



On the Problem of Identifying the Appropriate Price Variable to Study the Price-Volume Relation

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Abstract

Model selection tests and criteria are employed to identify empirically the most appropriate price variable for the purpose of studying the price-volume relation. Five different price variables are considered as explanatory variables in model selection tests, which are carried out on a bilateral basis using data on stock prices and trading volume in eleven markets/indices. The results show that the most appropriate price variable varies from one market to another although two price variables appear to be dominant: the extreme value variance and the absolute price change. The results do not provide much support for the notion of asymmetry in the price-volume relation. It is suggested that it may be useful to use non-nested model selection tests and criteria to identify the most appropriate price variable before testing for causality, which is the principal tool used for examining the price-volume relation.

Keywords: Price-volume relation, Stochastic volatility, Non-nested model selection tests

1. Introduction

The objective of this paper is to identify, on an empirical basis, the most appropriate price variable that can be used to study the price-volume relation in stock markets. This relation has attracted the attention of financial economists because of its implications for the functioning and regulation of financial markets. For example, if lagged volume determines current price volatility then current volume can be used to predict future volatility, implying the violation of the notion of informational efficiency. A finding like this can also be of use for regulators in deciding the desirability of market restrictions. Furthermore, the relation can be used to formulate a trading rule, if it turns out that current and past trading volumes convey information about future price movements. In his classic survey of studies of the price-volume relation, Karpoff (1987) put forward four reasons why this relation is important: (i) it provides insight into the structure of financial markets; (ii) it is important for event studies that use a combination of price and volume data from which to draw inferences; (iii) it is critical to the debate over the empirical distribution of speculative prices; and (iv) it has significant implications for research into futures markets.

Studies of the price-volume relation employ one or more of several price variables: the absolute price change, the price change per se (the signed price change), the conditional variance of the price change derived from ARCH and GARCH models, and the squared price change. The results of these studies seem to be sensitive to the choice of the price variable. For example, by using an ARCH specification, Lamoureux and Lastrapes (1990) found that volume has a positive contemporaneous but not a lagged effect on volatility. Conversely, Najand and Yung (1991) conclude, by using a GARCH specification, that the price-volume relation is not contemporaneous but rather lagged. On the other hand, Foster (1995) concludes, by using a GARCH specification, that price volatility is better explained by previous volatility rather than by contemporaneous or lagged volume. In earlier research, more evidence was found for positive correlation between volume and the absolute price change than between volume and the price change per se. Moosa and Bollen (2003) used non-nested model selection tests and information criteria to show that realised volatility (which is calculated from intra-day data) is more appropriate than measures based on GARCH models. The objective of this paper is to extend the work of Moosa and Bollen by “running

matches” between potential price variables in an attempt to find out the most suitable price variable, using data on 11 developed and emerging stock markets.

2. Background

Earlier work on the price-volume relation predominantly used one or both of the two price variables: the absolute price change and the price change per se. The choice between the price change per se and the absolute price change has implications for asymmetry in the price-volume relation, as using the absolute price change implies symmetry, meaning that large volumes are associated with large price changes, irrespective of the sign of the price change. This was the essence of Yin’s (1966) work, which sparked subsequent work on asymmetry in the price-volume relation.

With the popularisation of the ARCH/GARCH models in the 1980s, economists started using ARCH/GARCH measures of price volatility to study the price-volume relation. According to Foster (1995, p 937) the ARCH/GARCH measures are more objective than the biased measures of price volatility used previously (the absolute price change and the price change per se). One justification for using ARCH/GARCH models for investigating the price-volume relation is that heteroscedasticity in returns results from a mixture of distributions. Lamoureux and Lastrapes (1990) argue that the mixture of distributions hypothesis, advocated by Clark (1973) and by Epps and Epps (1976), can be represented by a GARCH model whose specification is derived from correlation in the directing variable: the rate of information arrival. The underlying argument goes as follows: when information (proxied by volume) enters the market in clusters, this leads to the clustering commonly observed in asset returns, which can be represented by a GARCH process. Arguably, this observation is also consistent with the sequential information arrival hypothesis due to Copeland (1976). While both hypotheses imply the presence of a positive contemporaneous relation between price volatility and volume, the lagged relation is portrayed differently: the sequential information arrival hypothesis predicts bidirectional causality whereas the mixture of distributions hypothesis (or at least one of its versions) predicts unidirectional causality running from volume to volatility.

