# A Simultaneous Equations Model of Returns, Volatility, and Volume with Intraday Trading Dynamics

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### Abstract

This paper extends the finance literature by modeling stock returns, volatility, and volume in a simultaneous equations model while incorporating the effects of trading dynamics on these three variables. Evidence shows that returns, volatility, and volume are interrelated. However, research typically examined them as three separate relationships between each pair of the three variables. Prior literature has also failed to examine the impact of intraday trading dynamics on returns, volatility, and volume. This study overcomes both limitations. Using a simultaneous equations model that incorporates feedbacks among these three variables, this study documents that intraday skewness has significant impacts on daily returns, volatility, and volume. In addition, the two-way relationships between the variables change significantly when they are estimated simultaneously. The findings in this study deepen our understanding of the relationships between returns, volatility, and volume and have important implications for traders, portfolio managers, and other market participants.

Keywords: Stock returns, Stock volatility, Stock volume, Intraday trading dynamics

## 1. Introduction

Finance literature has long suggested that human psychology can affect stock market behavior. Kramer (2001) suggests that human depression plays an important role in the intraday return pattern. Consequently, human optimism or positive feedback trading can also play important roles in generating returns, volatility, and volume. Bange (2000) asserts when investors are overconfident (or too optimistic) and hence slow to acknowledge and process information, positive feedback trading can result. DeLong, et. al (1990) suggest that feedback trading investors try to discover trends in past stock prices and make their investment decisions hoping that these trends will persist. Positive feedback trading asserts that investors expect past trends to continue and hence increase their holdings of equities after stock market run-ups and decrease their holdings after downturns. One consequence of this large number of feedback traders in the stock market is the potential predictability of stock returns, volatility, and volume.

Positive feedback trading is defined as intraday trading dynamics in this study. Intraday trading dynamics also indicate the existence of herding behavior among investors. Prior research shows that when investors herd, they do so primarily as positive feedback traders, expecting past trends to continue. This study measures intraday trading dynamics with the skewness of intraday returns and the logarithm of sequences to reversals ratio of intraday price change. We argue that the series of intraday returns can provide valuable information about the trading process.

Daily trading volume is the sum of all transactions that occur during a given day. When a transaction takes place, investors have no means by which to predict with certainty the closing price. However, they are able to obtain information about distribution and the sequence of prior price changes before either the closing price or the day's return is known. It is thus reasonable to assume that daily trading volume, daily volatility and daily return can be influenced by the sequence of price changes during a given day.

Relationships between stock returns, volatility, and trading volume have long been interests of financial academics. Existing literature shows that little has been conducted to examine the effects of intraday trading dynamics on the daily return-volatility-volume relationship. In addition, few studies investigate the relationships between stock returns, volatility, and volume altogether in a simultaneous framework. Prior studies have generally examined relationships of these three inter-related variables only in pairs. Finance literature [e.g. Tauchen and Pitts (1983),

Anderson (1996), Liesenfeld (1998), and Liesenfeld (2001)] shows returns, volatility, and volume are dynamically and simultaneously determined by the same information flow process, thus utilizing them in a simultaneous system to observe their relationships would be more beneficial.

The contribution of this study is two-fold. First, we demonstrate that intraday trading dynamics play a significant role in the determination of returns, volatility, and volume whether operating under a single equation model or under a simultaneous equations model. Second, we examine how the two-way relationships between returns, volatility, and volume change when estimated simultaneously. The simultaneous equations approach yields new insights into relationships between returns, volatility, and volume.

The remainder of this study is organized as follows. Sections 2 and 3 discuss the related research and the data. Sections 4 and 5 incorporate the methodology and empirical results. Section 6 concludes with a summary of the evidence.

### 2. Previous Research

In general, prior literature reports a positive contemporaneous relationship between returns and volume. Wood, et. al (1985) report a positive correlation between trading volume and magnitude of price change at the transaction level for stocks traded at NYSE for the period of 1971 to 1972 and for the year 1982. Jain and Joh (1988) observe a similar correlation on one-hour interval data of the market index from 1979 to 1983. Karpoff (1987) provides an extensive review of relations between returns and volume found in previous studies.

