The Sources of Variance in the Helsinki Stock Exchange: An Investigation of the Fundamental and the Transitory Variance

Bernard Ben Sita*

Abstract

We investigate the relationship between the fundamental and the transitory variance. We study how the transitory variance deviates from the fundamental variance. We use the Gonzalo and Granger (1995) permanent-temporary approach to decompose the variance common factor into a transitory and a permanent component. We find that the midquote returns variance contributes by about 64% of the common variance factor against 36% by the trade returns variance. Furthermore, inserting the ratio of volume expectation to duration expectation in the ARMA model and the vector error correction (VEC) model, we find that the short-term variance increases (decreases) when more (less) than 1 unit share is traded for 1 unit time.

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Swedish School of Economics and Business Administration, Department of Finance, Hietaniemenkatu 7, 00101 Helsinki, Finland. E-mail: **bernard.bensita@hanken.fi.** We are grateful to SIRCA, Sydney, Australia for providing access to data from Reuters Group.

1. Introduction

Common factor is an important concept in economics. In finance, the concept of common factor is associated with the market factor that systematically moves with the entire economy. In this respect, the Capital Asset Pricing Model (CAPM) identifies only one overwhelming market factor that is by construction an aggregate of many factors that can be industrial, technological, structural and human factors. Different extensions of the original CAPM put into perspective the ability of the market factor to capture, to reflect and to explain fundamental variations in the economy. In econometrics, the concept of common factor denotes a linear combination of factors with the properties that they are non-stationary when evolving in their own path, and stationary when combined linearly to each other. For example, in Gonzalo and Granger (1995), the common factor not only has permanent effects on its own path, but also temporary effects on the entire economy. This is equal saying that a long-term investment is highly valuable about its future payoffs, but also about its temporary effects on the overall corporate investment profitability. Hence, when sufficiently many factors are linear combinations, they result into one dominant factor that prices every thing. In market microstructure, a subfield of finance, the concept of common factor denotes private values with long-run impacts on prices. For example, in Hasbrouck (1995), the common factor follows a Martingale process, a process that survives temporary effects to live by the means of fundamental effects. Hence, the common factor is a driving force that keeps any process increasing or decreasing over a long period of time.

The purpose of this paper is to investigate the variance common factor on ultra-high frequency (tick by tick) price data using the Gonzalo and Granger (1995) model. Gonzalo and Granger (1995) establish that the common factor reflects the common share of different factors and their contributions to the realisation of value. The common factor of prices data consists of fundamental values with the property that they persist over time and transitory values with the property that they revert from time to time. Fundamental values are associated with fundamental factors whose unexpected changes generate fundamental variance in the asset. For stocks traded on exchanges, factors such as the quality of management, the values of the company's resources and technologies, the market shares in the market product, and the interest rates are determinants of price changes. However, when we put every factor in time perspective, in the very long run, all factors are transitory, thus it is conceptually motivated to use microstructure factors to study the price long-term effects. For stocks that trade on exchanges, transitory factors are trading factors (activities) that contribute to the realisation of the fundamental value. These factors produce effects that induce either price to change even though there is no news (Roll (1984)) or price to change gradually, sequentially or intensively (Glosten and Milgrom (1985), and Kyle (1985)). For concreteness, the fundamental variance originates from informed traders who show great care about the future value of the asset (there are long term traders) and the transitory variance originates from liquidity traders who are careless about the future value longing rather on the current value of the asset (there are short term traders).

The decomposition of the variance into a fundamental (permanent) and a transitory component strikes at the heart of market microstructure. Basically, market microstructure studies shed light on the causes bedding for short-term deviations between transaction prices and fundamental prices. Short-term deviations arise because of trading frictions and microstructure effects including inventory-carrying costs (e.g. Zabel (1981) and Amihud and Mendelson (1980)), order-handling (e.g. Brock and Kleidon (1992)), and adverse selection costs (e.g. Glosten and Milgrom (1985)). The decomposition of the total variance into a fundamental and a transitory variance component has a long history in market microstructure (e.g. Harris (1990), and Madhavan, Richardson and Roomans (1997)). A drawback with microstructure decompositions is that auto-correlated errors are often used in the decomposition of the variance (e.g. Madhavan et al. (1997)). Against this background, we use the Gonzalo and Granger permanent-transitory (PT) factor model to decompose the variance common factor into a permanent and a transitory component. The PT approach is similar to the Hasbrouck (1995) information share (IS) approach. The two approaches make use of a vector error correction (VEC) model and allow the separation of long run movements from short-run movements. The Gonzalo and Granger (1995) approach differs from the Hasbrouck (1995) approach in that the PT approach measures each market's contribution to the common factor on the basis of the error correction term, whereas the IS approach measures each market's relative contribution on the basis of the innovations from the VEC model. The two approaches have been concurrently applied in a large number of market microstructure studies (e.g. Booth, So and Tse (1999), Booth, Lin, Martikainen and Tse (2002), Upper and Werner (2002), and Grammig, Wellner and Schlag (2005)). For example Booth, So and Tse

(1999) use the PT approach to study price discovery in future, option and spot markets, and Booth, Lin, Martikainen and Tse (2002) use both the PT and the IS approach to investigate price discovery in the upstairs and the downstairs market.

Our study is related to Booth et al. (2002) in that as in their study, we use data from the Helsinki Stock Exchange that is small but dynamic exchange offering transaction opportunities both in spot and derivative securities. Whereas they establish that price discovery occurs mostly on the floor (downstairs) market (the asymmetry costs do not significantly affect trades on the upstairs market), we examine variance discovery on the downstairs market. In that our study contributes to the identification of the sources of variance in the Helsinki Stock Exchange[1]. We determine the contribution of the fundamental and transitory variance to the variance common factor. Motivated by market microstructure studies that price discovery occurs when liquidity providers adjust their prices for news (e.g. Glosten and Milgrom (1985)), we further distinguish this study by investigating the variance effects of liquidity and informed trading.

Renault and Werker (2002) extending the Engle (2000) model show that innovations in durations capture the speed by which private information is incorporated into prices and that duration expectations capture the intensity by which liquidity traders feed on price fluctuations. Extending our research to trading intensity is important since variance is positively related to trading intensity (Engle (2000)). Kyle (1985) establishes that

[1] The importance of identifying the sources of variance cannot be overstated. Variance greatly concerns traders and market regulators. Traders must be able to identify the source of variance in order to predict correctly future variance, and market regulators must distinguish between the two sources of variance in order to avoid taking measures that increase the transitory variance rather than decrease it.

imbalance in the order flow causes variance to increase, that is, when large transactions are traded for a short time interval. We capture this feature by taking the ratio of volume to duration. However, since we cannot compare volume and duration, we rather do it through their expectations. Durations and volumes are positive number whose processes are defined over distributions with positive supports. Following Engle and Russell (1998), we obtain the duration expectation by estimating the autoregressive conditional duration (ACD) model. Similarly, we put forth an autoregressive conditional volume (ACV) model for volumes. Since we normalized the duration and the volume series by adjusting their deterministic component away, their conditional means are expected to be 1. Hence, taking the ratio of volume to duration expectation is a powerful way to measure imbalances in the order flow. Against this background, we test that trading more than 1 share for 1 unit time increases variance.

We select 25 stocks among the most traded stocks in the Helsinki Stock Exchange that had more than 10,000 transactions over the sample period that runs from March 2 to December 30, 1999. The main results of this study are as follow. First, we find that when traders trade more than 1 share for 1 unit time, this creates order imbalance in the book. Thus, prices have to decrease to attract more liquidity. At the same time, informed traders consume more liquidity when they conduct their transactions on the side of trade that has attracted more liquidity. Second, we find that the fundamental variance contributes by about 64.4% to the variance common factor against 35.5% by the transitory variance. This result implies that prices do not deviate strongly from their equilibrium established in the near past. However, the deviation of the transitory variance from the fundamental variance is stronger for stocks with lower market capitalisation and that are infrequently traded. Third, we find that both liquidity trading and informed trading increase short-term variances. In particular, the variance increases when traders trade more than 1 share for 1 unit time. Overall, this study shows that market activity is strongly correlated with price variability, and that market regulators have to identify clearly the source of variance in order to take measures that reduce the transitory variance rather than to take measures that hamper the fundamental variance to adjust to news, and aggravate the transitory variance that determines largely the quality of the market.

This paper is organized as follows. In the next section is presented a model for the variance common factor following Gonzalo and Granger (1995). In this section is also derived the microstructure decomposition of variance. In the third section, a short presentation of trading activities in the Helsinki Stock Exchange is provided, the data sample is described, and finally different results on estimated models are presented. The fourth section gives the concluding remarks.

2. The description of the components of the variance

2.1 Liquidity and information variance effects

The canonical model of the efficient market hypothesis (EMH) entails that price equals the expected present value of future cash flows. Earlier studies have established that trade price is not efficient with respect to fundamentals rather efficient with respect to market beliefs. The beliefs-based price consists of a component due to fundamentals and another component due to the market perception about the asset value. In other words, it is not warranted that an asset is sold (purchased) only because its price equals the expected present value of future cash flows.