Studies of the price-volume relation using ARCH/GARCH price measures have produced mixed empirical evidence. Lamoureux and Lastrapes (1990) investigated actively traded stocks to find out whether the ARCH effect commonly found in stock returns is due to time dependence in the process generating information. The daily rate of information flow into the market was proxied by trading volume. The introduction of volume into the conditional variance equation was found to make the ARCH effect disappear from the equations representing the majority of stocks considered, a finding implying that volume can explain, and hence cause, price volatility. In order to avoid the simultaneity bias problem, lagged volume was used, but this variable was found to have little explanatory power. Najand and Yung (1991) examined the price-volume relation using data on T-bond futures with a GARCH model. The results revealed positive contemporaneous correlation between volume and volatility in only a few cases, a result that they attributed to simultaneity bias. When lagged volume was used, correlation became positive in all cases.

Although Foster (1995) claims that ARCH/GARCH measures of volatility are more appropriate than those previously used (the absolute price change and the price change per se), Moosa and Bollen (2003) argue that the concept of realised volatility (Anderson et al, 1999) is more appropriate than the GARCH measure. The problem with realised volatility, however, is that it is calculated from intra-day data, which makes it unusable in an investigation based on daily data. As an alternative to the ARCH/GARCH measures, Koopman et al (1999) advocate the use of stochastic volatility, which has two main attractions, compared to the more often-used ARCH/GARCH model. The first is that the stochastic volatility model is the discrete time analogue of the continuous time model used in option pricing (for example, Hull and White, 1987). The second is that the statistical properties of stochastic volatility are easy to determine. However, it must be mentioned that under certain conditions the stochastic volatility model is similar to a GARCH(1,1) model or an IGARCH(1,1) model. Stochastic volatility has never been used in studies of the price-volume relation.

Another price measure that has been used in studies of the price-volume relation and the maturity effect is the extreme value variance, which is calculated from the trading period’s high and low prices. For example, Serletis (1992) used this measure in his study of the price-volume relation in energy futures contracts, providing evidence for the presence of the maturity effect (futures prices become more volatile and volume increases as contracts approach maturity). Herbert (1995) used the same measure in his study of the natural gas futures contracts and found that past levels of trading volume influence current price volatility, and that past price volatility has much less effect on current trading volume.

The empirical work presented in this paper involves the use of model selection tests and criteria to identify the most appropriate price variable out of the five variables described in this section: the price change per se, the absolute price change, the squared price change, stochastic volatility and the extreme value variance. In each case of the eleven markets examined here, one price measure is tested against another, which gives ten “bilateral” cases for each market. In the following section, the tests and price measures are described.

3. Methodology

Volume can be specified as an ARDL model of a price variable as follows:

$$v_t = \delta + \sum_{i=1}^p \phi_i v_{t-i} + \sum_{i=1}^p \psi_i x_{t-i} + \xi_t \tag{1}$$

Where v is the (logarithm of) trading volume and x is a price variable. Consider the following two models, M_1 and M_2 , representing two versions of equation (1)

$$M_1 : v = X_1\beta_1 + \xi_1 \quad (2)$$

$$M_2 : v = X_2\beta_2 + \xi_2 \quad (3)$$

where X_1 is an observation matrix on lagged volume and lagged price variable x_1 , X_2 is an observation matrix on lagged volume and lagged price variable x_2 , β_1 and β_2 are unknown regression coefficient vectors, and ξ_1 and ξ_2 are disturbance vectors. The models M_1 and M_2 are said to be non-nested if the regressors of either of them cannot be expressed as an exact linear combination of the regressors of the other.