Chen et.al (2001) document a positive relation between volume and contemporaneous absolute value of the stock price change using index data for nine national markets, namely, the U.S., Japan, the U.K., France, Canada, Italy, Switzerland, the Netherlands, and Hong Kong from 1973 to 2000. Their model, however, only considers the effect of returns on contemporaneous volume and ignores the impact of volume on contemporaneous returns.

Kocagil and Shachmurove (1998) and Lee and Rui (2002) show that returns and volume are not exogenous to each other and are jointly determined. Using daily data from 1985 to 1995 of 16 major futures contracts in the U.S, Kocagil and Shachmurove (1998) find a positive contemporaneous relationship between volume and absolute return using a bivariate autoregressive model of volume and absolute returns. Using a similar bivariate model of returns and volume, Lee and Rui (2002) report a positive contemporaneous relationship between returns and volume on the daily market index from the New York, London and Tokyo exchanges. Though both Kocagil and Shachmurove (1998) and Lee and Rui (2002) use a bivariate autoregressive model of returns and volume, they fail to take volatility into account in their models. As returns, volatility, and volume are simultaneously determined, any model that ignores any one of these three variables is incomplete and could lead to incorrect inferences regarding the relationships between them.

Research results on the relationship between returns and volatility are mixed. Most of the studies focus on conditional, rather than unconditional, volatility. French et. al (1987) and Campbell and Hentschel (1992) find, with conditional volatility, a negative contemporaneous correlation between aggregate returns and aggregate volatility with an ARCH-like model. Similarly, Cheung and Ng (1992) find a strong negative intertemporal relationship between stock returns and conditional volatility by fitting EGARCH models to 251 firms on CRSP.

Studies by Duffee (1995) and Chen and Zhou (2001) provide more evidence pertaining to the contemporaneous relationships between returns and volatility. Duffee (1995) documents a positive contemporaneous relationship at the firm level between firm stock returns and firm stock volatility and a negative contemporaneous relationship at the aggregate level using daily data on the NYSE and AMEX from 1962 to 1991. Using daily returns on stocks traded at the NYSE from January 1963 to December 1995, Chen and Zhou (2001) also find a negative contemporaneous relationship between size portfolio returns and market volatility using an approach similar to that by Duffee (1995). This finding is consistent with results found at the aggregate level by Duffee (1995), but is inconsistent with the findings at the individual firm level by Duffee (1995).

The robust relationship between volatility and volume has been largely documented as positive. Jones, et. al (1994) examine the volatility-volume relationship using daily data on stocks traded on the NASDAQ-NMS system from 1986 to 1991. They observe a positive relationship between trading volume and contemporaneous volatility. They also find that the documented positive volatility-volume relationship reflects a positive relationship between volatility and the number of transactions. However, they find the size of a transaction has no impact on volatility. Chan and Fong (2000) draw a similar conclusion on the relationship between volume and contemporaneous volatility with research based on a random selected sample of NYSE-listed and NASDAQ-listed common stocks from July to December 1993. They argue that both the number of trades and the size of trades play significant roles in the

volatility-volume interaction. Daigler and Wiley (1999) also document a positive relationship between volatility and volume. However, they argue that it is the general public, who has no precise information on order flows, that drives the positive volatility-volume relationship. They also find that trading by clearing members and floor traders often decreases volatility. Darrat, Rahman, and Zhong (2003) use an EGARCH model to examine the contemporaneous correlation between trading volume and volatility of all the component stocks of DIJA and find no significant correlation between volume and volatility.

One commonality of studies by Jones, Kaul and Lipson (1994), Chan and Fong (2000), and Daigler and Wiley (1999) is that they involve only the impact on volatility from different components of trading volume and ignore the possible effect of volatility on trading volume. Wang and Yau (2000) use a three-equation structural model of trading volume, bid-ask spread, and price volatility for two financial and two metal futures from the CME and the COMEX from January 2, 1990 to April 29, 1994. They find a positive relationship between trading volume and volatility after other factors are controlled for. Although Wang and Yau (2000) allow volatility and volume to be jointly estimated, they fail to include returns into their simultaneous model.

Xu (2013) proposes a vector multiplicative error model for the dynamics of duration, volume and volatility to capture the dynamics of the trivariate system. He find that when a higher number of informed traders are present in the market, trades with larger size or times with greater activity are present in the market too. However, Xu (2013) does not explicitly consider returns in his model.