At a basic level, learning from trades, prices, volumes and times is the fundamental insight of the theoretical market microstructure (e.g. Kyle (1985), Glosten and Milgrom (1985), Easley and O'Hara (1987), Easley and O'Hara (1992)). In much of these models, transactions are made possible because liquidity traders maximize the liquidity utility while informed traders maximize the information utility. That is traders might observe the same prices but trade on different filtrations. For example, informed traders are recognized to utilize a bigger filtration than liquidity traders, and the flow of information determines the trader type in presence. A formal representation of a positive stochastic variable such as the stock price defined on a complete probability space (Ω, F, P) suggests that liquidity traders use a lower filtration containing all information at time t denoted by Θ_t, while informed traders use a bigger filtration containing anticipated information, denoted by Φ_t, that is $\Phi_t \supseteq \Theta_t$. Denote by $m_t = E\lfloor p_t^* | \Phi_t \rfloor$, where p_t^* is the log fundamental value and m_t is the expected value of p_t^*. When the log price p_t is the perfect mirror of m_t, $p_t - p_{t-1} = m_t - m_{t-1} = \varepsilon_t$. However, when $p_t - p_{t-1} = r_t$ deviates from ε_t, the relationship carries an additional error term so that $r_t = n_t - n_{t-1} + \varepsilon_t$, where n_t summarizes the effects of noise trading. The variance and the covariance bias are then respectively,

$$\mathrm{var}(r_t) = E\lfloor \sigma_\varepsilon^2 + 2\sigma_n^2 - 2n_t n_{t-1} \rfloor = \sigma_\varepsilon^2 + 2\sigma_n^2 . \tag{1}$$

$$\operatorname{cov}(r_t, r_{t-1}) = E\left[-n_{t-1}^2\right] = -\sigma_n^2 . \tag{2}$$

We provide calculations of Equations (1) and (2) in the appendix. Two important properties emerge from Equations (1) and (2). First, Equation (1) denotes that the total variance increases substantially under noise trading and that the proportion of the total variance of price changes attributable to noise trading is given by $\pi = 2\sigma_n^2 / \left(\sigma_\varepsilon^2 + 2\sigma_n^2\right)$. It is also clear from Equation (1) that the variance due to noise trading summarizes the costs associated with trading, thus noise trading has both positive and negative effects on price discovery and the formation of prices in organised markets. Relating Equation (1) to the models of Easley and O'Hara (1992), Glosten and Milgrom (1985), and Diamond and Verrecchia (1988), it appears that (i) in the absence of informed traders in the market the total variance equals $2\sigma_n^2$, (ii) in the absence of liquidity traders the total variance equals σ_ε^2 and (iii) when both liquidity and informed traders are present in the market the total variance equals $\sigma_\varepsilon^2 + 2\sigma_n^2$. Nonetheless, Brushing aside that informed traders might bluff to create illusion in liquidity, it is hard to believe that informed traders can trade by themselves. Black (1986) shows that the market closes in the absence of liquidity traders.

Second, Equation (2) implies that noise trading induces the first-order serial correlation in returns. What is known, as noise trading is in reality a summary of different effects due to trading activities and the absence of trading. For example, the bid/ask bounce hypothesis of Roll (1984) states that in the absence of news, the price is expected to bounce between the bid and the ask price whenever a trade occurs. In addition, the non-synchronous hypothesis of Lo and MacKinlay (1990) entails that in the absence of trade in a given stock, later reaction to news about common factors induces a positive serial correlation in price changes. In summary, different studies (Easley and O'Hara (1992), Diamond and Verrecchia (1987), Roll (1984), and Lo and MacKinlay (1990)) imply that "the absence of trade" that is tantamount to "non-trading periods" has implications on the variance and the autocorrelation structure of price changes. Numerous studies have investigated the variance pattern under trading and non-trading periods (e.g. French and Roll (1986), and Hansen and Lunde (2005)). Unlike French and Roll (1986) and Hansen and Lunde (2005) investigating the variance of price changes when markets are open and when markets are closed, in this study we investigate the variance of price changes about trading and non-trading periods within the trading day.

Hence, following assumptions are made:

(i) Informed traders are present in the market with probability δ in the sense of Easley and O'Hara (1992),

(ii) Liquidity traders are permanently established in the market from the start of the trading day to its end, and adopt the clustering trading pattern advocated in Admati and Pfleiderer (1988), and

(iii) Trading is smooth in the sense that trading frictions and microstructure effects do not induce volatility.

The three assumptions ensure that the expected variance can be written as

$$E\left[\sigma_r^2\right] = \delta^2\sigma_\varepsilon^2 + 2(1-\delta)^2\left[\sigma_n^2 - \rho_n\right], \tag{3}$$

where $\rho_n = \mathrm{cov}(n_t, n_{t-1})/\mathrm{var}(n_{t-1})$ capturing the clustering effect of liquidity traders. It appears from Equation (3) that (i) when $\delta = 0$, a positive clustering effect depletes the variance due to liquidity trading, and (ii) when $\delta = 1$, the benefit with clustering in trading vanishes. Even though informed traders do not show trading pattern, they prefer to trade when ρ_n is positive and large because the higher ρ_n, the greater the likelihood of trading anonymously is. This is consistent with assumption (ii) emphasizing that liquidity traders not only choose the right time to trade but also accommodate informed traders under their dominant trading pattern (Admati and Pfleiderer (1988)). Assumption (iii) is important as a wealth of studies attribute the variance under liquidity trading to trading frictions (e.g. Madhavan et al. (1997), and Harris (1990)).

2.2 Variable descriptions

Empirically, equation (3) takes the form of $E\left[\sigma_t^2\right] = E\left[\sigma_t^2 \middle| \Phi_t\right] + E\left[\sigma_t^2 \middle| \Theta_t\right]$, where σ_t^2 is a variance proxy, Φ_t is the filtration at time t of informed traders, and Θ_t is the filtration of liquidity traders. Two concepts are associated with informed trading. The concept of acceleration and the concept of speed, both associated with the idea that informed traders will trade intensively as much as possible whenever possible because of the transitory character of information. In Amihud and Mendelson (1987) the adjustment speed associated with the variance due to informed trading is given by $\beta/(2-\beta)$, and to liquidity trading by $2/(2-\beta)$, where β is an adjustment coefficient capturing the price reaction under random walk, and noise trading, respectively. In what follows, β is a coefficient relating the transitory variance under liquidity trading to the fundamental variance under informed trading. Trading intensity has several proxies. Many studies use trading volume as a proxy for trading intensity (e.g. Lamoureux and Latrapes (1990), and Andersen (1996)). Recently, the advent of transactions data has been an opportunity to introduce transaction time in the analysis of variance in financial markets (e.g. Engle (2000), Manganelli (2002), and Spierdijk (2004)). We synthesize the two proxies for trading intensity to study the conjugate effect of trading volumes and trade durations on the transitory variance.

Definition 1

Let $x_t = T_t - T_{t-1}$ be the trade duration in seconds for T_t the transaction time and its expectation be $x_t = E[x_t | x_{t-1}, x_{t-2}, ..., x_1] = \psi_t^x [x_{t-1}, x_{t-1}, ..., x_1] = \psi_t^x$. Let $x_t = \psi_t^x w_t$, where w_t is identically and independent distributed (iid) with a density function $\Gamma(w, \phi)$ defined under positive supports such as the Weibull and the exponential distribution. Assuming the Weibull distribution the duration process is given by

$$\psi_t^x = \omega + \sum_{j=1}^{k} \alpha_j x_{t-j} + \sum_{j=1}^{q} \beta_j \psi_{t-j}^x ,$$

where $\omega \geq 0$, $\alpha_j \geq 0$ and $\beta_j \geq 0$, and k and q determine the order of the Autoregressive Conditional Duration (ACD) model.

Definition 2

Let trading volume v_t be characterized by information momentum in small and large trading volumes, then ψ_t^v represents volume expectations at time t conditional on past volumes and past volume expectations so that ψ_t^v follows an autoregressive conditional volume (ACV) process mimicking the linear ACD model of some order according to definition 1.

Definition 3

Let $\xi_t^x = x_t / \psi_t^x$ and $\xi_t^v = v_t / \psi_t^v$ be the non-parametrical standardized duration (volume) residuals that are iid. Following Renault and Werker (2002), we measure the information filtration of liquidity traders in terms of the ratio of the expected volume to the expected duration, that is, $\Lambda_t^L = \psi_t^v / \psi_t^x$, and the information filtration of informed traders in terms of the ratio of the covariance of the volume standardized residual to the covariance of the duration standardized residual, that is, $\Lambda_t^I = C_t^v / C_t^x$, where $C_t^x = \left(x_t / \psi_t^x\right)\left(\left(x_t / \psi_t^x\right) - 1\right)$ and $C_t^v = \left(v_t / \psi_t^v\right)\left(\left(v_t / \psi_t^v\right) - 1\right)$. The mean expectation of $E\left[\Lambda_t^L\right]$ is 1, and that of $E\left[\Lambda_t^I\right]$ is 0. Λ_t^L and Λ_t^I capture the risk associated with trading in pure electronic books and are measures for order flow imbalances.

Definition 4

Let m_t be given by $\left(A_t + B_t\right)/2$, where A_t is the ask price and B_t is the bid price, then we assume that the midquote price is the proxy for the efficient price that is unobservable to liquidity traders who observe p_t the trade price. The first difference of m_t is given by $r_{1t} = \ln(m_t) - \ln(m_{t-1})$, and that of p_t by $r_{2t} = \ln(p_t) - \ln(p_{t-1})$. Following Engle (2000) the return per unit time is obtained by dividing r_{1t} and r_{2t} by the square root of the trade durations as $\tilde{r}_{1t} = r_{1t} \big/ \sqrt{x_t}$ and $\tilde{r}_{2t} = r_{2t} \big/ \sqrt{x_t}$, respectively.