The first of the non-nested model selection tests is the *JA* test due to Fisher and McAleer (1981). The test statistic for the null hypothesis that M_1 is preferred to M_2 is the t ratio of λ in the OLS regression

$$y = X_1\beta_1 + \lambda(A_2X_1\hat{\beta}_1) + u \quad (4)$$

where $A_2 = X_2(X_2'X_2)^{-1}X_2'$. The null hypothesis is rejected if the coefficient λ is statistically significant as indicated by its t ratio. Similarly, the test statistic for the null hypothesis that M_2 is preferred to M_1 is rejected is the t ratio of μ in the regression

$$y = X_1\beta_2 + \mu(A_1X_2\hat{\beta}_2) + w \quad (5)$$

where $A_1 = X_1(X_1'X_1)^{-1}X_1'$. The null hypothesis is rejected (meaning that M_2 is not preferred to M_1) if the coefficient μ is statistically significant as indicated by its t ratio. If the null hypothesis is rejected in both cases, then both models are misspecified.

The second test is the encompassing test due to Deaton (1982), Dastoor (1983), and Mizon and Richard (1986). For the null hypothesis that M_1 is preferred to M_2 the encompassing test statistic is the F statistic for testing the null that $\Omega = 0$ in the regression

$$v = X_1\Pi + X_2^*\Omega + u \quad (6)$$

where X_2^* denotes the variables in M_2 that cannot be expressed as an exact linear combination of the regressors of M_1 . Similarly, a test statistic can be calculated for the null that M_2 is preferred to M_1 . The results are interpreted in the same way as in the case of the *JA* test.

The two selection criteria used for the same purpose are the Akaike Information criterion (*AIC*) and the Schwartz Bayesian Criterion (*SBC*). Let L_1 and L_2 be the maximum log-likelihood functions of models M_1 and M_2 respectively. The *AIC* for the choice between the two models (Akaike, 1974) is calculated as

$$AIC(M_1 : M_2) = L_1 - L_2 - (k_1 - k_2) \quad (7)$$

where k_1 and k_2 are the number of estimated coefficients for M_1 and M_2 respectively. M_1 is preferred to M_2 if $AIC(M_1 : M_2) > 0$, and vice versa.

The *SBC* for the choice between the two models is calculated as

$$SBC(M_1 : M_2) = L_1 - L_2 - \frac{1}{2}(k_1 - k_2)\log(n) \quad (8)$$

where n is the sample size. Again, M_1 is preferred to M_2 if $SBC(M_1 : M_2) > 0$, and vice versa.

Now, we turn to a description of the price variables. If p_t is the logarithm of the price, then the price change per se is

$\Delta p_t = p_t - p_{t-1}$, the absolute price change is $|\Delta p_t|$, and the squared price change is $(\Delta p_t)^2$. The concept of stochastic volatility, which is used in this paper, can be found in Shephard (1996) and in Ghyles et al (1996). Define the rate of return as $r_t = \Delta p_t$, and assume that it is generated by the process

$$r_t = k\varepsilon_t e^{(h_t/2)} \tag{9}$$

where h_t is a measure of stochastic volatility that follows the process

$$h_{t+1} = \phi h_t + \eta_t \tag{10}$$

such that $\varepsilon_t \sim IID(0,1)$, $\eta_t \sim NID(0, \sigma_\eta^2)$ and $|\phi| \leq 1$. Here, k is a scale factor, ϕ is a parameter and η_t is a disturbance term that is assumed to be uncorrelated with ε_t . If ϕ is close to one, the stochastic volatility model is similar to a GARCH(1,1) model, and if ϕ is exactly one, such that h_t is a random walk, then the model is similar to an IGARCH(1,1) model.

It is relatively easy to estimate the stochastic volatility model by using a quasi-maximum likelihood method, which requires the transformation of the observations to

$$\log r_t^2 = \kappa + h_t + \xi_t \tag{11}$$

where

$$\xi_t = \log \varepsilon_t^2 - E(\log \varepsilon_t^2) \tag{12}$$

$$\kappa = \log k^2 + E(\log \varepsilon_t^2) \tag{13}$$

To avoid the problem arising from the possibility that some of the observations are zero, Breidt and Carriquiry (1996) suggest the following Taylor series-based transformation:

$$\log r_t^2 \cong \log(r_t^2 + cs_r^2) - cs_r^2 / (r_t^2 + cs_r^2) \tag{14}$$

where s_r^2 is the sample variance of r_t and c is a small number.