While there is an extensive empirical literature on the three two-way relationships between returns, volatility, and volume, their findings are inconsistent and ambiguous. This lack of clarity and consistency may be due to the fact that the inter-relationship of the variables has not been examined. This study seeks to remedy that.

### 3. Data

To mitigate the thin trading problem and firm-specific risk, this study focuses on the DJIA index, which is comprised of 30 blue-chip stocks. Daily returns and daily trading volume are obtained from the COMPUSTAT database, and the intraday data are taken from Pi Trading Company. The sample period covers January 1998 to December 2013.

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.

$$R_{it} = \log(P_{it} + D_{it}) - \log P_{i(t-1)}$$
(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 the sum of absolute returns (SAR) using the equation by Anderson and Bollerslev (1998) based on five-minute horizon returns. Anderson et. al (2001) suggest using five-minute horizon for transaction level data since 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.

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

where  $\sigma_{it}$  is the daily volatility of security i on day t,  $R_{itp}$  is the return of security i at the p<sup>th</sup> five-minute horizon on day t, where *n* is the number of five-minute intervals during the day.

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.

#### 4. Methodology

In this study, intraday trading dynamics are measured by the skewness of intraday returns. Bookstaber and Clarke (1985) suggest that feedback-driven trading adds positive skewness to return distributions. Taylor and Yoder (1999) apply this assertion to compare the performance of load and no-load funds. These studies support the use of intraday skewness to measure the positive feedback effect in intraday trading dynamics. A positive intraday skewness

suggests greater positive feedback effects, while a negative intraday skewness indicates the lack of positive feedback trading during the day.

Intraday trading dynamics are also measured by the logarithm of sequences to reversals ratio of intraday price change. The sequences to reversals ratio is proposed by Cowles and Jones (1937) and has been used widely to test for randomness of stock prices. Cowles (1960) concludes that the sequences to reversals ratio disclose a tendency toward persistence in stock price movements. Therefore, sequences to reversals ratios can reasonably be used to measure the intraday positive feedback effect. Since the sequences to reversals ratio is always positive, we create a logarithm of the ratio. A positive value indicates that there are more sequences to reversals in the return series, and thus a greater positive feedback effect, while a negative value indicates the lack of a positive feedback effect.

The existence of and the magnitude of intraday dynamics, as measured herein, are expected to affect daily trading. When positive intraday skewness occurs, the return sequence has more positive changes and investors become optimistic about the stock. This optimism is likely to cause investors to trade more frequently. When negative intraday skewness occurs, the return sequence has more negative changes and investors become confused, which causes investors to delay their decisions until more information is available.

A high positive realization of logarithms of sequences to reversals ratio reveals a similar situation. It indicates either a buy-side or a sell-side positive feedback effect in the market where investors become optimistic and tend to trade more frequently. By contrast, a high negative realization of logarithms of sequences to reversals indicates that the return moves up and down so frequently that there is no pattern of persistence in the series. Similar to when negative intraday skewness occurs, until they receive new information, investors would be likely to delay their investment decision.

### 4.1 Single Equation Model Specification

To gauge the impact of intraday trading dynamics on returns, volatility, and volume, this study first focuses on a single equation model of these three variables. In the returns equation, we use lagged values of returns to control the autocorrelation in return series. Contemporaneous daily volatility and daily volume are also included to observe their effect on returns. In the volatility equation, we include the lagged values of daily volatility to control the persistence in volatility that has been observed in prior research. We also include contemporaneous return and volume in the model. Similarly, in the volume equation, we include the lagged values of daily volume to control the relationship in volume. Contemporaneous daily returns and daily volatility are also included to observe their effect on returns.