Definitions (1) and (2) provide measures for trading intensity. The emphasis is on trading speed in definition (1), while it is on trading acceleration in definition (2). Informed traders might accelerate to increase the speed, but since they drive behind liquidity traders and cannot take them over, they will drive safe until the next crossroad. For example, in Admati and Pfleiderer (1988), liquidity traders will not only trade in clusters but also choose carefully the time to trade. In that, a situation where informed traders will be first to arrive in the market is much unlikely because informed traders are rather associated with negative liquidity. In definition (3) duration and volume are split in information and liquidity component. Since liquidity trading depends on the trading history, expectations characterize their trading pattern distinguishing them from informed traders associated with innovations. Definition (4) provides two measures of the logarithmic return, the first measure related to the unobservable price process and the second to the observable price process.

2.3 Estimated models

A. The components of the return

In the presence of microstructure effects, the log-return is calculated with error generated by the mechanics of the trading process. Evidence indicates that this error accounts for a large proportion of the variance. Investigating 274 NYSE stocks, Madhavan et al. (1997) report that approximately 60% of the total variance of price changes is attributable to microstructure effects. Different scaling estimators are proposed in the literature to adjust the return for its seasonal component. Engle (2000) uses a piecewise function of the time of day to adjust the return. Andersen and Bollerslev (1997) use a flexible Fourier form to model the intraday periodic volatility components. A drawback with these estimators is that the definition range of the return is changed and neither can we identify clearly the deterministic component that has been adjusted away. A natural way to adjust the return for its seasonal component is by estimating an autoregressive moving average (ARMA) models incorporating trading friction variables[2].

$$\tilde{r}_{it} = a_0 + a_1 \tilde{r}_{it-1} + a_2 e_{it-1} + \sum_{j=1}^{3} \varphi_j D_{jt} \Delta_t^L + \sum_{j=1}^{3} \phi_j D_{jt} \Delta_t^I + \sum_{k=0}^{K} \beta_k Q_{t-k} + e_{it}\,, \tag{4}$$

Where D_{jt} is a dummy variable (i) taking 1 when $\Delta_{tj}^c < 1$ and 0 otherwise for $c = L, I$ and $j = 1$, (ii) taking 1 when $1 < \Delta_{tj}^c < 2$ for $j = 2$ and 0 otherwise, and (iii) taking 1 when $\Delta_{tj}^c > 1$ for $j = 3$ and 0 otherwise; Q_t is the trade indicator variable taking 1 when $m_t < p_t$, 0 when $m_t = p_t$ and -1 when $m_t > p_t$ and K is the maximum lag to be included.

[2] By using an ARMA model to adjust the raw return, we assume that the seasonal effects are additive. Thus subtracting these effects from the return gives robust errors with expectation at 0.

The AR coefficient a_1 captures any autocorrelation induced by non-synchronous trading while the MA coefficient a_2 captures any potential negative first order serial correlation induced by the bid-ask bounce. We insert also some trading variables in the ARMA(1,1) model that are correlated with the seasonal component. The coefficient ϕ_j captures the effect of informed trading on the return. The coefficient φ_j captures the effect of liquidity trading on price changes. The point with Equation (4) is to obtain serially uncorrelated error terms.

B. The deterministic component of the duration and the trading volume

It is established from different studies (e.g. Goodhart and O'Hara (1997)) that the bid-ask spread, the trading volume, the volatility, and the duration exhibit strong seasonal patterns corresponding to the U-shaped pattern. We use a scaling estimator to adjust these variables for their seasonal components. Since the seasonal component is mostly time related, we construct a scaling estimator on the basis of the time of day. Regressing the durations and volumes on times, we adjust the trade duration and the trading volume in the following way,

$$\tilde{x}_t = x_t / E[x_t \mid f(t)], \tag{5}$$

$$\tilde{v}_t = v_t / E[v_t \mid f(t)], \tag{6}$$

where

$$f(t) = \beta_0 + \beta_1(k_1 - t;(t > k_1);0) + \beta_2(k_2 - t;(t > k_2);0) + \beta_3(t - k_3;(t > k_3);0), \tag{7}$$

where k_i are nodes fixed at 46800, 55800, and 63000 seconds, and t is the time of the day. The nodes are given in seconds since midnight. The data used in this study is from the Helsinki Stock Exchange. In 1999, the continuous trading session was held between 10.30am and 5.30pm (in seconds from 37800 seconds to 63000 seconds). Against this background, the first node of Equation (7) is fixed at 1.00pm and covers the openings, the second fixed at 3.30pm and covers the lunchtime and the third fixed at 5.30pm and covers the closings. $f(t)$ is a piecewise function of the times of the day. By regressing the duration (volume) on $f(t)$, we get fitted values that are used as proxy for the efficient scaling estimator. The adjusted series is obtained by dividing the raw series by the scaling factor. The adjusted duration and volume variable are used to estimate the ACD(1,1) and the ACV(1,1) model, respectively.

C. The variance common component model

Müller et al. (1997) study the impact of short-term traders and long-term traders on volatility and find that the information flow between the two groups is asymmetric. Precisely, the trading activities of short-term traders are positively correlated with trading periods with high volatility, while long-term traders ignore moment-to-moment volatility. The behaviour of short-term traders and long-term traders is dictated by speculation and hedging motives as modelled in Llorente et al. (2002). It follows that volatility should be modelled with both a short-term and a long-term component. Müller et al. (1997) use lagged correlation between what they define as the "coarse" volatility that is the volatility over the week and the "fine" volatility that is the variance across the trading days of the week. We rather take another approach to model the two components of the variance offering the advantage to study the proportion of volatility that can be attributed to the long-term traders and to short-term traders, respectively. For that we use the Gonzalo and Granger (1995) approach on the common factors. The Gonzalo and Granger (1995) have mostly been used to model price discovery for a stock that is traded in multiple exchanges and to study information flow between related markets. Examples of studies that apply the Gonzalo and Granger (1995) approach to investigate price discovery are Booth, So and Tse (1999), and Grammig, Melvin and Schlag (2005). However, this study is the first to use a variance approach in the investigation of the common factor between long-term and short-term traders.

$$\begin{aligned} |e_{1t}| &= \delta_1\left[|\widetilde{r}_{1t}| - \alpha|\widetilde{r}_{2t}|\right] + \sum_{j=1}^{3}\theta_{10j}|e_{1t-j}| + \sum_{j=1}^{3}\vartheta_{11j}D_{tj}\Delta_t^L + \sum_{i=1}^{3}\vartheta_{12j}D_{tj}\Delta_t^I + \eta_{1t} \\ |e_{2t}| &= \delta_2\left[|\widetilde{r}_{1t}| - \alpha|\widetilde{r}_{2t}|\right] + \sum_{j=1}^{3}\theta_{20j}|e_{2t-j}| + \sum_{j=1}^{3}\vartheta_{21j}D_{tj}\Delta_t^L + \sum_{j=1}^{3}\vartheta_{22j}D_{tj}\Delta_t^I + \eta_{2t} \end{aligned}, \tag{8}$$

where e_{1t} and e_{2t} are errors from the ARIMA models, α is an adjustment coefficient to news, δ_i are error correction coefficients weighting the contribution of the transitory and the fundamental variance, $\left[|\widetilde{r}_1| - \alpha|\widetilde{r}_2|\right]$ is the variance error correction, θ_{i0j} are coefficients capturing the short-term effects on variances, ϑ_{i1j} are coefficients capturing the variance effects of liquidity trading, ϑ_{i2j} are coefficients capturing the variance effects of informed trading, D_{tj} are piecewise dummy variables capturing the variance effects of liquidity and informed trading, Δ_t^L is the ratio of the volume expectation to the duration expectation, Δ_t^I is the ratio of the volume residual to the duration residual, and η_{it} are error terms, assumed to be zero mean vectors of serially uncorrelated errors with the covariance matrix:

$$\Omega = \begin{bmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_2\sigma_1 & \sigma_2^2 \end{bmatrix}, \tag{9}$$

Where σ_1^2 is the variance of the midquote returns variance, σ_2^2 is the variance of the trade returns variance, and $\rho\sigma_1\sigma_2$ is the covariance between the midquote returns variance and the trader returns variance. Equation (8) establishes the relationship between the long-term and the short-term variance. The coefficient δ_i represents the long-run equilibrium between the variance attributable to informed trading and the variance attributable to liquidity trading. The coefficient α captures the convergence speed to news. The coefficient θ_i captures the short-run variance dynamics. Equation (8) examines also the variance effects of trading intensity. We will expect liquidity trading to feed on variances. Similarly, we will expect informed trading decrease variances. Equation (8) is modelled using absolute values. The fundamental reason is that absolute returns show more persistence than squared returns (e.g. Ding, Granger and Engle (1993), and Forsberg and Ghysels (2004)). Forsberg and Ghysels (2004) show that absolute returns have variance properties that are powerful in dealing with sampling errors and jumps, and in forecasting future variances.