The last price measure used in this paper is the extreme value variance, which is calculated from the high and low prices as follows:

$$\sigma^2 = [\log(p^H) - \log(p^L)] / 4 \log 2 \tag{15}$$

where p^H is the high price, p^L is the low price for the trading period. This measure of volatility is several times more efficient than conventional estimator as pointed out by Garman and Klass (1980) and Parkinson (1980).

4. Data and Empirical Results

The empirical results presented in this paper are based on daily data on the stock prices (market indices) and trading volume in the following markets: the U.S. (represented by the Dow Jones Industrial Average, the S&P500 index and the NASDAQ index); the U.K. (represented by the FTSE), France (the CAC index); Spain (the Madrid General Index, IGBM); Japan (Nikkei Dow Jones); Hong Kong (the Hang Seng Index); Korea (the Seoul Composite Index, KOSPI); Canada (Toronto 500 index) and Mexico (Mexico Stock Index, IPC). The sample data, which was obtained from the Yahoo Finance website, covers periods that vary from one market to another. In general, sample sizes range between 258 and 1000 observations.

As explained earlier, model selection tests and criteria are applied to pairs of price measures for each market, giving a total number of 110 cases (10 cases per market or price index). Figure 1 shows the frequency of the underlying price measure appearing superior to the price measure it is tested against using the aggregate results of all markets. The extreme value variance appears to be the most successful of the five variables, outperforming the other price variable in 30 per cent of the cases (where a case involves two price variables in a particular market). This is followed by the absolute price change, which outperforms by far its traditional rival, the price change per se. The latter comes last in the league.

Although stochastic volatility appears in third place in the aggregate data covering all markets, it does not dominate in any single market, as shown in Table 1, which reports the most appropriate measure on a market by market basis. Here, the extreme value variance is the most appropriate price variable in the U.S. (DJIA and the S&P500), Japan, Canada and Mexico. The absolute price change turns out to be the best performer in the U.S. (NASDAQ), U.K., France, and Hong Kong. In the other two markets the squared price change and the price change per se turn out to be the most appropriate price variables in Spain and Korea, respectively. Tables 2-5 show selected detailed results of testing the price change per se against the four

other variables, reporting the test statistics for the two non-nested model selection tests (*JA* and *EN*) and the information criteria (*AIC* and *BIC*). For example, Table 2 shows that M1 is rejected against M2 and that M2 is not rejected against M1, implying that the absolute price change (the price variable in M2) is superior to the price change per se (the price variable in M1). The only exception to this results is the case of the Korean market, where M1 is not rejected against M2 but M2 is rejected against M1, implying the superiority of the price change per se in this market. Similar stories can be gleaned from the other tables but they invariably show the inferiority of the price change per se, implying that the direction of change in the price does not really matter.

5. Concluding Remarks

The objective of this paper was to detect the most appropriate stock price variable to be used in studies of the price-volume relation. Five different price variables were employed as the explanatory variables in model selection tests on a bilateral basis. By running these tests 110 times to cover the five price variables and eleven markets, pair wise, the results revealed some results that can be summarised as follows:

1. The most appropriate price variable to be used in examining the price-volume relation varies from one market to another although two price variables appeared to be dominant: the extreme value variance and the absolute price change.
2. In only one market out of eleven (Korea) does the price change per se appear to be the most appropriate price variable. This does not provide much support for the notion of asymmetry in the price-volume relation, as it seems that what matters for volume is a big price change, irrespective whether it is a positive or a negative change.
3. Although stochastic volatility appears to be the most appropriate variable in 21 out of 110 cases, it is not the most appropriate variable for any single market.

One can perhaps safely conclude that it may be useful to use non-nested model selection tests and information criteria to identify the most appropriate price variable before testing for causality, which is the main tool used to examine the price-volume relation. It may be the case that choosing the wrong price variable constitutes a measurement error, which would have repercussions for the validity of inference based on the empirical results.