$$R_{it} = \alpha_i^R + \lambda_i^R R_{i(t-1)} + \rho_{i1}^R \sigma_{it} + \beta_{i1}^R V_{it} + \varphi_i^R skew_{it} + \gamma_i^R R R_{it} + \eta_{it}^R$$
(3)

$$\sigma_{it} = \alpha_{i}^{\sigma} + \lambda_{i}^{\sigma} \sigma_{i(t-1)} + \rho_{i1}^{\sigma} V_{it} + \beta_{i1}^{\sigma} R_{it} + \varphi_{i}^{\sigma} skew_{it} + \gamma_{i}^{\sigma} RR_{it} + \eta_{it}^{\sigma}$$

$$\tag{4}$$

$$V_{it} = \alpha_{i}^{V} + \lambda_{i}^{V} V_{i(t-1)} + \rho_{I1}^{V} \sigma_{it} + \beta_{I1}^{V} R_{it} + \varphi_{I}^{V} skew_{it} + \gamma_{I}^{V} R R_{it} + \eta_{it}^{V}$$
(5)

where  $\sigma_{it}$  is the daily volatility for security i on day t,  $V_{it}$  is the trading volume for security i on day t, measured by daily turnover ratio, and  $R_{it}$  is the daily return of security i on day t. The lagged values of  $R_{it}$ ,  $\sigma_{it}$ , and  $V_{it}$ are used to control the persistence in return, volatility and trading volume.  $skew_{it}$  is the intraday skewness calculated from intraday five-minute horizon data.  $RR_{it}$  is the natural logarithm of sequences to reversals ratios of price changes in five-minute horizon data. The single equation regression is used to investigate how relationships between returns, volatility, and volume change after incorporating the effect of intraday trading dynamics.

# 4.2 Simultaneous Equations Specification

Prior research examines returns, volatility, and volume in pairs only and fails to incorporate their interrelation. To overcome this limitation, we construct a simultaneous equations model. Using the same specification as for single equation, we estimate return equation, volatility equation and volume equation simultaneously. In this simultaneous system, daily returns, daily volatility, and daily volume are treated as endogenous variables, while intraday skewness and logarithms of sequences to reversals ratio are treated as exogenous variables, which measure intraday trading dynamics.

This simultaneous system includes the equation (6), (7) and (8). The simultaneous model has a very similar setup with each single equation model, but is estimated together using 3SLS method.

$$R_{it} = \alpha_i^R + \lambda_i^R R_{i(t-1)} + \rho_{i1}^R \sigma_{it} + \beta_{i1}^R V_{it} + \varphi_i^R skew_{it} + \gamma_i^R R R_{it} + \eta_{it}^R$$
(6)

$$\sigma_{it} = \alpha_{i}^{\sigma} + \lambda_{i}^{\sigma} \sigma_{i(t-1)} + \rho_{i1}^{\sigma} V_{it} + \beta_{i1}^{\sigma} R_{it} + \varphi_{i}^{\sigma} skew_{it} + \gamma_{i}^{\sigma} RR_{it} + \eta_{it}^{\sigma}$$

$$\tag{7}$$

$$V_{it} = \alpha_i^V + \lambda_i^V V_{i(t-1)} + \rho_{I1}^V \sigma_{it} + \beta_{I1}^V R_{it} + \varphi_I^V skew_{it} + \gamma_I^V RR_{it} + \eta_{it}^V$$
(8)

Where  $\sigma_{it}$  is the daily volatility for security i on day t,  $V_{it}$  is the trading volume for security i on day t, measured by daily turnover ratio, and  $R_{it}$  is the daily return of security i on day t. The lagged values of  $R_{it}$ ,  $\sigma_{it}$ , and  $V_{it}$ are used to control the persistence in return, volatility and trading volume.  $skew_{it}$  is the intraday skewness calculated from intraday five-minute horizon data.  $RR_{it}$  is the natural logarithm of sequences to reversals ratios of price changes in five-minute horizon data.

In this simultaneous model, contemporaneous volatility, contemporaneous volume and past realizations of returns determine the returns. Similarly, contemporaneous return, contemporaneous volume, and past realizations of volatility determine volatility. Likewise, volume is determined by contemporaneous returns, contemporaneous volatility and past realizations of volume. The feedback effects between returns, volatility, and volume are therefore incorporated into the simultaneous equations model.

For unique and consistent estimates of the parameters in this simultaneous equations system, each of the three equations (return equation, volatility equation and volume equation) needs to be uniquely identified. Order condition and rank condition are both used to check whether each equation is exactly identified [see Greene (1997)]. Order condition asserts that the total number of variables (endogenous and exogenous) missing from the equation under consideration must be equal to the number of endogenous variables in the system minus one. Since our endogenous variables total three in number - daily returns, daily volatility, and daily volume - the total number of variables missing from each equation should equal to two. This is true in our system given the model specification. By design, the return equation doesn't include past volatility and past volume; the volatility. Each equation is thus missing two variables. All of the equations in the system are identified precisely according to order condition. However, order condition is necessary but not a sufficient condition for identification. Instead, rank condition needs to be satisfied.