Unlike the Hasbrouck (1995) information share model decomposing the variance impacts into a transitory and a permanent component on the basis of the error terms of Equation (8), the Gonzalo and Granger (1995) model decomposes the common factor into a transitory and a permanent component on the basis of the error correction term. From Equation (8) the common factor is a linear combination of m_t and p_t whose long-run coefficients can be expressed as the sum of $\delta_1 m_t$ and $\delta_2 p_t$, where δ_i can be considered as the weights of the common factor. Constraining δ_i, we require δ_1 and δ_2 to sum to one, that is $\delta_1 + \delta_2 = 1$. Hence, under the null hypothesis the contribution attributable to the fundamental variance is 100%, that is $\delta_1 = 1$ and $\delta_2 = 0$. Similarly, we might hypothesize that the contribution attributable to the transitory variance to be 100%, that is, $\delta_1 = 0$ and $\delta_2 = 1$. These hypotheses establish the link between Equation (2) and Equation (8).

3. Empirical results

3.1 Data

We use transactions data for 25 stocks from the Helsinki Stock Exchange (HEX)[3]. The 25 stocks were selected on the basis that each stock should at least have 7500 transactions during the sample period running from March 2 to December 30, 1999. HEX is a small but a dynamic exchange dominated by few world-class securities. There are three trading lists in HEX. The 25 stocks of this study are from the main list that includes all the blue-chip companies with established market positions. The two other lists are the I-list

[3] HEX is since 2003 operated by OMX Exchanges, which is a division of OMX, a listed company headquartered in Stockholm, Sweden that owns and operates the largest integrated securities market in Northern Europe and is a provider of marketplace services and solutions for the financial and energy markets.

incorporating midsize companies with stable market operations, and the New Market list including companies with great growth potential from an international perspective. The 25 stocks are named and further presented in the appendix. The data is obtained from Reuters through SIRCA Australia, and includes trade and quote prices, time of transactions, and volume of transactions. Trading on HEX is organized in three main trading sessions: The opening session from 9:30am to 10:10am, under which authorized broker-dealers are allowed to enter their publicly invisible sell and buy orders into the system. The continuous trading session is held from 10:30am to 5:30pm during which orders are submitted with price and time priority. The after market session is split in an evening session from 5:30 to 6:00pm and a morning session from 9:00 to 9:30pm the following day. Under these after market sessions, transactions are matched under the conditions prevailing during the preceding continuous trading session.

3.2 Data preparation

We study the contribution of the fundamental and the transitory variance to the total variance on the basis of transactions data. Using transactions data is challenging in number of ways. The most significant drawback with transactions data is that not all the transactions are equally informative. In principle more data is preferably to coop with the statistical and the mathematical properties of the distribution, however the statistical and mathematical properties impose at the same time restrictions on the definition range of the data. A fundamental restriction is that the data observations should be independent. Another equally important restriction is that the data observations must display some variation in order to apply methods that are thought to summarize information under some probability distribution conditions. Once we have dealt with these problems, transactions data are essential to study questions concerning the understanding of market behaviour, and the testing of short-term hypotheses on variance, liquidity and market transparency.

In this paper we deal with these problems in two different ways. First, we prepare the data in such a way that we are only left with transactions that show variations in prices. In that we follow partly Engle and Russell (1997) by eliminating some transactions on the basis of the transaction prices. In Engle and Russell (1997), the difference between two consecutive prices should be at least equal to a given constant. We are less restrictive than that. We only thin the price process under the criteria that two consecutive prices should be different, that is, we ignore the price at time t-1 if it equals the price at time t and in such a case we add the trading volume of the price at time t-1 to the trading volume of the price at time t. After all, we aggregate the trading volumes for transactions occurring at the same time and price. Second, we adjust the data for the time of day effects. Adjusting the duration and the volume gives normalized series that can be accommodated in some useful way. For example, we might take the ratio of volume to duration, as their expectations are 1 to investigate the effect of trading more volume for a very short of time.

<Insert Table 1 about here>

Dividing the third column denoted as SMPL3 by the column denoted as SMPL1, we find that on average only 24% of the original number of observations remain after the process is thinned. The decrease is more severe for stocks toward the top of Table (1) than for stocks toward the bottom of the table. Table (1) reports also the mean statistics of the trade price (PRICE), the midquote price (MPRICE), the trade duration (DUR) and the trading volume (SIZE). These are variables we use to estimate different models. The means of PRICE and MPRICE are close to each other for the 25 stocks. The durations between transactions are increasing in trading activities. For example, it takes about 90 seconds to observe a price change on NOK1V the stock at the top of the table, whereas it takes bout an half hour to observe a price change on KCI1V, the stock at the bottom of the table. The size of the transaction is related to the price level. The lower the price level, the higher the volume traded on that price.

3.3 Estimating the Weibull-ACD and the Weibull-ACV model

There are several distributions with positive supports that can be used to estimate the ACD and the ACV model. Engle and Russell (1998) introduce the Exponential and the Weibull distribution, and provide some indications on the usefulness of each of the two distributions in capturing persistent features in the data. For actively traded stocks with a large number of clustered transactions, the exponential distribution adequately fits the data, but for infrequently traded stocks the Weibull distribution provides a better data fit because the Weibull distribution operates with a shape parameter that accommodates adequately very long durations.

<Insert Table 2 about here>

Table (2) presents results for ACD and ACV model estimates. The models are estimated with the BFGS algorithm due the nonlinearity of the models. The models did not have trouble to converge with the initial values provided. The ACD(1,1) and ACV(1,1) model are estimated using the Weibull distribution with a shape parameter, γ_k. The Weibull-log likelihood is

$$L = \sum_{t=1}^{N} \ln\left(\frac{\gamma}{\widetilde{z}_t}\right) + \gamma \ln\left(\frac{\Gamma\left(1+(1/\gamma)\widetilde{z}_t\right)}{\psi_t^z}\right) - \left(\frac{\Gamma\left(1+(1/\gamma)\widetilde{z}_t\right)}{\psi_t^z}\right)^{\lambda}, \tag{10}$$

where $\widetilde{z}_t$ is either $\widetilde{x}_t$ the adjusted duration or $\widetilde{v}_t$ the adjusted volume and $\Gamma(.)$ is the gamma function, and N is the number of observations. The Weibull parameter is on average 0.88. For stocks toward the top of Table (2), the Weibull parameter is over 1. For stocks toward the bottom of the table, the Weibull parameter is below 1, implying that the longer the observed duration, the less likely that a transaction will occur at that time. The parameters of the ACV and the ACD model are expected to be positive, and the sum of α_k and β_k to be less than 1 for the existence of the unconditional mean. The results of Table (2) exclude on the basis of non-stationary duration mean process and negative coefficients only two stocks, FSC1V and KCI1V. For the volume mean process only one stock (TJT1V) shows negative coefficients. On average persistence in trading intensity is higher on duration data (about 0.9196) than on volume data (about 0.864). Table (2) shows that durations and volumes capture well the traditional volatility regularities. Even though durations and volumes do not in the first place predict variance, they do forecast well future trading intensities. The crux with the ACD and the ACV estimates of Table

(2) is that they represent the volatility path from time and volume perspective. Since both duration and volume are proxy for trading intensity, we put forth the ratios of volume to duration. Following Renault and Werker (2002), we insert the ratios in an ARMA(1,1) model in a VEC model to investigate their effects on the mean and the variance, respectively.

3.4 Reporting the mean statistics of the estimated variables

Table (3) presents mean statistics for the adjusted duration (DURS), the adjusted volume (SIZES), the liquidity trading ratio (LIQR), the informed trading ratio (INFR), the variance of the midquote absolute return (VAR1), the variance of the trade absolute return (VAR2), and the covariance (COV12) and the correlation (COR12) between the midquote absolute return and the trade absolute return. Following Equation (7), the duration and the volume are seasonally adjusted for the time of day effect. This is accomplished by regressing the duration and the volume on the time of day variables defined over three segments capturing the three trading periods with different trading intensities. The adjustment is done by dividing the raw series by the fitted values from the regression. The adjusted series are more convenient to work with since their expectations are at 1. The VAR1, VAR2, and COV12 are elements of the variance-covariance matrix of the VEC model.

<Insert Table 3 about here>

The definition range of the adjusted duration and volume varies from stock to stock. In Table (3), only their mean statistics are reported. The mean of the adjusted series are close to 1, suggesting that the estimator constructed on the time of day effects scales efficiently the duration and the volume series. The results of the W-ACV and the W-ACD model are used to compute the liquidity trading variable and the informed trading variable. Except for two stocks (OUTAS and MESBS), the null hypothesis that LIQR = 1 is rejected for most of stocks, implying that more than 1 share is traded for 1 unit time. The rejection is even stronger for INFR.

The variance-covariance matrix of the VEC model is important for comparing the PT with the IS approach. According to Baillie et al. (2002), the two approaches give about the same result about the contribution of factors to the common factor when the innovations of the VECM are not contemporaneously correlated. Table (3) shows that the correlation between the midquote absolute return and the trade absolute return is on average 29.6%. Nonetheless, some stocks present very low correlation coefficient, implying that we might use for those stocks the variance-covariance matrix and the coefficient multipliers to estimate the contribution of the fundamental and the transitory to the total variance. In Table (5) we report these contributions using the PT approach. Table (4) shows that variances are increasing in the number of transactions since the stocks toward the bottom of the table show higher variances than stocks toward the top of the table. As we use the midquote absolute return as proxy for the fundamental variance and the trade absolute return as proxy for the transitory variance, the variance per unit time of the fundamental variance is on average 0.015%, whereas the variance per unit time of the transitory variance is much higher, 0.074%.