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Notes

Note 1. For recent work on the price-volume relation, see Gallo and Pacini (2000), Moosa and Korczak (2000), Moosa and Silvapulle (2000), Huang and Yang (2001), Lee and Rui (2002), Bohl and Henke (2003), Ciner (2003), Moosa et al (2003), and Lucey (2005). Lo and Wang (2000) analyse the concept of trading volume and consider its implications for portfolio theory.

Note 2. In Karpoff's survey of studies of the price-volume relation, only one out of 19 studies failed to find positive correlation between the absolute price change and volume, but four out of 16 studies failed to find support for positive correlation between the price change per se and volume.

Note 3. Those using the absolute price change include Clark (1973), Epps and Epps (1976), Westerfield (1977), Cornell (1981), Harris (1983), Tauchen and Pitts (1983), and Rutledge (1984). Those who used the price change per se include Epps (1975, 1977), Hanna (1978), Rogalski (1978), James and Edmister (1983), and Smirlock and Starks (1985). Those using both of these variables include Godfrey et al. (1964), Ying (1966), Morgan (1976), Comiskey et al (1984), Harris (1984) and Wood et al (1985). Only one study (Granger and Morgenstern, 1970) used the squared price change as an alternative to the absolute price change.

Note 4. Using the absolute price change is based on the belief that "it takes volume to make prices move", whereas using the price change per se is based on the belief that "volume is relatively heavy in bull markets and light in bear markets".

Note 5. Studies dealing with the issue of asymmetry in the price-volume relation include Smirlock and Starks (1985), Jain and Joh (1988), Bessembinder and Seguin (1993), Assogbavi et al (1995), Brailsford (1996), Moosa and Korczak (2000), Cooper et al (2000), Moosa et al (2003), and Griffin et al (2004).

Note 6. The essential difference between the two hypotheses rests on the speed with which the new equilibrium is reached following the arrival of new information. The sequential information arrival hypothesis allows a number of incomplete equilibria to be realised before the final equilibrium is reached. The mixture of distributions hypothesis, on the other hand, allows the final equilibrium to be reached immediately. Both of these hypotheses have been used to explain the relation

between trading volume and the absolute price change. Harris (1983, 1984) points out that the mixture of distributions hypothesis implies positive correlation between volume and the price change per se if the conditional mean of the price process is proportional to the number of information arrivals.

Note 7. These conditions will be stated in the following section where the stochastic volatility model is specified.

Table 1. The Most Appropriate Price Variable

Market	Price Variable
U.S. (DJIA)	Extreme value variance
U.S. (S&P500)	Extreme value variance
U.S. (NASDAQ)	Absolute price change
U.K. (FTSE)	Absolute price change
France (CAC)	Absolute price change
Spain (IGBM)	Squared price change
Japan (NDJ)	Extreme value variance
Hong Kong (Hang Seng)	Absolute price change
Korea (KOPSI)	Price change per se
Canada (Toronto 500 Index)	Extreme value variance
Mexico (IPC)	Extreme value variance

Table 2. Model Selection Tests and Criteria (Price Change per se vs the Absolute Price Change)

Market	Testing	<i>JA</i>	<i>EN</i>	<i>AIC</i>	<i>BIC</i>
DJIA	M1 vs M2	8.38*	70.25*	-34.45	-34.45
	M2 vs M1	0.91	0.83		
S&P500	M1 vs M2	-5.74*	29.88*	-95.44	-77.44
	M2 vs M1	-0.71	0.50		
NASDAQ	M1 vs M2	-5.24*	34.24*	-87.00	-72.00
	M2 vs M1	-3.97*	15.78*		
FTSE	M1 vs M2	-2.44*	5.93*	-2.49	-2.49
	M2 vs M1	-0.99	0.97		
CAC	M1 vs M2	-5.53*	30.53*	-14.39	-14.39
	M2 vs M1	-0.69	0.48		
IGBM	M1 vs M2	-1.00	0.99	0.17	0.17
	M2 vs M1	-1.15	1.33		
NDJ	M1 vs M2	-1.54	2.38	-0.48	-0.48
	M2 vs M1	-1.20	1.43		
HS	M1 vs M2	3.83*	57.90*	-88.09	-88.09
	M2 vs M1	2.87*	8.65*		
KOPSI	M1 vs M2	-0.76	0.58	10.19	4.68
	M2 vs M1	-3.37*	8.31*		
Toronto 500	M1 vs M2	2.21*	4.90*	-2.44	-2.44
	M2 vs M1	-0.22	0.05		
IPC	M1 vs M2	-10.73*	115.10*	-47.65	-47.65
	M2 vs M1	-3.86*	14.91*		

