2. Andersen, T. G., and T. Bollerslev. (1998). Deutsche mark-dollar volatility: intraday activity patters, macroeconomic announcements, and longer run dependences. *Journal of Finance*, vol. 53 (February 1998), pp. 219–265.
3. Anderson, T., T. Bollerslev, F. Diebold, and K. Ebens (2001), The distribution of realized stock return volatility, *Journal of Financial Economics*, Vol. 61 (July 2001), pp. 43-76.
4. Campbell, J. Y. (1991), A variance decomposition for stock returns, *Economic Journal*, Vol. 101 (March 1991), pp. 157-179.
5. Campbell, J. Y. and J. Ammer (1993), What moves the stock and bond markets? A variance decomposition for long-term asset returns, *Journal of Finance*, Vol. 48 (March 1993), pp. 3-37.
6. Campbell, J., S. Grossman, and J. Wang (1993), Trading volume and serial correlation in stock returns, *Quarterly Journal of Economics*, Vol. 108 (November 1993), pp. 905-939.
7. Campbell, J. Y., and R. J. Shiller (1988), Stock prices, earnings, and expected dividend, *Journal of Finance*, Vol. 43 (July 1988), pp. 661-676.
8. Campbell, J. Y., and R. J. Shiller (1989), The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies*, Vol. 1 (Fall 1989), pp. 195-228.
9. Cochrance, J. H. (1991), Volatility tests and efficient markets, *Journal of Monetary Economics*, Vol. 27 (April 1991), pp. 463-485.
10. De Long, J. B., A. Shleifer, L. H. Summers, and R. J. Waldman (1990), Noise trader risk in financial markets, *Journal of Political Economy*, Vol. 98 (August 1990), pp. 703-738.
11. He, H. and J. Wang (1995), Differential information and dynamic behavior of stock trading volume, *Review of Financial Studies*, Vol. 8 (October 1995), pp. 919-972.
12. Karpoff, J. M. (1987), The relationship between price changes and trading volume: a survey, *Journal of Financial and Quantitative Analysis*, Vol. 22 (May 1987), pp. 109-126.
13. Kmenta, J. (1986), *Elements of econometrics*, New York: Macmillan.
14. Lee, B. (1996), Time-series implications of aggregate dividend behavior, *Review of Financial Studies*, Vol. 9 (Summer 1996), pp. 589-618.
15. Lee, B. (1998), Permanent, temporary, and non-fundamental components of stock prices, *Journal of Financial and Quantitative Analysis*, Vol. 33 (March 1998), pp. 1-32.
16. Lee, B. and O. M. Rui (2001), Empirical identification of non-informational trades using trading volume data, *Review of Quantitative Finance and Accounting*, Vol. 17 (December 2001), pp. 327-350.
17. Marsh, T. A. and R. C. Merton (1986), Dividend variability and variance bounds tests for the rationality of stock market prices, *American Economic Review*, Vol. 76 (June 1986), pp. 483-498.
18. Mixon, S. (2001), Volatility and volume: news or noise, *The Financial Review*, Vol. 36 (November 2001), pp. 99-118.
19. Schwarz, G. (1978), Estimating the dimension of a model, *The Annals of Statistics*, 6 (No.2, March), pp. 461-464.
20. Wang, J. (1994), A model of competitive stock trading volume, *Journal of Political Economy*, Vol. 102 (February 1994), pp. 127-168.