3.5 Estimating the ARMA model incorporating trading variables

Engle (2000) inserts a duration variable in an ARMA(1,1) model to study the effects of duration on price changes. The Easley and O'Hara (1992), Admati and Pfleiderer (1988), and Diamond and Verrecchia (1988) model suggest that watching time might reveal the identity of traders in presence. Instead of using duration and volume in isolation to study their effects on price changes and variances, we accommodate the two trading intensity by taking the ratio of volume to duration.

<Insert Table 4 about here>

Table (4) presents results on the first-order autoregressive coefficient a_1, the first-order moving average coefficient a_2, the liquidity trading proxy coefficient φ_j, the informed trading proxy coefficient ϕ_j, and the trade indicator coefficient β_j. The liquidity trading coefficient and the informed trading coefficient are sum of three slope dummy variables and the trade indicator coefficient is the sum of the current and lag 1 coefficient. The Wald test is used for the test of the summed coefficients that they are 0 under the null hypothesis. The ARMA model is estimated both for the midquote and the trade return, however for brevity the AR(1) and the MA(1) coefficient in Table (4) are those only from the midquote return equation. The AR(1) and the MA(1) coefficients are all significant, suggesting that trading frictions and microstructure effects have great influence on the midquote return process.

The liquidity trading coefficient is on average negative (-.0007) in the midquote equation and positive (.048) in the trade equation, suggesting that trading intensity is reversal in the midquote return process and persistent in the trade return process. The informed trading coefficient is on average positive in the two return processes. The liquidity trading coefficient shows that when traders trade more than 1 share for 1 unit time, this creates order flow imbalances in the book. Thus, prices have to decrease to attract more liquidity. At the same time informed traders consume more liquidity when they conduct their trades on the side of trade that has attracted more liquidity. The informed trading coefficient indicates that informed traders consume available liquidity on either side of trade. In that prices change when traders realize that liquidity is lacking on either side of trade, thus large prices are changed when liquidity is lacking rather than by concealed information which is the cause rather than the effect. The trade indicator coefficient is negatively related to price changes. On average, price decreases by 0.008 Euro immediately after a trade at ask has occurred.

3.6 Estimating the VECM: the long run and the short-run effects on variances

Table (5) presents the long-run estimate coefficients of the VECM on the fundamental and the transitory variance. We used the Gonzalo and Granger (1995) approach to test the long-run and the short-run relationship that might exist between the midquote returns variance and the trade returns variance. Glosten and Milgrom (1985) model powerfully the mechanism by which prices are revised in financial markets. In their model, traders arrive to market sequentially in an anonymous and random fashion, and trade one unit share at prices provided by market makers. Informed traders trade on their information whereas exposed traders (market makers and liquidity traders) learn from the volume and the price statistics (the extension by Easley and O'Hara (1992) introduce the time statistics to learn about the identity of the traders). News are incorporated into prices (bid and ask prices) when market makers revise timely their prices. An important assertion is that traders learn sequentially and discover at the end of the period the asset true value so that prices are at the end of the period efficient. Hence, there will be different transitory equilibriums before prices converge to zero spread. This dynamic is represented here with a VEC model that captures both short and long run trading dynamics in the process of price formation.

<Insert Table 5 about here>

Table (5) presents long-run coefficients of the VEC model, extended by inserting an error adjustment coefficient α. The adjustment parameter is intended to capture the speed of reaction by which the transitory variance adjusts to news. It follows that this coefficient represents the common information between traders as trades constitute the common information set. This is consistent with market microstructure asserting that trades convey information (Easley et al. (1997)). The second set of coefficients capturing the long-run relationship between variance deviations and the variances is given by δ_i. This coefficient captures the long-run relationship between the fundamental and the transitory variance. In the unrestricted VECM the coefficients are allowed to take any value, whereas in the restricted model they are forced to sum to 1.

To account for heteroskedasticity and autocorrelation in the residuals of the VECM, the coefficient standard errors are corrected using the heteroskedasticity autocorrelation consistent matrix (Newey and West (1987)). Table (5) shows that the adjustment coefficient α is greater for stocks toward the bottom of the table than stocks toward the top of the table. For example, the transitory variance deviates from the fundamental variance by 0.004 for NOK1V the most traded stock on HEX, whereas the deviation is larger for KCI1V, the less traded stock of the sample. The information share results of the Gonzalo and Granger (1995) model are estimated by restricting the long-run coefficients to sum to 1. As shown in Table (5) the values of δ_i indicate that 64.4% of the variance common factor is contributed by the fundamental variance against 35.6% by the transitory variance. Considering each stock in isolation, Table (5) shows that the contribution of the fundamental variance to the variance common factor is greater when the deviation of the transitory variance is low. The results of Table (5) establish that the midquote returns variance is the mechanism by which information is impounded in prices on HEX.

<Insert Table 6 about here>

Table (6) reports results on short-term variance and trading intensity effects. The first set of coefficients θ_j captures the lagged variance effects on current variances. The second and the third set of coefficients ϑ_j capture the variance effects of liquidity trading and informed trading, respectively. The coefficients are obtained both from the midquote returns variance equation and the trade returns variance equation. For brevity, the coefficients are summed and tested by Wald test under the null hypothesis that the sum is 0. The Wald test rejects the null hypothesis for most of the three sets of coefficients. The results on lagged variances indicate that in a model including short-term and long-term effects, short-term variances are strongly reversal. The results on the variance effects of liquidity trading and informed trading indicate that liquidity and information trading increase variance in the short-run. These short-term effects reveal that variance increases when traders transact more than 1 share for one unit time since this creates imbalances in the order flow. In Kyle (1985) market makers set prices that clear the market, and determine these prices on the basis of the aggregate traded quantity of informed and uninformed traders. However, quantities are fully revealing only when we relate them to the time it takes the market to clear. Hence by dividing the normalized volume to the normalized duration, we get a proxy for trading intensity capturing imbalances in the order flow. The results of Table (6) demonstrates that the sign of trade is not enough to separate the liquidity from the informed trading effect since both liquidity and informed traders transact often on the same side. It is rather the magnitude of the coefficient that captures the effect due to the two types of traders. This is a plausible explanation that can be given to the results of Table (6) on the variance effects of liquidity and informed trading.

4. Conclusion

The trust of this paper was to investigate the variance common factor between the fundamental and the transitory variance of 25 stocks from the Helsinki Stock Exchange.

The fundamental variance was defined in terms of midquote absolute returns and the transitory variance was defined in terms of trade absolute returns. Motivated by market microstructure studies that trades convey information, we investigate the speed by which the transitory variance adjusts to news. Whereas trades are revealing, there are still function of the bid and ask prices. In that they deviate time from to time from the true value maintained by market makers (liquidity providers) transacting on the basis of public information.

To investigate the relationship between the fundamental and the transitory variance, we use the vector error correction (VEC) model that extends the vector autoregressive (VAR) model by inserting a long-run term in the VAR model. Two popular models are used in the literature to represent the link between long-run and short-run effects. Using the PT approach, we find that the transitory variance deviates strongly from the fundamental variance, the lower the stock market value. We find also that much of variance contribution originate from midquote prices (fundamental prices) than from trade prices. On average the contribution to the long run variance attributable to the midquote returns variance is greater than the contribution attributable the trade returns variance. It means that in the long-run the variance is determined by midquote prices that accounts for about 64.4% of the long-run variance against 35.6% for trade prices. Overall, this study reveals the importance for market regulators to adequately attribute the origin of variance in the market in order to take measures that reduce the transitory variance rather than to take measures that aggravate it.

Appendix I

Equation 1 is computed as

$$
\begin{aligned}
\operatorname{var}(r_t) &= (n_t - n_{t-1} + \varepsilon_t)^2 \\
&= \varepsilon_t^2 + n_t n_{t-1} + n_t \varepsilon_t - n_{t-1} n_t + n_{t-1}^2 + n_t \varepsilon_t + \varepsilon_t n_t + \varepsilon_t n_{t-1} + \varepsilon_t^2 \\
&+ \underbrace{E[n_t^2]}_{\sigma_n^2} - \underbrace{2E[n_t n_{t-1}]}_{\rho_n} + \underbrace{2E[n_t \varepsilon_t]}_{=0} + \underbrace{E[n_{t-1}^2]}_{\sigma_n^2} + 2\underbrace{E[\varepsilon_t n_{t-1}]}_{=0} + \underbrace{E[\varepsilon_t^2]}_{\sigma_\varepsilon^2} \\
&= 2\sigma_n^2 + \sigma_\varepsilon^2 - 2\rho_n
\end{aligned}
$$