* Significant at the 0.05 level

Table 3. Model Selection Tests and Criteria (Price Change per se vs the Squared Price Change)

Market	Testing	<i>JA</i>	<i>EN</i>	<i>AIC</i>	<i>BIC</i>
DJIA	M1 vs M2	6.84*	46.76*	-23.13	-23.13
	M2 vs M1	0.58	0.33		
S&P500	M1 vs M2	-7.02*	45.23*	-64.09	-58.09
	M2 vs M1	-1.08	1.16		
NASDAQ	M1 vs M2	8.79*	34.62*	-44.57	-38.57
	M2 vs M1	3.07*	9.42*		
FTSE	M1 vs M2	-1.42	2.01	-0.50	-0.50
	M2 vs M1	-1.01	1.01		
CAC	M1 vs M2	-5.25*	27.56*	-13.23	-13.23
	M2 vs M1	-0.33	0.11		
IGBM	M1 vs M2	1.24	1.54	-0.21	-0.21
	M2 vs M1	1.06	1.12		
NDJ	M1 vs M2	-1.53	2.35	-0.30	-0.30
	M2 vs M1	-1.32	1.75		
HS	M1 vs M2	11.59*	134.35*	-55.78	-58.23
	M2 vs M1	2.17*	8.79*		
KOPSI	M1 vs M2	5.62*	7.48*	-4.61	0.90
	M2 vs M1	2.45*	7.79*		
Toronto 500	M1 vs M2	1.83	3.36	-1.62	-1.62
	M2 vs M1	-0.36	0.13		
IPC	M1 vs M2	-6.68*	44.65*	-12.32	-12.32
	M2 vs M1	-4.41*	19.47		

* Significant at the 0.05 level

Table 4. Model Selection Tests and Criteria (Price Change per se vs Extreme Value Variance)

Market	Testing	<i>JA</i>	<i>EN</i>	<i>AIC</i>	<i>BIC</i>
DJIA	M1 vs M2	5.21*	18.19*	-72.13	-48.12
	M2 vs M1	0.44	0.19		
S&P500	M1 vs M2	-7.85*	46.90*	-129.63	-114.62
	M2 vs M1	-1.12	1.26		
NASDAQ	M1 vs M2	-11.26*	40.96*	-83.96	-71.95
	M2 vs M1	-4.82*	23.23*		
FTSE	M1 vs M2	-1.99*	3.98*	-1.51	-1.51
	M2 vs M1	-0.99	0.97		
CAC	M1 vs M2	5.35*	28.67*	-13.67	-13.67
	M2 vs M1	-0.48	0.23		

IGBM	M1 vs M2	0.08	.01	0.57	0.57
	M2 vs M1	1.06	1.13		
NDJ	M1 vs M2	-2.19*	4.81*	-1.31	-1.31
	M2 vs M1	-1.48	2.20		
HS	M1 vs M2	-2.31*	40.62*	-72.17	-67.26
	M2 vs M1	-2.36*	13.01*		
KOPSI	M1 vs M2	-3.71*	13.73*	5.24	-0.27
	M2 vs M1	-3.40*	9.42*		
Toronto 500	M1 vs M2	3.32*	11.02*	-5.52	-5.52
	M2 vs M1	-0.05	0.003		
IPC	M1 vs M2	-9.93*	45.24*	-55.85	-50.85
	M2 vs M1	-3.65	13.31*		

* Significant at the 0.05 level

Table 5. Model Selection Tests and Criteria (Price Change per se vs Stochastic Volatility)