Equation	$R_{it}$	$\sigma_{_{it}}$	V <sub>it</sub>	$R_{i(t-1)}$	$\sigma_{_{i(t-1)}}$	$V_{i(t-1)}$	skew <sub>it</sub>	RR <sub>it</sub>
Returns	1	$ ho_{i1}^{\scriptscriptstyle R}$	$\beta_{i1}^{R}$	$\lambda^{\scriptscriptstyle R}_i$	0	0	$\varphi_i^{\scriptscriptstyle R}$	$\gamma_i^R$
Volatility	$eta_{i1}^{\sigma}$	1	$ ho_{i1}^{\sigma}$	0	$\lambda_i^\sigma$	0	$arphi_i^\sigma$	$\gamma_i^{\sigma}$
Volume	$\boldsymbol{\beta}^{\scriptscriptstyle V}_{\scriptscriptstyle I1}$	$ ho_{I1}^{\scriptscriptstyle V}$	1	$oldsymbol{eta}^{\scriptscriptstyle V}_{\scriptscriptstyle I2}$	0	0	$\pmb{arphi}_I^V$	$\gamma_{I}^{V}$

The rank condition is satisfied in the above matrix. We are thus able to obtain unique and consistent estimates for all the parameters in this system. The standard three-stage least squares method is used to estimate the system, which takes into consideration the correlations between equations.

#### 5. Empirical Results

Empirical results from both the single and the simultaneous equations models are presented in this section. Table 1 depicts the estimation results of daily return under a single equation model with and without various intraday trading dynamics.

With no intraday dynamics in the model, the return is negatively affected by contemporaneous volatility, which is consistent with French et. al (1987) and Campbell and Hentschel (1992). When intraday dynamics are introduced, the negative contemporaneous relationship between return and volatility still holds. Intraday skewness is shown to have a significant positive impact on daily return. This indicates the existence of positive feedback trading which leads to increased returns. In addition, the logarithm of sequences to reversal ratio is shown to have some impact on daily return.

	-			
Variables	Return	Return	Return	Return
	0.0021**	0.0013	0.0022*	0.0017*
Constant	(0.0009)	(0.0008)	(0.0009)	(0.0008)
L D. t	-0.0346	0.0153	-0.0346	0.0157
Lag Return	(0.0211)	(0.0187)	(0.0211)	(0.0187)
V-1-4114	-0.3585**	-0.1781**	-0.3591**	-0.1800**
Volatility	(0.0590)	(0.0524)	(0.0591)	(0.0523)
37.1	0.0248	-0.0124	0.0246	-0.0137
Volume	(0.0219)	(0.0193)	(0.0219)	(0.0193)
т. 1		0.0038**		0.0038**
Intraskew		(0.0001)		(0.0001)
<i></i>			-0.00005	-0.0003*
Seqrev			(0.0001)	(0.0001)

m 1 1 1	<b>C</b> <sup>1</sup>	<b>-</b>	c	D .	1.1	<b>T</b> , 1		- ·
Table I	Single	Eduation	tor	Returns	with	Intraday	Trading I	Dynamics
rable r.	Single	Lquation	101	Returns	VV I LII	muaday	i raung i	Jynamics

Note: Volatility is measured by intraday return volatility calculated from intraday return, Volume is measured by turnover ratio, Standard errors are given in parenthesis,

\*\* and \* : significant at 1% and 5% level; respectively.

Table 2 displays the estimation results of daily volatility when a single equation model is applied. The positive impact of lagged volatility on volatility is significant, which is consistent with Jones, et. al (1994) and Chan and Fong (2000). Volatility is persistent with and without the existence of intraday trading dynamics. Volatility is also negatively affected by contemporaneous returns and positively affected by contemporaneous volume. In addition, intraday skewness plays an important role in explaining daily volatility. Intraday skewness is found to negatively affect volatility. This result suggests that positive feedback trading reduces volatility, while a lack of persistence increases volatility. Results also show the effects of logarithms of sequences to reversals ratio on volatility is very minimal in this single equation model.