Equation 2 is computed as

$$
\begin{aligned}
\operatorname{cov}(r_t, r_{t-1}) &= (n_t - n_{t-1} + \varepsilon_t)(n_{t-1} - n_{t-2} + \varepsilon_{t-1}) \\
&= \underbrace{E[n_t n_{t-1}]}_{=0} - \underbrace{E[n_t n_{t-2}]}_{=0} + \underbrace{E[n_t \varepsilon_{t-1}]}_{=0} \\
&- \underbrace{E[n_{t-1} n_{t-1}]}_{\sigma_n^2} + \underbrace{E[n_{t-1} n_{t-2}]}_{=0} - \underbrace{E[n_{t-1} \varepsilon_{t-1}]}_{=0} \\
&+ \underbrace{E[\varepsilon_t n_{t-1}]}_{=0} + \underbrace{E[\varepsilon_t n_{t-1}]}_{=0} + \underbrace{E[\varepsilon_t \varepsilon_{t-1}]}_{=0} \\
&= -\sigma_n^2
\end{aligned}
$$

Equation (3) is computed as

$$
\begin{aligned}
\operatorname{var}(r_t) &= [\delta \varepsilon_t + (1-\delta)(n_t - n_{t-1})]^2 \\
&+ \delta^2 \underbrace{E[\varepsilon_t^2]}_{\sigma_\varepsilon^2} + 2\delta(1-\delta)\underbrace{E[\varepsilon_t n_t]}_{=0} + 2\delta(1-\delta)\underbrace{E[\varepsilon_t n_{t-1}]}_{=0} \\
&+ (1-\delta)^2 \underbrace{E[n_t^2]}_{=\sigma_n^2} - 2E(1-\delta)^2 \underbrace{E[n_t n_{t-1}]}_{\rho_n} + (1-\delta)^2 \underbrace{E[n_{t-1}^2]}_{\sigma_n^2} \\
&= \delta^2 \sigma_\varepsilon^2 + 2(1-\delta)^2 \sigma_n^2 - 2\delta(1-\delta)^2 \rho_n \\
&= \delta^2 \sigma_\varepsilon^2 + 2(1-\delta)^2 \left(\sigma_n^2 - \rho_n\right)
\end{aligned}
$$

Appendix II

In this appendix is given the name of the companies and their trading codes during the sample period that runs from March 2 to December 30, 1999. The number of shares outstanding is the number of shares at the end of 1999. The trading code is used in the text body rather than the security name (company).

Trading Code	Companies	Number of Shares (1999)
NOK1V	Nokia Oyj	1 158 236 186
SRA1V	Sonera Oyj	722 000 000
RAIVV	Raisio yhtyma	36 442 760
UPM1V	UPM-Kymmene Oyj	266 568 957
MTA1V	Merita Oyj	833 662 944
STERV	Stora Enso Oyj	550 658 501
JOT1V	JOT-Automation Group	170 617 200
TIE1V	TietoEnator Oyj	77 014 923
FUM1V	Fortum Oyj	784 782 635
HEPEV	Helsinki Puhelin Oyj	51 619 492
POS1V	Perlos Oyj	51 220 000
SAMAS	Sampo Oyj	60 560 000
HPHAV	HPH Holding	84 314 450
FSC1V	F-Secure Oyj	26 804 875
MESBS	Metsa-Serla Oyj	102 658 875
POHBS	Pohjola B	21 452 918
EIMAV	Eimo Oyj	9 800 000
STF1V	Stonesoft Oyj	52 536 140
RTRKS	Rautaruuki Oyj	138 886 445
TJT1V	TJ Group Oyj	17 574 175
OUTAS	Outokumpu Oyj	124 529 660
ELQAV	Elcoteq Oyj	12 738 500
HARAS	Hartwall Oyj	53 150 000
TPO1V	Tampereen puhelin Oyj	40 222 490
KCI1V	KCI Koncecranes	15 000 000

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Table 1
Data preparation and some summary statistics
SMPL1 is the original data simple including all the transactions during the sample period that runs from March 2 to December 30, 1999. SMPL2 is the sample after consecutive prices are set to be different to each other. SMPL3 is the sample after consecutive trading volumes at the same time and same price have been aggregated, and transactions from the opening and after market session have been deleted. PRICE is the transaction price. MPRICE is the midquote price obtained as the average price of the ask and the bid price at time t. DUR is the transaction duration. SIZE is the aggregate size. PRICE, MPRICE, DUR and SIZE are averages over the sample period.

STOCKS	SMPL1	SMPL2	SMPL3	PRICE	MPRICE	DUR	SIZE
NOK1V	445 357	124 651	55 783	98.74	98.74	90.90	7 715
SRA1V	121 532	32 024	21 047	29.21	29.24	238.53	9 140
RAIVV	66 072	20 065	14 352	8.32	8.32	333.22	7 905
UPM1V	58 277	13 249	10 994	31.18	31.18	448.15	10 961
MTA1V	52 835	11 022	9 456	5.43	5.43	520.72	35 242
STERV	40 210	9 348	8 093	12.25	12.25	594.52	24 368
JOT1V	39 309	12 395	9 518	21.62	21.61	505.04	4 811
TIE1V	39 030	11 915	9 338	36.34	36.34	524.42	3 793
FUM1V	28 510	7 989	6 980	4.70	4.69	702.75	9 855
HEPEV	25 526	7 605	6 225	47.90	47.91	767.90	2 408
POS1V	24 478	7 249	5 570	15.71	15.71	551.37	4 343
SAMAS	24 131	7 017	5 933	30.27	30.26	807.03	4 243
HPHAV	23 767	7 523	5 949	22.94	22.95	503.06	2 301
FSC1V	20 279	6 077	3 270	25.69	25.68	251.21	1 956
MESBS	15 327	3 939	3 503	8.66	8.66	1251.70	10 706
POHBS	14 224	3 812	3 326	50.43	50.42	1279.77	4 991
EIMAV	13 901	5 250	4 224	18.50	18.50	1014.33	2 289
STF1V	11 711	4 407	3 586	19.14	19.13	1062.14	1 684
RTRKS	11 516	2 919	2 681	6.25	6.25	1566.55	11 461
TJT1V	10 840	4 338	3 500	17.82	17.82	1115.00	1 327
OUTAS	10 535	2 973	2 713	11.30	11.30	1615.21	6 941
ELQAV	10 428	3 874	3 236	10.03	10.02	1203.56	1 926
HARAS	10 079	3 661	3 174	12.84	12.84	1398.54	2 369
TPO1V	9 897	3 568	2 996	6.98	6.98	1447.48	3 321
KCI1V	7 668	2 331	2 047	29.71	29.70	1721.53	4 453

Table 2
The estimates of the W-ACD(1,1) and W–ACV(1,1) model

The W-ACD(1,1) and the W-ACV(1,1) model are $\psi_{k,t} = \omega_k + \alpha_k \tilde{z}_{k,t-1} + \beta_k \psi_{k,t-1}$, where $\psi_{k,t}$ is the expected duration for $k=1$ and the expected volume for $k=2$, $\tilde{z}_t$ is $\tilde{x}_t$ the adjusted duration for $k=1$, and $\tilde{z}_t$ is $\tilde{v}_t$ the adjusted volume for $k=2$. The Weibull distribution is given by equation (10), where γ_k is the Weibull parameter. For $\gamma_k = 1$, the process follows an exponential distribution. The linear ACD and ACV model implies that $\omega_k \geq 0$, $\alpha_k \geq 0$, $\beta_k \geq 0$, and $(\alpha_k + \beta_k) \leq 1$.

STOCKS	ω_1	α_1	β_1	γ_1	ω_2	α_2	β_2	γ_2
NOK1V	0.0040	0.0271	0.9692	1.4610	0.0348	0.0856	0.8794	0.8902
SRA1V	0.0020	0.0411	0.9574	1.0969	0.0118	0.0476	0.9401	0.7432
RAIVV	0.0060	0.0679	0.9272	1.0239	0.0146	0.0409	0.9431	0.7573
UPM1V	0.0066	0.0408	0.9527	0.9471	0.0154	0.0403	0.9433	0.7375
MTA1V	0.0121	0.0507	0.9374	0.9198	0.1666	0.1626	0.6728	0.7061
STERV	0.0152	0.0544	0.9304	0.8895	0.0275	0.0374	0.9342	0.7250
JOT1V	0.0021	0.0470	0.9509	0.9713	0.0007	0.0220	0.9762	0.6693
TIE1V	0.0037	0.0554	0.9418	0.9179	0.0158	0.0341	0.9485	0.7034
FUM1V	0.0359	0.0719	0.8950	0.9201	0.0618	0.0436	0.8790	0.6204
HEPEV	0.0108	0.0646	0.9252	0.8632	0.0202	0.0308	0.9463	0.6791
POS1V	0.0023	0.0558	0.9430	0.9356	0.0142	0.0459	0.9349	0.6452
SAMAS	0.0066	0.0410	0.9529	0.8337	0.0939	0.0613	0.8329	0.6635
HPHAV	0.0038	0.0389	0.9574	0.9391	0.0111	0.0151	0.9719	0.7165
FSC1V	-0.0004	0.0404	0.9619	1.1683	0.0189	0.0548	0.9217	0.7330
MESBS	0.0220	0.0477	0.9310	0.7645	0.0490	0.0247	0.9225	0.8102
POHBS	0.0134	0.0595	0.9283	0.7361	0.0571	0.0664	0.8640	0.7039
EIMAV	0.0067	0.0642	0.9303	0.8413	0.0800	0.0545	0.8432	0.6206
STF1V	0.0016	0.0588	0.9404	0.8375	0.0693	0.0449	0.8683	0.6560
RTRKS	0.0129	0.0270	0.9589	0.7419	0.0732	0.0263	0.8921	0.6913
TJT1V	0.0074	0.0344	0.9525	0.6469	0.9822	-0.0022	-0.1357	0.6907
OUTAS	0.0370	0.0715	0.8877	0.6879	0.2483	0.0738	0.6466	0.6690
ELQAV	0.0043	0.0654	0.9312	0.8222	0.0042	0.0100	0.9848	0.6617
HARAS	0.0154	0.0491	0.9363	0.7731	0.0509	0.0364	0.9044	0.6805
TPO1V	0.0097	0.0720	0.9203	0.7726	0.7512	0.0453	-0.0088	0.6373
KCI1V	1.9538	0.0007	-0.7764	0.6410	0.0060	0.0167	0.9750	0.6419
MEAN	0.0878	0.0499	0.8697	0.8861	0.1151	0.0448	0.8192	0.6981