Market	Testing	<i>JA</i>	<i>EN</i>	<i>AIC</i>	<i>BIC</i>
DJIA	M1 vs M2	-8.04*	64.65*	-31.43	-31.43
	M2 vs M1	-1.17	1.36		
S&P500	M1 vs M2	-8.59*	47.88*	-46.21	-43.21
	M2 vs M1	-0.52	0.27		
NASDAQ	M1 vs M2	-8.08*	28.49*	-70.68	-55.67
	M2 vs M1	-3.97*	15.79*		
FTSE	M1 vs M2	-0.25	8.21*	-12.81	-5.94
	M2 vs M1	-0.93	0.87		
CAC	M1 vs M2	-4.89	23.91*	-11.29	-11.28
	M2 vs M1	-0.79	0.62		
IGBM	M1 vs M2	-0.50	0.25	0.51	0.51
	M2 vs M1	-1.13	1.27		
NDJ	M1 vs M2	-1.60	2.56	-0.69	-0.69
	M2 vs M1	-1.09	1.18		
HS	M1 vs M2	13.33*	177.59*	-73.39	-75.85
	M2 vs M1	2.50*	10.03*		
KOPSI	M1 vs M2	-1.07	1.15	9.92	4.41
	M2 vs M1	-2.52*	8.33*		
Toronto 500	M1 vs M2	1.71	2.93	-1.47	-1.47
	M2 vs M1	0.04	0.002		

IPC	M1 vs M2	10.61*	112.63*	-49.59	-49.59
	M2 vs M1	2.96*	8.76*		

* Significant at the 0.05 level

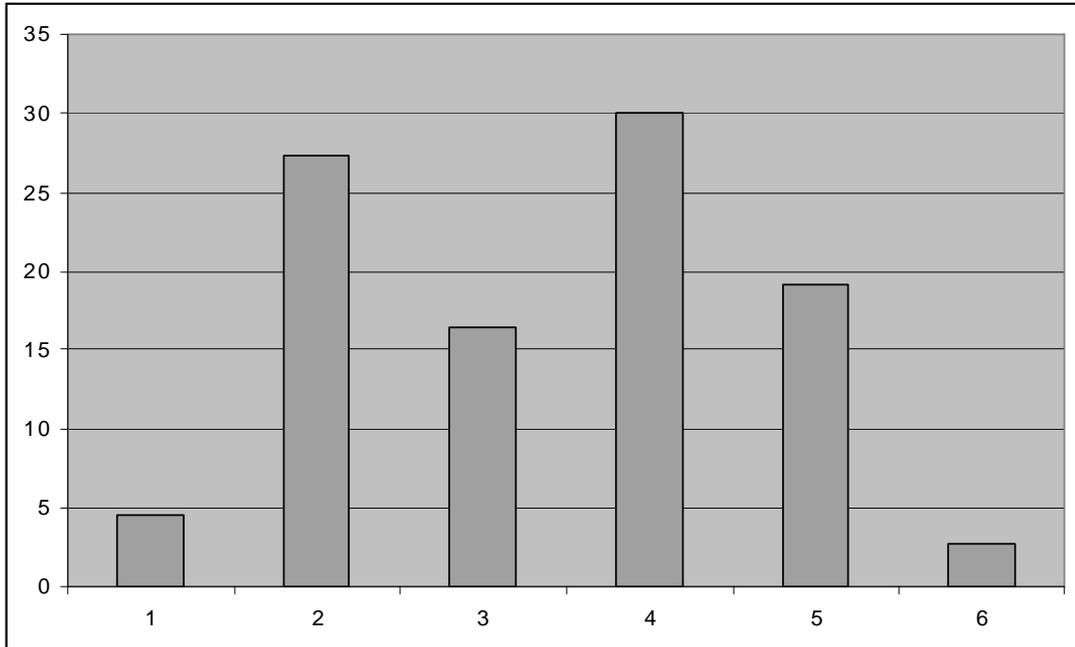


Figure 1. The Frequency of Superiority over Another Price Variable (%)

1: Price change per se, 2: Absolute price change, 3: Squared price change, 4: Extreme value variance, 5: Stochastic volatility, 6: Inconclusive