Variables	Volatility (1)	Volatility	Volatility	Volatility
	-0.0004*	-0.0004*	-0.0004*	-0.0004*
Constant	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Determ	-0.0558**	-0.0476**	-0.0558**	-0.0478**
Return	(0.0042)	(0.0048)	(0.0042)	(0.0049)
Les Valatilite	0.7950**	0.7938**	0.7948**	0.7936**
Lag Volatility	(0.0116)	(0.0116)	(0.0116)	(0.0116)
Valuera	0.0546**	0.0555**	0.0544**	0.0553**
Volume	(0.0044)	(0.0044)	(0.0044)	(0.0044)
Ter tao alsossa		-0.0001**		-0.0001**
Intraskew		(0.00003)		(0.00003)
Seqrev		-0.00004	-0.00003	
			(0.00003)	(0.00003)

Table 2. Single Equation for Volatility with Intraday Trading Dynamics

Note: Volatility is measured by intraday return volatility calculated from intraday return, Volume is measured by turnover ratio, Standard errors are given in parenthesis,

\*\* and \* : significant at 1% and 5% level; respectively.

Table 3 shows the estimation results of daily volumes in single equation model. The significant positive impact of lagged volume indicates the persistence of volume. Contemporaneous volatility also has a significant positive effect

on volume, a finding consistent with Jones, et. al (1994) and Chan and Fong (2000). The intraday skewness plays a significantly positive role in explaining the trading volume. In contrast, the logarithm of sequences to reversals ratio has no significant impact on trading volume. Overall results suggest that intraday positive feedback trading does contribute significantly to increased daily volume.

Variables	Volume	Volume	Volume	Volume
	0.0099**	0.0099**	0.0100**	0.0100**
Constant	(0.0006)	(0.00067)	(0.0006)	(0.0006)
Datum	-0.0060	-0.0284	-0.0060	-0.0292
Return	(0.0148)	(0.0168)	(0.0148)	(0.0168)
Valatility	0.4395**	0.4458**	0.4385**	0.4447**
Volatility	(0.0403)	(0.0403)	(0.0403)	(0.0403)
Log Volumo	0.6622**	0.6604**	0.6620**	0.6600**
Lag Volume	(0.0150)	(0.0150)	(0.0150)	(0.0150)
Intro als ass		0.00037**		0.0003**
Intraskew		(0.0001)		(0.0001)
Seqrev			-0.0001	-0.0001
			(0.0001)	(0.0001)

 Table 3. Single Equation for Volume with Intraday Trading Dynamics

Note: Volatility is measured by intraday return volatility calculated from intraday return, Volume is measured by turnover ratio, Standard errors are given in parenthesis,

\*\* and \* : significant at 1% and 5% level; respectively.

The results from single equation models show that intraday skewness plays an important role in generating returns, volatility, and volume. Intraday skewness leads to increased returns and trading volume but reduced volatility for the day. We also found a negative contemporaneous two-way relationship between return and volatility, and a positive contemporaneous two-way relationship between volume and volatility. Both volatility and volume have a persistent pattern.

Table 4 depicts the findings in a simultaneous equations model with and without intraday trading dynamics. Panels A, B, and C of table 4 provide the estimations under a simultaneous equations model for returns, volatility, and volume, respectively. For each panel, the three models include intraday skewness, the logarithms of sequences to reversals ratio and both intraday skewness and logarithms of sequences to reversals ratio, respectively.

Panel A shows that both contemporaneous volatility and lagged return have significant positive impact on returns under the simultaneous equations model. This is different from the results from the single equation model. Evidence also supports an important role intraday skewness plays in explaining returns under the simultaneous system. This is consistent with the findings under the single equation model.

Panel B indicates that volatility is persistent and has a significant positive effect from lagged volatility. However, the negative effect of contemporaneous return on volatility is not significant under a simultaneous model. This differs from the results documented under the single equation model. In addition, the intraday skewness was found to have a significant negative impact on volatility under the simultaneous model, a finding consistent with that under the single equation model.

Data in Panel C support that daily volume is persistent and is positively affected by lagged volume significantly. However, the positive relationship between volume and volatility documented under the single equation model is not found under the simultaneous framework. As with the single equation model, the intraday skewness appears to have a positive impact on volume under the simultaneous model.