Table 3
The summary statistics of the adjusted and estimated variables

DURS is the average of the adjusted durations, SIZES is the average of the adjusted trading volumes, LIQR is the average of the ratio of the expected volumes to the expected durations, INFR is the average of the ratio of the volume innovations to duration innovations, VAR1 is the variance from the midquote return equation in the VEC model, VEC model stands for the vector error correction model, VAR2 is the variance from the transaction return equation in the VEC model, COV12 is the covariance between the transaction and the midquote return equations, and COR12 is the correlation between the innovations from the equation of the midquote returns in the VEC model and the innovations from the equation of the transaction returns.

STOCKS	DURS	SIZES	LIQR	INFR	VAR1	COV12	VAR2	COR12
NOK1V	0.9999	1.0004	1.0453	3.8147	0.0038	0.0032	0.0061	0.6707
SRA1V	0.9997	1.0002	1.3016	3.9247	0.0018	0.0003	0.0165	0.0597
RAIVV	0.9975	1.0000	1.3777	3.8989	0.0031	0.0016	0.0264	0.1725
UPM1V	0.9988	1.0002	1.1065	3.9684	0.0060	0.0031	0.0072	0.4677
MTA1V	0.9973	1.0517	1.1412	3.9538	0.0008	-0.0011	0.0287	-0.2338
STERV	0.9979	0.9990	1.1164	3.8335	0.0078	0.0029	0.0095	0.3361
JOT1V	0.9977	1.0003	1.8066	3.6258	0.0043	0.0031	0.0336	0.2578
TIE1V	0.9963	0.9999	1.4089	4.2184	0.0063	0.0018	0.0116	0.2100
FUM1V	0.9945	1.0003	0.9174	3.9312	0.1748	0.0196	0.0295	0.2727
HEPEV	0.9948	1.0022	1.1987	4.1819	0.0089	0.0134	0.0333	0.7817
POS1V	0.9929	1.0000	1.5977	4.1091	0.0158	0.0097	0.0220	0.5206
SAMAS	0.9920	1.0036	1.0464	4.2141	0.0064	0.0041	0.0261	0.3167
HPHAV	0.9988	1.0026	1.1044	3.4844	0.0077	0.0035	0.0101	0.4021
FSC1V	1.0027	1.0095	1.7709	3.9676	0.0070	0.0025	0.0398	0.1524
MESBS	1.0025	0.9999	1.0070	4.4728	0.0024	0.0030	0.0487	0.2813
POHBS	0.9956	1.0000	1.1036	4.3126	0.0186	0.0283	0.1861	0.4809
EIMAV	0.9895	1.0000	1.0815	4.1034	0.0044	0.0057	0.0560	0.3648
STF1V	1.0075	1.0000	1.4542	4.0635	0.0122	0.0051	0.1316	0.1265
RTRKS	1.0126	1.0006	0.9834	4.0819	0.0122	0.0074	0.0515	0.2952
TJT1V	2.5574	1.0006	1.3743	4.6596	0.0145	0.0026	0.1711	0.0529
OUTAS	0.9860	1.0017	1.0074	4.5250	0.0062	-0.0004	0.1036	-0.0149
ELQAV	1.0036	0.9999	1.3074	4.5470	0.0021	0.0051	0.2160	0.2414
HARAS	0.9821	1.0018	1.0070	4.3380	0.0121	0.0238	0.1953	0.4900
TPO1V	0.9864	1.0961	0.9612	4.5144	0.0123	0.0186	0.1384	0.4501
KCI1V	0.9529	1.0003	0.8312	5.5027	0.0195	0.0164	0.2524	0.2339
MEAN	1.0575	1.0068	1.2023	4.1699	0.0148	0.0073	0.0740	0.2956

Table 4
The ARMA(1,1) Model including trading variables
The estimated models are

$$r_{it} = a_0 + a_1 r_{it-1} + a_2 e_{it-1} + \sum_{j=1}^{3} \varphi_j D_{jt} \Delta_{tj}^{L} + \sum_{j=1}^{3} \phi_j D_{jt} \Delta_{tj}^{I} + \sum_{k=0}^{K} \beta_k Q_{t-k} + e_{it},$$

where r_{it} is the midquote return for $i=1$ and the trade return for $i=2$, $\Delta_{jt}^{L} = \psi_t^v / \psi_t^x$ the ratio of the volume expectation to the duration expectation, $\Delta_t^I = C_t^v / C_t^x$ the ratio of the volume innovation to duration innovation for $C_t^v = \left[\left(\widetilde{v}_t / \psi_t^v\right)\left(\left(\widetilde{v}_t / \psi_t^v\right) - 1\right)\right]$, where $\widetilde{v}_t$ is the adjusted trading volume and $C_t^x = \left[\left(\widetilde{x}_t / \psi_t^x\right)\left(\left(\widetilde{x}_t / \psi_t^x\right) - 1\right)\right]$, $\widetilde{x}_t$ is the adjusted duration, and D_t is a series of dummy variables for $j=1$ when $\Delta_{jt}^k < 1$, $j=2$ when $1 < \Delta_{jt}^k > 2$ and $j=3$ when $\Delta_{jt}^k > 1$.

STOCKS			Midquote Equation			Trade Equation		
	a_1	a_2	$\sum_{j=1}^{3}\varphi_j$	$\sum_{j=1}^{3}\phi_j$	$\sum_{j=1}^{3}\beta_j$	$\sum_{j=1}^{3}\varphi_j$	$\sum_{j=1}^{3}\phi_j$	$\sum_{j=1}^{3}\beta_j$
NOK1V	-0.6230	0.6327	-0.0030	-0.0023	0.0020	-0.0028	-0.0064	-0.0020
SRA1V	0.6212	-0.6419	-0.0095	0.0079	0.0004	-0.0030	0.0098	0.0012
RAIVV	0.3261	-0.3441	-0.0065	0.1406	-0.0078	0.0203	0.2673	-0.0153
UPM1V	0.1686	-0.2121	-0.0049	0.0781	-0.0119	0.0104	0.2343	-0.0085
MTA1V	-0.4307	0.3932	-0.0303	0.0193	-0.0183	-0.0016	0.0137	0.0073
STERV	0.2519	-0.2655	-0.0001	-0.0288	-0.0095	-0.0022	0.0020	-0.0043
JOT1V	-0.7999	0.8364	-0.0107	0.0249	-0.0326	-0.0162	0.4269	-0.0199
TIE1V	-0.1954	0.1949	0.0063	-0.0086	-0.0012	-0.0004	-0.0134	-0.0052
FUM1V	3.1570	0.2173	0.1566	0.4744	0.0216	0.0074	0.3383	-0.0013
HEPEV	-0.2216	0.4014	-0.0201	0.0043	-0.0102	-0.0032	0.0279	-0.0057
POS1V	-0.7868	0.8067	0.0176	0.0038	-0.0157	0.0142	0.0334	-0.0042
SAMAS	-0.9828	0.9862	0.0027	0.0009	-0.0021	0.0002	0.1318	-0.0100
HPHAV	-0.6718	0.6758	-0.0116	-0.0131	-0.0031	-0.0002	-0.1363	-0.0017
FSC1V	0.7005	-0.7481	-0.0013	0.0205	-0.0055	0.0058	0.0301	-0.0011
MESBS	-0.1351	0.0652	0.0833	-0.0168	0.0005	-0.0301	-0.3268	-0.0085
POHBS	0.1398	0.1131	0.0850	0.3735	-0.0579	0.6443	1.4994	0.1292
EIMAV	0.2643	-0.2254	-0.0004	0.3525	-0.0054	0.0485	0.7321	-0.0136
STF1V	0.6217	-0.5876	-0.0221	0.3447	-0.0060	0.0102	0.6997	-0.0028
RTRKS	0.2735	-0.2478	-0.1413	0.0074	0.0019	-0.3469	0.1201	-0.0170
TJT1V	0.0634	-0.0552	-0.0998	1.2010	-0.0133	0.9072	2.2110	-0.0638
OUTAS	0.7922	-0.8063	0.0163	0.0082	-0.0019	-0.0136	-0.0182	-0.0064
ELQAV	1.0559	-1.0825	-0.0428	0.0681	-0.0190	0.5047	0.9709	-0.0956
HARAS	0.6863	-0.7202	-0.0114	0.0209	-0.0008	-0.0240	0.8085	-0.0296
TPO1V	0.6675	-0.6769	0.0892	0.0118	-0.0042	-0.0003	0.0467	0.0044
KCI1V	0.7924	-0.8853	-0.0584	-0.0608	-0.0043	-0.5209	-0.1188	-0.0040
MEAN	0.2294	-0.0870	-0.0007	0.1213	-0.0082	0.0483	0.3194	-0.0071

Table 5
The estimates of the VECM: Test of the long run effects
The following model is estimated. Reported are the long-run coefficients.

$$|e_{1t}| = \delta_1 \left[|\tilde{r}_{1t}| - \alpha |\tilde{r}_{2t}| \right] + \sum_{j=1}^{3} \theta_{10j} |e_{1t-j}| + \sum_{j=1}^{3} \vartheta_{11j} D_{tj} \Delta_t^L + \sum_{i=1}^{3} \vartheta_{12j} D_{tj} \Delta_t^I + \eta_{1t}$$

$$|e_{2t}| = \delta_2 \left[|\tilde{r}_{1t}| - \alpha |\tilde{r}_{2t}| \right] + \sum_{j=1}^{3} \theta_{20j} |e_{2t-j}| + \sum_{j=1}^{3} \vartheta_{21j} D_{tj} \Delta_t^L + \sum_{j=1}^{3} \vartheta_{22j} D_{tj} \Delta_t^I + \eta_{2t}$$

Where e_{kt} is the error term from the ARMA(1,1) model, $\tilde{r}_{1t}$ is the midquote return, $\tilde{r}_{2t}$ is the trade return, Δ_{jt}^L is the ratio of the expected volume to the expected duration, Δ_t^I is the ratio of the volume innovation to the duration innovation, D_t is a series of dummy variables for $j=1$ when $\Delta_{jt}^k < 1$, $j=2$ when $1 < \Delta_{jt}^k > 2$ and $j=3$ when $\Delta_{jt}^k > 1$. One asterisk (*) means that the coefficient is significant at 5% statistical level, at least.

STOCKS	The Unrestricted Equation			The Restricted Equation: $\delta_1 + \delta_2 = 1$	
	δ_1	δ_2	α	δ_1	δ_2
NOK1V	0.4540*	0.4701*	0.0037*	0.4004*	0.5996*
SRA1V	0.7233*	0.6905*	-0.0173*	0.7711*	0.2289*
RAIVV	0.7985*	0.7106*	0.0385*	0.8085*	0.1915*
UPM1V	0.5445*	0.6285*	0.1272*	0.5100*	0.4900*
MTA1V	0.8757*	0.5027*	-0.0238*	0.9137*	0.0863*
STERV	0.5883*	0.6119*	0.0716*	0.4698*	0.5302*
JOT1V	0.8837*	0.6641*	0.1284*	0.8759*	0.1241*
TIE1V	0.6101*	0.5962*	0.0048*	0.5008*	0.4992*
FUM1V	1.1335*	0.9452*	0.7711*	0.9930*	0.0070
HEPEV	1.0951*	0.9082*	0.4865*	0.9988*	0.0012
POS1V	0.4504*	0.5886*	0.0267*	0.3030*	0.6970*
SAMAS	0.6881*	0.7334*	0.0457*	0.6566*	0.3434*
HPHAV	0.5177*	0.5951*	0.0093*	0.3738*	0.6262*
FSC1V	0.7361*	0.6894*	0.0356*	0.7351*	0.2649*
MESBS	0.8653*	0.7786*	0.0516*	0.8623*	0.1377*
POHBS	0.8937*	0.6372*	0.2940*	1.0016*	-0.0016
EIMAV	0.8847*	0.7906*	0.1065*	0.9136*	0.0864*
STF1V	0.8217*	0.7634*	0.0430*	0.8506*	0.1494*
RTRKS	0.6478*	0.7425*	0.0186*	0.6022*	0.3978*
TJT1V	0.8378*	0.6251*	0.0477*	0.8722*	0.1278*
OUTAS	0.8168*	0.6334*	-0.0042*	0.8063*	0.1937*
ELQAV	0.1812*	0.5266*	0.7616*	0.0837*	0.9163*
HARAS	0.1877*	0.7906*	0.8561*	0.2392*	0.7608*
TPO1V	0.1734*	0.6559*	0.7827*	0.3001*	0.6999*
KCI1V	0.2254*	1.0245*	0.8220*	0.2482*	0.7518*
MEAN	0.6654	0.6921	0.2195	0.6436	0.3564

Table 6
The estimates of the VECM: The short-run effects

The following models are estimated. Reported in this table are the short-term coefficients.

$$|e_{1t}| = \delta_1 \left[|\widetilde{r}_{1t}| - \alpha |\widetilde{r}_{2t}| \right] + \sum_{j=1}^{3} \theta_{10j} |e_{1t-j}| + \sum_{j=1}^{3} \vartheta_{11j} D_{tj} \Delta_t^L + \sum_{i=1}^{3} \vartheta_{12j} D_{tj} \Delta_t^I + \eta_{1t}$$

$$|e_{2t}| = \delta_2 \left[|\widetilde{r}_{1t}| - \alpha |\widetilde{r}_{2t}| \right] + \sum_{j=1}^{3} \theta_{20j} |e_{2t-j}| + \sum_{j=1}^{3} \vartheta_{21j} D_{tj} \Delta_t^L + \sum_{j=1}^{3} \vartheta_{22j} D_{tj} \Delta_t^I + \eta_{2t}$$

Where e_{kt} is the error term from the ARMA(1,1) model, r_{1t} is the midquote return, r_{2t} is the trade return, Δ_{jt}^L is the ratio of the expected volume to the expected duration, Δ_t^I is the ratio of the volume innovation to the duration innovation, D_t is a series of dummy variables for $j=1$ when $\Delta_{jt}^k < 1$, $j=2$ when $1 < \Delta_{jt}^k > 2$ and $j=3$ when $\Delta_{jt}^k > 1$. One asterisk (*) means that the sum of the three coefficients is significant at 5% statistical level, at least. The Wald test is used for testing the sum of the coefficients.

STOCKS	Midquote Equation			Trade Equation		
	$\sum_{k=1}^{3}\theta_{10k}$	$\sum_{j=1}^{3}\vartheta_{11k}$	$\sum_{j=1}^{3}\vartheta_{12k}$	$\sum_{k=1}^{3}\theta_{20k}$	$\sum_{j=1}^{3}\vartheta_{21k}$	$\sum_{j=1}^{3}\vartheta_{22k}$
NOK1V	-0.0037*	-0.0013*	-0.0009*	-0.1794*	-0.0145*	0.0006*
SRA1V	-0.0052*	-0.0011*	-0.0049*	-0.5613*	-0.0169*	-0.0018*
RAIVV	0.0018*	-0.0075*	-0.1028*	-0.1324*	-0.0539*	-0.2115*
UPM1V	-0.0338*	-0.0054*	-0.0556*	-0.0847*	-0.0326*	-0.2334*
MTA1V	-0.0201*	-0.0345*	0.0072*	-0.6050*	-0.0207*	0.0108*
STERV	0.0065*	-0.0191*	-0.0172*	-0.1096*	-0.0305*	0.0021*
JOT1V	-0.0444*	-0.1126*	-0.0715*	-0.0131*	-0.0908*	-0.3894*
TIE1V	0.0006*	-0.0040*	-0.0011*	-0.2266*	-0.0233*	-0.0045*
FUM1V	-0.2614*	-0.2323*	-0.4213*	0.0022*	-0.1038*	-0.2965*
HEPEV	-0.1557*	-0.1110*	-0.0148*	-0.0412*	-0.0840*	-0.0051*
POS1V	-0.0143*	-0.0136*	-0.0028*	-0.1909*	-0.0702*	-0.0154*
SAMAS	0.0008*	-0.0154*	-0.0007*	-0.1107*	-0.0781*	-0.1068*
HPHAV	-0.0006*	-0.0057*	-0.0071*	-0.0619*	-0.0434*	-0.1013*
FSC1V	-0.0430*	-0.0234*	-0.0298*	-0.3437*	-0.0647*	-0.0223*
MESBS	-0.0491*	-0.0658*	-0.0195*	-0.0591*	-0.0876*	-0.2693*
POHBS	-0.0912*	-0.2925*	-0.3861*	-0.1884*	-0.8872*	-1.3677*
EIMAV	-0.0129*	-0.0155*	-0.3128*	-0.1020*	-0.1618*	-0.7129*
STF1V	-0.0291*	-0.0549*	-0.2415*	-0.1336*	-0.1519*	-0.5639*
RTRKS	-0.0190*	-0.1781*	0.0001*	-0.1153*	-0.5243*	-0.0581*
TJT1V	0.0168*	-0.0414*	-1.0264*	-0.0116*	-1.2756*	-2.1575*
OUTAS	-0.0094*	-0.0215*	-0.0001*	-0.4050*	-0.1584*	0.0825*
ELQAV	-0.8960*	-0.0006*	-0.0001*	-0.4539*	-1.1019*	-1.2536*
HARAS	-0.0135*	-0.1078*	0.0267*	-0.0399*	-0.3024*	-0.5387*
TPO1V	-0.0868*	-0.0894*	0.0132*	-0.2202*	-0.1787*	0.0899*
KCI1V	-0.5804*	-0.2202*	0.0359*	-0.3448*	-0.6714*	0.2327*
MEAN	-0.0937	-0.0670	-0.1054	-0.1893	-0.2491	-0.3156