	Pa	nel A: Returns	
Variables	Return	Return	Return
0	-0.0017	-0.0020	-0.0014
Constant	(0.0012)	(0.0013)	(0.0012)
Log Dotum	0.0379*	-0.0039	0.0384*
Lag Return	(0.0190)	(0.0217)	(0.0190)
<b>X</b> 7 - 1 - 4:1:4	0.1493*	0.1150	0.1480*
Volatility	(0.0632)	(0.0722)	(0.0632)
Values	-0.0019	0.0331	-0.0033
Volume	(0.0277)	(0.0316)	(0.0277)
Tutus alsoss	0.0039**		0.0039**
Intraskew	(0.0001)		(0.0001)
Commen		0.0000	-0.0002
Seqrev		(0.0001)	(0.0001)

### Table 4. Simultaneous Equations for Returns, Volatility, and Volume

	Par	nel B: Volatility	
Variables	Volatility	Volatility	Volatility
Constant	0.0018	0.0101	0.0022
Constant	(0.0012)	(0.0211)	(0.0012)
Return	-0.9923	4.0036	-0.9760
Ketulli	(0.5489)	(11.7007)	(0.5320)
Lee Veletilite	0.9323**	0.4388	0.9291**
Lag Volatility	(0.0786)	(1.1462)	(0.0761)
Volume	-0.0458	-0.1549	-0.0474
volume	(0.0277)	(0.3628)	(0.0274)
Intraskew	-0.0035*		-0.0035*
Intraskew	(0.0018)		(0.0018)
C a grant		0.0000	-0.0002
Seqrev		(0.0006)	(0.00018)

Panel C: Volume			
Variables	Volume	Volume	Volume
Constant	0.0110**	0.0296	0.01168**
Constant	(0.0019)	(0.0604)	(0.0017)
Datar	-1.4899	9.7142	-1.4640
Return	(0.8266)	(36.0915)	(0.8040)
<b>T7 1 (11)</b>	0.0712	-1.2215	0.0653
Volatility	(0.1432)	(4.1811)	(0.1395)
Loo Volumo	0.6891**	0.4685	0.6871**
Lag Volume	(0.0315)	(0.8473)	(0.0311)
T., (	0.0058*		0.0058*
Intraskew	(0.0029)		(0.0029)
C a mart		0.0000	-0.0004
Seqrev		(0.0014)	(0.00028)

Note: Volatility is measured by intraday return volatility calculated from intraday return, Volume is measured by turnover ratio, Standard errors are given in parenthesis,

\*\* and \* : significant at 1% and 5% level; respectively.

To summarize, intraday skewness is found to have a significant impact on the daily returns, volatility, and volume under both a single equation model and a simultaneous model. This indicates the existence of positive feedback trading in the stock market. When estimated simultaneously, the only robust contemporaneous relationship is the positive impact on return from contemporaneous volatility.

### 6. Conclusion

This study documents significant impact of intraday skewness on daily returns, volatility, and volume under both the single equation model and the simultaneous model. In general, intraday trading dynamics positively affect returns and volume but negatively affect volatility. This supports that positive feedback trading increases returns and volume but reduces volatility.

When estimated in pairs under the single equation models, this study finds that (1) return is negatively affected by contemporaneous volatility, (2) volatility is negatively affected by contemporaneous returns and positively affected by contemporaneous volatility. However, under the simultaneous model, the only contemporaneous relationship found is the positive impact which contemporaneous volatility has on returns. All other documented contemporaneous relationships under a single equation model cease to exist.

Practically, these findings have important implications for market participants. Since intraday trading dynamics can be useful to explain daily returns, volatility, and volume, intra-month and intra-week trading dynamics may as well be useful in explaining monthly and weekly return, volatility, and volume. These results also seem to validate the reasoning behind the stated investment strategy of many market participants, e.g., technicians who actively monitor the movement of stock prices within each day. Future research would be useful in determining which technical indicators of intra-day trading dynamics best help predict daily return, volatility, and trading volume and to what degree. While the results presented here imply that intraday trading dynamics can provide valuable information about daily stock returns, future research could focus on determining if transactions costs for trading based on such relationships that may be higher lead to net profits.

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